Long-term Follow-up of Hydrocephalus Patients and Prediction of Risk Factors using Machine Learning

By

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Abstract

Hydrocephalus is a disorder when an excessive amount of cerebrospinal fluid (CSF) accumulates inside the subarachnoid space, which can lead to an enlargement of the ventricular system of the brain and increase the pressure inside the head.

Paediatric population, adults, and most elderly ones can be affected by hydrocephalus. This neurological condition can have an excellent diagnosis if treated. However, it also can be life threatening if not treated correctly. With the increasing roll-out of ‘digital hospitals’, electronic medical records, new data capture and analysis technologies, as well as a digitally enabled health consumer, the healthcare workforce is required to become digitally literate to manage the significant changes in the healthcare landscape. In this study, Machine learning techniques are employed for the long-term follow-up for hydrocephalus patients, for which a data set of 3,262 records of ICP signals of shunted patients from Alder Hey Hospital, was used. Six popular machine-learning based classifiers have been evaluated for the classification of monitoring shunted patients and produce the required risk assessments to follow up shunted patients within a supervised learning setting, which are Ensemble Bagged Tree, Ensemble Boosted Tree, Fine Tree, Quadratic SVM, Gaussian SVM and Cubic SVM. The classifier Ensemble Boosted Tree achieved the highest aggregate performance outcomes of accuracy 98.90, sensitivity 100, specificity 100 and precision of 100. The study concludes that using machine learning techniques represents an alternative procedure that could assist healthcare professionals, as well as the specialist nurse and junior doctor to improve the quality of care and follow-up with hydrocephalus disorder.

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List of Abbreviations

Cerebral Fluid	CSF
Machine Learning	ML
Intracranial Pressure	ICP
Normal-pressure Hydrocephalus	NPH
UK National Health Service	NHS
Idiopathic Intracranial Hypertension	IIH
Lower Pressure	LP
Differential Pressure	DP
Ventriculoperitoneal Shunt	VPS
Computed Tomography	CT
Magnetic Resonance Imaging	MRI
Cerebral Perfusion Pressure CPP	CPP
Cerebral Blood Flow	CBF
Ventricular Drain	EVD
Artificial Intelligence	AI
Principle Component Analysis	PCA
Support Vector Machine (SVM)	SVM
Artificial Neural Networks (ANN)	ANN
Body Mass Index (BMI	BMI
Tumor Tissue Microarray (TMA)	TMA
Percentage of Training Data	PTD
True Positive Rate	TPR
True Negative Rate	TNR

Chapter 1 Introduction

1.1 Overview

Hydrocephalus is considered as a common disease treated by paediatric neurosurgeons. Hydrocephalus is a complex condition caused by physical or functional obstruction of cerebral fluid (CSF) flow. Hydrocephalus disease can be inherited or acquired [1]. This functional obstruction leads to progressive ventricular dilatation. Different studies showed that 1.1 in 1,000 infants have hydrocephalus; there have been few systematic assessments of the causes of hydrocephalus in this age group, which makes it a challenging condition to approach as a scientist or as a clinician [2].

Medical societies have utilised technology in the development of medical information systems. These developments aim to improve the deployment of technology in medical applications. Professional systems and many artificial intelligence techniques have been used and developed to improve decision support tools for decision-makers. The integration between technology and healthcare provides the medical systems to manage the chronic disease burden and support our ageing population as well as reducing healthcare costs and supporting clinical decision making [3].

Machine learning (ML) has proven to be a great tool that allows classifying large data sets and making predictions about the world. Classification determines the category an object belongs to and regression deals with obtaining a set of numerical input or output examples that are used to discover functions to find a suitable output from a given input. Mathematical analysis of ML algorithms and their performance is a well-defined branch of theoretical computer science, often referred to as computational learning theory. Machine learning algorithms have been developed to propose new methods with theoretical algorithms. Machine learning algorithms can develop techniques for applying real-life situations [4].

The goal for implementing machine learning techniques is to utilise experience, improve performance and for obtaining correct predictions and classification. The inspiration for using machine-learning techniques is to handle a hypothetically unlimited amount of data and process them to achieve excellent accuracy and performance.

Classification techniques (classifier) provide grouping with a set of symbols into several classes that depend on their attributes (features). A feature is considered as one characteristic of a symbol that can help in accumulating each class. The data type is considered to be one of the essential factors that affect the success of a learning method. The medical data set in this study is a supervised learning method that can learn from the training sets that involved input features and the target values (Classes) [5]. Inadequate training instances make it relatively hard for machine learning techniques to predict the target values of the medical data sets accurately. It is crucial to decrease the number of random features using a dimensionality reduction procedure to achieve high accuracy and performance [6]. In this study, the feature extraction approach is used to map the best data set of Intracranial Pressure (ICP) signals as an input to machine learning. The enhancement of communication technologies and their implementation in the medical sector have successfully changed the way of life, by improving healthcare facilities and outcomes. Healthcare organisations are continually attempting to enhance patient care by providing cost-effective care, better infrastructure, and quality of services [7] [8]. It is so vital for shunted patients to be monitored regularly and provide them with the proper response needed. The main contribution of this research is to develop and design a model that monitors and follows up shunted patients and gives them the chance to record data regularly, which can be accessed at any time by clinicians.

The automated follow-up system will provide an option to modify the medical delivery method from the traditional way into the automatic way. There are significant aspects required to build smart home systems in terms of allowing people to manage their health with out-of-hospital care. The backbone of the proposed research is to develop an intelligent system that monitors shunted patients regularly. The system is based on machine learning algorithms and a ready-to-use web application that aims to provide shunted patients much more flexibility for managing their conditions.

1.2 Research Statement

Hydrocephalus is considered as a complicated neurological disorder. It is an enlargement of the ventricular system of the brain and increases the pressure inside the head. This enlargement is caused by the insufficient passage of cerebrospinal fluid (CSF) from its point of production within the cerebral ventricles to its point of absorption into the systemic circulation. In other words, an imbalance between the production of CSF and its absorption could lead to one of three types of hydrocephalus: communicating, non-communicating and normal pressure hydrocephalus (NPH) [9].

The initial monitoring and follow up of shunted patients are an essential part of ongoing patient safety. Most regional neuroscience centres are monitoring large cohorts of shunted patients from their region and outside. This process is often for the remainder of the patient's life with little evidence-based for how and when they should be seen as out-patients. Moreover, this process places a massive burden on the patients and their families in terms of travel, time off work, school and any other daily life aspects. In general, the shunt failure rate seems to be unchanging despite advances in neurosurgical practice; as shown by numerous follow-up studies. 30 to 40 % of shunted paediatric patients have a shunt failure within the first year [8]. A follow-up study showed that 51.4% of 344 hydrocephalus children at 12 different centres had shunt failure. The overall shunt survival rate drops by 21% over four years, starting at 62% in the first year and ending at 41% in the fourth year [10]. Another long-term study analyses the clinical follow-up evaluations of 1,015 patients with a shunt. The median age of patients was 41.6, and the mean follow-up time was 9.2 years.

There are two problems, which are still open to investigation and solve:

1. How can we use advances in computer technologies to help clinicians managing long-term follows up for patients with hydrocephalus (who are already shunt dependent)?
2. How can we use advances in data science to help junior clinicians to make their own decisions in diagnosing hydrocephalus based on the senior clinician's decisions?

1.3 Research Goal, Aims and Objectives

1.3.1 Research Goal

The research goal is to implement an intelligent approach to follow-up, and management of shunted patients, which employs novel approach supported by machine learning techniques to improve the procedure of alerting the medical team in neurology clinics according to risk levels. In this research, the use of the intelligent approach will be a novel pathway to manage the waiting list according to risk levels, therefore improve neurology clinics' work and increase the capacity of the current service model by designing a data quality framework to describe all the essential measures for data processing and analysis, making use of sophisticated statistical methods. This helps to ensure that the data is clean enough and valid to train different machine learning algorithms. These intelligent risk assessment models will be tested and evaluated using different performance metrics to demonstrate their prediction power.

1.3.2 Research Aims

The main aim of this research is to provide a robust and sufficient risk assessment model as well as alerting the medical team of patients with hydrocephalus. The intelligent approach employs a novel method supported by machine learning for this purpose and initialising a user-friendly follow-up platform that will support long-term monitoring of shunted patients and involve them in managing their conditions. We will work towards these aims by addressing the following objectives.

1.3.3 Research Objectives

Tailoring a decision support system can significantly improve the way patients suffering from hydrocephalus are treated and followed. The key objective of this research is to produce an intelligent decision support system that will learn and evolve to help with the proper therapeutic decisions for the treatment of specific symptoms caused by hydrocephalus. The research objectives will be achieved by examining further the current approaches and evaluating the best methods and combinations of the approaches of how proper analysis and support for decision making can be achieved.

A breakdown of the research objectives is provided hereunder:

1- To produce a comprehensive literature review.

2- To understand the process of monitoring shunted patients that carried out by clinicians.

3- To gather a sufficient dataset that is required for this research.

4- To define a method to select the ICP signals and convert it to numeric.

5- To define a method to develop an improved follow-up platform by including more parameters required by neurologists and according to patients' willingness.

6- To define a method to predict the risk assessments for a given patients scenario.

7- To implement a working prototype of the proposed methodology and evaluate its performance.

1.4 Research Contribution

Currently, no intelligent mobile application has yet been developed to manage patients diagnosed with hydrocephalus. Therefore, the new proposed system will help to manage all patients diagnosed with hydrocephalus and have implanted shunts. Those patients are challenging to follow and to apply specific treatment plans because of the complexities involved when treating patients with hydrocephalus. The proposed system will enhance and improve the decisions made by physicians and neurosurgeons when applying new treatment plans and following up patients. It will also help to cut down unnecessary hospital visits, as most of the patients will send their symptoms and headache pain events to their assigned physician using their mobile phone while they are following a specific treatment plan. Physicians will be able to help address the needs of their patients without the need for a physical meeting. The developed follow-up platform allows physicians and neurosurgeons to collect and analyse new information about the behaviour of their patients and the success of the treatment plans applied on their patients. The new intelligent system will be able to analyses (knowledge data discovery) the data collected from patients, physicians and neurosurgeons. The new intelligent system will adapt to new environments and learn from new data inputted by all the users concerned, thus refining and altering treatment plans using the appropriate artificial intelligence techniques. It will facilitate the management of patients' history and keep them informed about any changes regards to the treatment plan they are following. It will help physicians and neurosurgeons decide on what works best in terms of materials (type /size of shunt placed inside the patient), treatment plans and drugs used on their specific patients and eliminate unnecessary costs of unwanted/unused materials purchased as the system will recognise and help physicians to indicate which worked best on their patients. Finally, it will reduce time wasted on unnecessary tests that will be carried out to specify what treatment plan best suits the patient concerned. The following are a summary of the main research contributions.

1- Developing a ground truth data to follow-up hydrocephalus patients by combining the neurologists' decisions in addition to patients' data via the developed application. This approach will provide a robust base for the upcoming decision support system model as well as provide instance-based evidence for a trainee doctor.

2- The development of follow-up mobile health application/system for long-term follow up of shunted patients and involve them in managing their conditions. Our follow-up platform has the potential to reduce avoidable expenses for the NHS, by reducing unnecessary visits on the one hand, and enabling clinicians to work faster and more efficiently in managing their patients, on the other.

3- Intelligent approach for follow up and risk assessment will improve patient experience, safety and quality of life utilising proper prognosis together with lowering the potential for the occurrence of medical errors.

1.5 Thesis Structure

The thesis is distributed into seven chapters, each part covering a specific area of the research work. The remainder of this thesis is structured as follows:

- **Background (Chapter 2):** This chapter discusses what Hydrocephalus disease is, the types of hydrocephalus, causes and current diagnosis and management for the disease. The current techniques used to follow up patients with hydrocephalus have also been introduced in this chapter. In addition, it demonstrates the different machine learning types and techniques, big data and its impact on healthcare.

- **Literature Review (Chapter 3):** This chapter considers different machine learning models, learning algorithms, and classification techniques. It also presents a literature review related to hydrocephalus. Furthermore, it provides the approaches used for exploring data analysis which is utilised to complete this empirical study.
- **Research workflow (Chapter 4):** Presents an overview of the research wok. It demonstrates a flowchart with research outlines. It discusses patient monitoring using M-health applications and demonstrates an analysis for a questionnaire, which investigates the user's acceptance of healthcare technology. In addition, it demonstrates each step of the research workflow for clearer and better vision. Finally, the chapter closes with a summary section.
- **Proposed Methodology and data preparing (Chapter 5**): This chapter defines the ICP signals in detail. It is also explains feature extraction and how it is used for preparing the ICP data set for the purpose of selecting a ready to use ICP data set. The development of IOS System (HydroApp) is illustrated in this chapter. Moreover, the chapter presents the automation of clinical approach in following up hydrocephalus patients.

  The proposed methodology framework and experimental set-up for ICP signals have also been presented in this chapter; with machine learning classifiers and prototype implementations to demonstrate applicability in real-world applications. It discusses the data preparation process. In this scenario, this chapter focused on addressing the missing values, oversampling, identifying outliers, and data normalisation technique. The performance techniques metrics were also evaluated illustrated in this chapter. Experimental set-up for the model is discussed in chapter 5.
- **Predictive models (Chapter 6):** This chapter discusses the performance metrics simulation results and analysis for the various machine-learning models that have been

selected in this research work. The chapter also elaborates more in further discussion about each of the used classifier based on the performance evaluation metric techniques (Sensitivity, Specificity, precision, accuracy). A Computation of the confusion matrix was also preformed in this chapter.

- **Conclusion and Future works (Chapter 7):** The final chapter presents the fundamental research and discusses its outcomes. This chapter demonstrates the constraints on the methodology framework and experimental set-up and outlines future work, which is recommended for other researchers to find suitable solutions to improve the research domain.

Chapter 2 Background Information

2.1 Introduction

Hydrocephalus is understood to be a complicated neurological disorder caused by "the dynamic imbalance between the production and absorption of cerebrospinal fluid (CSF) leading to enlarged vortices", or stated more explicitly, a condition that is attributed to the increased CSF amount in the ventricles caused by a disruption in flow, absorption, or formation [11][12]. In adults, there is about 150 cubic cm of CSF in the subarachnoid space and the ventricular system within the brain [13]. The CSF surrounds the brain, the spinal cord, and is present in the ventricular system in the brain. The CSF supports brain weight, protects it from shocks, and plays a vital role in the absorption of the toxic by-products of metabolism [14]. Intracranial pressure (ICP) could be an indicator of a neurological disorder known as hydrocephalus, which is currently managed by the shunting procedure. The following is an overview of hydrocephalus and ICP.

2.2 Hydrocephalus

Hydrocephalus can be thought of an imbalance in the production/resorption of CSF [15]. The average production and flow of CSF lead to an increased intracranial volume and pressure. Whereas in a tumour, the outflow of the CSF is physically blocked [16]. Therefore, the word Hydrocephalus means water (from hydro) on the brain (from cephalus) [17]; there are different forms of hydrocephalus as shown in **.**

Table 2.1.

Table 2.1 Hydrocephalus forms

Non-communicating Hydrocephalus	Obstruction of flow within ventricles.
Communicating Hydrocephalus	Impaired CSF re-absorption in arachnoid granulations or obstruction of flow in subarachnoid space leads to increase ICP, papilledema, herniation.
Normal Pressure Hydrocephalus	A type of communicating hydrocephalus, where CSF is not absorbed by the arachnoid villi Dilated ventricles with a triad of dementia, ataxia, and urinary incontinence.
Hydrocephalus ex-vacuo	Excess CSF in regions of brain atrophy (Ex. Alzheimer's disease)

- **Non–communicating (Obstructive) hydrocephalus**

Obstructive hydrocephalus is caused because of the obstruction of the CSF passages (foraminae or aqueduct), which cause an increase in the size of the lateral ventricles and the third ventricles. However, the usual condition that obstructs the aqueduct of Sylvius is a bleed or aqueductal stenosis (e.g. ependymoma, this kind of a tumour can arise in the fourth ventricle), causing a blockage and cause non-communicating hydrocephalus [18].

- **Communicating Hydrocephalus**

In this form, there is communication between the ventricles. The main problem is the impaired CSF resorption by the arachnoid villi. Meningitis may cause inflammation of arachnoid villi. As resorption of CSF is impaired throughout the system, all ventricles will be affected. Therefore, the patient will have dilation in third, fourth and lateral ventricles [19].

- **Normal Pressure Hydrocephalus (NPH)**

The diagnosis of NPS involves a triad of patient signs and symptoms; gait disturbance (magnetic gait), cognitive decline, and urinary incontinence [20]. The hypothesised cause of NPH is the effect of ICP peaks leading to chronic mechanical stress on ventricular walls; this will affect the ventricular dilatation and clinical impairment [21]. **Figure *2.1*** shows the ventricles of the brain.

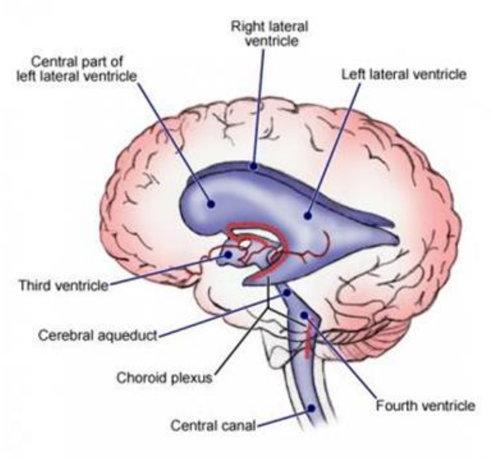


Figure 2.1 ventricles of the brain [24]

The following section describes the most ventriculoperitoneal shunt that includes two types of valves; Meithka valves and Codman valves, as well as a description of ICP signals.

2.2.1 Ventriculoperitoneal Shunt

Ventriculoperitoneal shunt (VPS) is the most common technique to manage CSF circulation disturbances in children and adults. VPS is prone to problems such as mechanical malfunctions, like obstruction of valve or catheter, catheter disconnection or migration, over drainage, and infection. A shunt typically contains a couple of catheters and a one-way valve. The valve regulates the amount, flow direction, and pressure of CSF out of the brain's ventricles [22].

Recently Meithke group has improved shunt valves by moving from differential pressure (DP) technique to adjustable units, which can adjust pressure level according to clinical conditions. Anti-siphon devices and gravitational valves (G valves) represent the comparison of the rising hydrostatic pressure column when the patient is in the upright position. Such devices prevent extreme CSF drainage without affecting shunt performance while the patient is in the standing position. The new telemetric device to measure the ICP is the sensor reservoir that consists of two units, implanted internal sensor reservoir and external reader unit. **Figure *2.2*** presents the external reader unit for intracranial pressure (ICP). This unit displays and stores data; the storage is linked to the antenna. The antenna is placed near the implant to initiate transcutaneous ICP measurement.

Figure 2.2 The reader unit for ICP data display and storage [23]

The ICP is monitored by supplying energy from the reader unit to the sensor reservoir. In contrast, ICP can be continuously monitored by transferring ICP data from the sensor reservoir to the reader unit. The implanted internal sensor reservoir is the first long-lasting implantable pressure measuring unit within a shunt system. It is attached into a reservoir for a ventricular drainage system and conveys pressure values using non-invasive, telemetry techniques through a display unit. **Figure *2.3*** shows the implanted internal sensor [24].

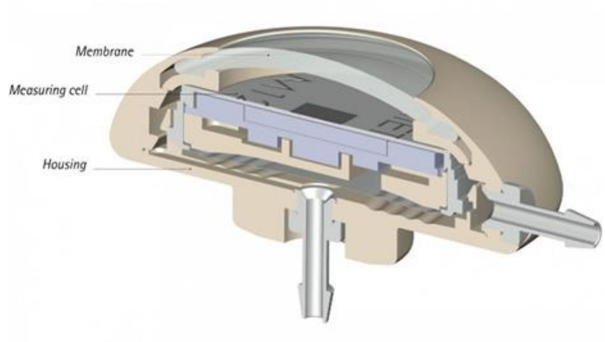


Figure 2.3 The implanted internal sensor reservoir that used to measure the ICP [25]

Codman Hakim programmable valve is one of the most popular valves for hydrocephalus shunt. It allows for customised treatment regimens via the use of an externally applied and codified magnetic field [25]. Clinicians may adjust valve settings according to the patient's condition, i.e. increasing or decreasing settings. Settings could be reduced for Hakim valves by 10 mm H_2O to 20 mm H_2O when there is a concern of having high pressure while patients are lying down. Likewise, settings could be reduced by two mmHg at a time for Miethka valves. If the patient has a drop in ICP, it is preferable to lie down due to gravity while monitoring patients for symptoms like headache. In the absence of symptoms, it is preferred to monitor the ICP for quite a while. Occasionally, severe drainage might lead to bleeding in the brain [26]. Valve settings could be increased by two mmHg at a time for Miethka valves or by two or up to 20 mm H_2O for Hakim valves according to the patient's condition. Specialists typically evaluate the size of ventricles, associated symptoms, and the ICP readings, and subsequently decide to adjust valves' settings or not. With the absence of symptoms, specialists would prefer to monitor the case for another night [25].

The initial monitoring and follow-up of shunted patients is an essential part of ongoing patient safety as clinicians can decide the risk assessment as soon as possible—most regional neuroscience centres follow up large cohorts of shunted patients from their region and outside. In general, the shunt failure rate seems to be unchanging despite advances in neurological practice; as shown by numerous follow-up studies. 30 to 40 % of shunted paediatric patients have a shunt failure within the first year [8]. A follow-up study showed that 87.4% of 124 hydrocephalus children had the first-time shunt when under 18 years old. The estimated mean age was 5.35 years. 21.1% were younger than six months, whereas 33.9 children were between 6 and 12 months. Moreover, 31.2% of children were between 1 and 6 years old, 11% were between 7 and 12 years old [27]. Another long-term study analyses the clinical follow-up evaluations of 1,015 patients with a shunt. The median age of patients was 41.6, and the mean follow-up time was 9.2 years. The overall shunt failure rate was 46.3%, and most of the shunt revisions within the first months after shunt placement [28]. UK National Health Service (NHS) estimated that 4 out of 10 shunts would malfunction.

This study aims to provide a robust and sufficient risk assessment model and an alerting capability to inform the medical team about their shunted patients. Our proposed intelligent approach employs a novel machine learning system for this purpose and initialising a user-friendly follow-up platform that supports long-term monitoring of shunted patients and involves them in managing their conditions.

2.2.2 Shunt Malfunction

Shunt malfunction presents in many ways. Patients are taught to identify the signs - headache, nausea, vomiting, and lethargy. If these symptoms come on acutely and are severe, the patient will always present to their closest emergency department. The real-world management of shunt malfunctions is more complicated than just that scenario. Patients often complain of subtle changes - behavioural change, change in sleep patterns, mild irritability, and low concentration. An ICP measurement is instrumental in these cases and may prevent unnecessary computed tomography (CT) scans and over-treatment of shunt malfunction. If a patient or their clinician is worried about the possibility of raised ICP, (i.e. the shunt is not working optimally for the patient or may be malfunctioning) and the patient has an implanted ICP monitor it is possible to check the ICP without an invasive procedure.

2.2.3 Symptoms

Symptoms are signs that appear on patients in case of shunt dysfunction or for a change in the ICP readings. The more patients have symptoms, the more they have to be monitored unless they have another reason for these symptoms.

2.2.3.1 Double Vision

Double vision known as seeing two images of a single object instead of one. Double vision happens when the ventricular enlargement develops pressure on the eye nerves [29]. The following areas require to check double vision symptoms; infectious and Inflammatory, the Scalp for giant cell arteritis, sphenoid and skull base in trauma and increased intracranial pressure [30]. Double vision is considered a significant symptom for shunted patients as they feel pain behind the eyes, and it is considered as an indication for dilatation of ventricles. So any patient who has double vision, should be monitored to control his ICP.

2.2.3.2 Irritability

Irritability can happen when the patient feels annoyed with regular daily habits. The patient becomes more sensitive to stressful situations. Many factors can cause irritability, such as life stress, a lack of sleep, low blood sugar levels, and hormonal changes. Patients may experience confusion or difficulty concentrating, rapid heartbeat or fast or shallow breathing. Other possible causes of irritability are: hormonal imbalance includes diabetes, hyperthyroidism polycystic, ovary syndrome, menopause and raised ICP in shunted patients who have hydrocephalus. Cerebellar inflammation for shunted patients may cause irritability and headache for the patients. Hence, the patient feels irritable; he needs to be monitored to investigate whether the reason is a rise of the ICP readings or from another illness [31]. Usually, clinicians try to contact the patients to have more history about the patient's symptom like how long the patient has been irritable, does it happen all day or at certain times or are they better at the start of the day or end of the day. Also, clinicians ask the patients if they prefer to lie down or sit up.

2.2.3.3 Drowsiness

Drowsiness is occurring when the patient Feels abnormally sleepy or tired during the day. Drowsiness may lead to additional symptoms, such as forgetfulness or falling asleep at inappropriate times and considered as a significant symptom for shunted patients. Usually, drowsiness happens in cases of under drainage and causes a decrease in consciousness, and it is considered a red flag sign of raised ICP. If the patient is drowsy and difficult to wake or just sleeping more than usual, it is considered as a warning sign for patients to contact the hospital. Drowsiness is one of the symptoms that may indicate shunt malfunction. When the patient feels drowsiness suddenly, he must be monitored continuously as it could be a sign' of intracranial hypertension in a shunted patient [32].

2.2.3.4 Fever

Normal body temperature is different for everyone and changes during the day. A high temperature, usually considered to be 38C or above, is called fever [33]. Fever symptom is an indication raised ICP. On the other hand, it can occur because of another illness. Therefore, clinicians should check the reason for the fever and check other signs to find out whether the reason is because of high ICP. Fever could happen with other illnesses, so clinicians should make sure that the High temperature may occur because of a problem in the shunt or the ICP readings, it could be more significant if it occurs in conjunction with other symptoms. In this case, patients should be monitored and reviewed. However, if the patient has a fever without any obvious reason, he should be observed and seen by a doctor.

2.2.3.5 Weakness

Weakness is defined as a feeling of body fatigue or tiredness. When the patient experiences weakness they may not be able to move a particular part of their body correctly. The symptom of weakness can be described as a lack of energy to move specific muscles or even all muscles in the body. Furthermore, it comes under drowsiness and irritability. Patients can feel weak because of the pressure in the head. Generally, the weakness symptom depends on the patient's status as well.

2.2.3.6 Nausea

Nausea is the feeling of an urge to vomit. Nausea can be acute and short-lived, or it can be for an extended period. When prolonged, it is a debilitating symptom. It can originate from problems in the brain or organs of the upper gastrointestinal tract. The clinical presentation varies by age: vomiting and nausea are the most frequent signs in older children. At the same time, infants experience more often with raised intracranial pressure symptoms such as nausea, vomiting, irritability and bulging fontanel [32]. Nausea is considered as individual sign presence for shunted patients, some patients have complete shunt blockage, and they never get nauseous, or vomit. In contrast, some patients may have full function shunt, and they are nauseous most of the time. Therefore, it is a very distinctive sign, but all patients need to be monitored in case they have nausea.

2.2.4 Intracranial Pressure

In 1951, Guillaume and Janny performed the intracranial pressure measurements (ICP) to measure the ventricular fluid pressure signals using the electromagnetic transducer. In 1960, Nils Lundberg invented the modern ICP measurements. Nils Lundberg proposed a safe, modern method associated with the intracranial pathology. Intracranial pressure (ICP) is of great interest to clinicians because ICP analysis provides evidence of effective hydrocephalus treatment [29]. Traumatic brain injuries caused by road traffic accidents, sports injury, assault or explosions may cause brain damage resulting in swelling which can obstruct CSF flow, or traumatic subarachnoid blood may prevent CSF resorption. Therefore, an acute rise in ICP may occur, further damaging the brain tissue [30]. The insufficient absorption of CSF is considered as a severe threat for patients.

Clinicians consider CSF dynamics such as hydrocephalus. The ICP is the main characteristic of the hydrocephalus disease. In the subarachnoid, ICP can be measured during an infusion test that consists of an artificial elevating of ICP through the fluid's infusion. Many proposed methods to measure and analyse the Hydrocephalic ICP signals include the traditional spectral analysis and nonlinear techniques. The nonlinear studies found that when the pressure values are in the highest range, the ICP signals show the lowest sample entropy values. The brain pressure could be high, idiopathic intracranial hypertension (IIH) or low-pressure intracranial hypotension, CSF leak. Decisions for operations are based on the ICP. Lumbar puncture opening pressures often estimate ICP; operation’s decisions are taken based on the pressure measurements in the path [31]. However, this method has some challenges, such as:

1. Technical problems: an artefact of position and sometimes cannot be performed with Chiari.
2. The single number of time point: No pulse curve, cannot detect episodic changes.
3. Mixed disorders: Cannot distinguish and may exacerbate CSF leak/IIH patients.

Clinicians use ICP readings to diagnose IIH patients where headache symptoms appear or persist despite treatment. However, if there is no definitive papilledema, marginal or variable lower pressure (LP) findings, it could be normal high range pressure. ICP reading can be used in diagnosing CSF leaks, clinical hypotension symptoms, positional headache with no definitive magnetic resonance imaging (MRI) signs brain or spine [32].

Cerebral perfusion pressure (CPP) is the pressure that pushes the blood to the brain, hence influences the cerebral blood flow (CBF). The normal CPP is between 60 and 100 mm Hg [33]. When CPP falls too low, the brain is not perfused, and the brain tissue dies. ICP readings are essential to calculate the CPP and the mean arterial pressure (MAP), whereas the formula is "CPP = MAP – ICP". Consequently, to estimate the CPP, we need to know the patient's blood pressure to determine the measurement of MAP and ICP [34]. The earliest indication of increasing ICP is a mental status, like feeling restless, confused, and responding to questions. However, irregular breathing is another indicator of increasing ICP, including Cheyne–Stokes that leads to hyperventilation then apnoea. Nerves to optic oculomotor are the late indicator of increasing ICP that may include double vision, unequal pupils, the optic nerve's swelling. Moreover, decorticate posturing or flaccid is the worst case of increasing ICP [35].

ICP is a vital component in the diagnosis of hydrocephalus. In the subarachnoid, the ICP can be measured during an infusion test that consists of an artificial elevating of the ICP through the fluid's infusion.

The normal ICP is between 0 and 20 cmH_2O. Clinicians look at the ICP signals for between 10 and 15 minutes at different times. If raised ICP is sustained for least 10-15 minutes, more observations are required. However, clinicians consider whether the patient is symptomatic at that time [36].

In the case of raised ICP for more than one hour, they check the patient's clinical status; lying down/ being upright, difficulty waking him up, headache or vomiting. If any of these signs are present, the patient is advised to visit the closest emergency department.

If the patient is asymptomatic and has high ICP, the patient is advised to visit the neurosurgical clinic to recheck the pressure and assess shunt functionality. On the other hand, if the child is unconscious, usually clinicians decide to admit the patient in the hospital for emergency surgery.

If the child is awake and has high pressure with symptoms, it is preferred to admit, check the ventricular size with CT scan and observe overnight. Consequently, if the patient does not improve, they proceed to emergency surgery for shunt exploration +/-revision. [37][38].

The collected data from the IOS system and ICP signals will be the main data in this research.

2.2.5 The Current Method of Diagnosing Hydrocephalus

Hydrocephalus is the most common disease treated by paediatric neurosurgeons. Hydrocephalus is an initial increase in intraventricular pressure, resulting in pathologic dilation of the cerebral ventricles with an accumulation of CSF. Usually, hydrocephalus requires lifelong vigilance by various health care professionals. Nonsurgical clinicians often have questions about disease recognition, shunt infection, and shunt malfunction to treat children with hydrocephalus, with or without shunts. Imaging modalities such as non-sedated magnetic resonance imaging and non-shunt surgery have changed the landscape of the primary paediatric clinician's interaction.

The diagnosis of the disorder is challenging as it may imitate many other neurological conditions as it has no independent biomarker. Careful history taking, a keen and detailed physical examination, and pertinent imaging studies can lead to an early diagnosis. However, it becomes even more challenging as most cases are diagnosed by invasive cerebrospinal fluid (CSF) removal tests [39].

Clinicians depend on ICP readings that are extracted from a Rumedic device. Patients are provided with this portable device to record their ICP regularly. Ordinarily, the clinician's team import the readings to be visually analysed. The clinicians decide based on the patient's feedback and ICP readings. However, the patient should wait for his regular appointment or book a new one. This process takes time and effort from the patients and the clinician team. It also is difficult for patients to record all the details, especially if it is a long time of feeling unwell.

2.3 Machine Learning

ML has proven to be a great tool that allows classifying large data sets and making predictions about the world. Classification determines the category an object belongs to and regression deals with obtaining a set of numerical input or output examples that could be used to discover functions for finding a suitable output from a given input. Mathematical analysis of ML algorithms and their performance is a well-defined branch of theoretical computer science, often referred to as computational learning theory [4].

ML has taken a massive forward step for examining useful data that are collected from personal monitoring devices and mobile apps, electronic health records, and surgical robots that have been developed to help in medical operations. ML-based applications could improve health outcomes and the quality of life for patients and could also reduce the cost for clinical institutions [40]. ML tools and methods can be applied to several forms of healthcare data (structured and unstructured). There are powerful ML techniques for structured data, like classical support vector machine, neural network, and deep learning. Natural language processing is considered as unstructured data. ML is used in different health fields, like cancer, neurology, and cardiology [40]. ML can be used in early detection and diagnosis, treatment, and outcome prediction and prognosis evaluation. ML has a spreadable role to help clinicians to make better clinical decisions. The big data analytic methods have become a vital application. The availability of healthcare data will help to answer relevant clinical questions;

powerful ML techniques can unlock clinically relevant information hidden in the massive amount of data that can support clinical decision making. ML has been used to assist in diagnosing cancer, analysing the clinical images to identify skin cancer [41]. A machine learning system has been developed to restore the control of movement in patients with quadriplegia [42] by testing the power of an offline man/machine interface that uses the discharge timings of spinal motor neurons to control upper-limb prostheses [43]. Another ML system to diagnose the heart disease through cardiac image has been released by US Food and Drug Administration (FDA) to provide automated, editable ventricle segmentations based on conventional cardiac MRI images [44].

2.3.1 Types of Machine Learning

Machine learning techniques are categorised into three types:

A. **Supervised Machine Learning:** The machine-learning task of finding a function from labelled data. Labelled data is a data set with an independent variable/s and a dependent variable. As shown in **Figure *2.4*** , the data set contains, input attributes (independent variables) and a labelled class column that is the target variable (desired output); supervised ML analyses the data by establishing a relationship between a labelled class and the independent feature variables. Therefore, we pass the data set to the learning algorithm. This supervised learning algorithm tries to find patterns and relationships between the input's attributes, dependent label class, and independent variable. Based on the relationship, it identifies the model, which is called the predictive model and based on the predictive model, it is also going to predict the output of these sets of records. To check the output performance, we review the expected result with the design output and see how accurate the model design is. There are two main techniques for the supervised model: Classification and Regression. Classification predicts results from a data set, which have dependent variables categorical or unordered like medical imaging or speech recognition. Regression is used to predict the outcome from a data set with dependent variables of continuous values or ordered values [45].

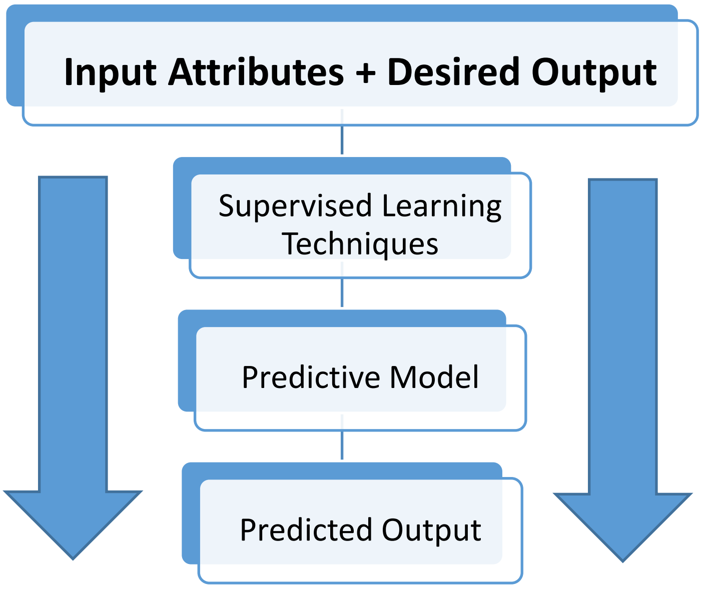


Figure 2.4 Supervised learning technique model

B. Unsupervised Machine Learning: The machine-learning task of exploring the data to derive some inferences /insights from the data set. The labelled variable is not present in the unsupervised learning data set. **Figure *2.5*** shows the unsupervised analyses. Some techniques are needed like dimension reduction, clustering; and association analysis techniques are used to analyse the unlabelled data. The dimension reduction techniques are used to reduce the number of data variables; some dimension reduction techniques use principal component analysis (PCA) and factor analysis [46]. However, if the same data reduce the number of records (cases), clustering techniques can be used. Analysis techniques are commonly used in e-commerce; for example, the e-commerce portal tries to give the customer the associated products related to their interests. In unsupervised learning techniques, we directly get an output. The supervised learning technique has input attributes and desired outcome if we compare the supervised and unsupervised learning techniques. The algorithm tries to find the relationship between the target variable and the independent variables; based upon that, it builds a predictive model to predict an output. A predictive model can be used for future predictions and can be used for new data sets. Whereas the unsupervised model has an input data that goes to the unsupervised learning technique to get an output, in this case, we cannot use this technique for future use [47].

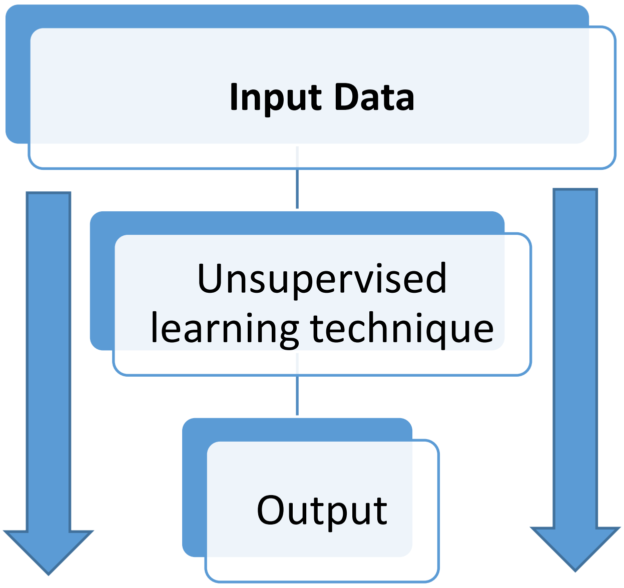


Figure 2.5 Unsupervised learning model

C. **Reinforcement Machine Learning:** is learning by interacting with space or an environment. However, reinforcement machine learning is an agent to determine the consequences of its actions, rather than from being Pattern mining [48]. It selects its action based on its experiences to provide new choices. In other words, Reinforcement machine learning learns from its knowledge by giving feedback from the output. Reinforcement machine learning is already used in experience-driven sequential decision-making that selects its action based on its experience (exploitation) and also by new choices (exploration) [49].

2.4 Machine Learning Classifiers

Classification is a process of categorising a given set of data into classes. It can be performed on both structured and unstructured data. The process starts with predicting the class of given data points as it is often referred to as target, label or categories. There are many machine learning algorithms for classification. This chapter will discuss three machine learning classification algorithms: Support vector machine, decision tree, and ensemble.

2.4.1 Support Vector Machine Algorithm

Support Vector Machine (SVM) is a supervised learning method that builds classification models using a converted set of high-dimensional features. SVM can be applied to continuous, binary, and categorical outcomes similar to Gaussian, logistic, and multinomial regression [50]. SVM learns from the past input data and predicts future prediction as output. The maximum space to separate two classes is called distance margin D+ and D-. A hyperplane is a distance between the support vector and the hyperplane; the distance should be as far as possible. The closest data points to the hyperplane are known as support vectors **Figure *2.6*** represents the classes of observations. The solid line indicates the decision boundary; the dashed lines denote the upper and lower margins. Triangles and squares represent the two classes (y values). Larger triangles and squares represent support vectors. Misclassified observations on the wrong side of the decision boundary are circled.

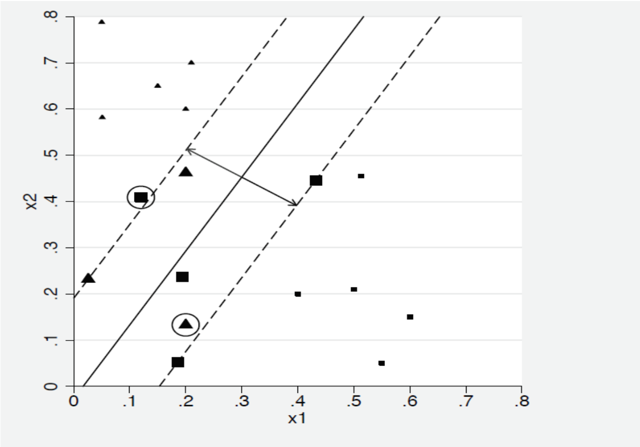


Figure 2.6 Two none-spreadable classes of observations [51]

If each observation has a mass measurement and a height measurement, then the data would be 2-dimensional. When the data are 2-dimensional, a support vector classifier is a line, and in this case, the soft margin from these two points [51].

If the observation has a mass, height and age, then the data would be 3-dimensional. The age represents the depth, so observations would appear more significant when they are younger, and they look smaller when the observations are older. When the data are 3-dimensional, the support vector classifier forms a hyperplane instead of a line. Support vector classifier classifies new observations by determining the hyperplane's chosen side. SVM can start with data in a relatively low dimension; like starting the data in one dimension. SVM can move the data to a higher dimension, for example, moving the data from 1-dimension to 2-dimensions. SVM can find the support vector classifier that separates the more top dimensional data into two groups [52]. To classify non-linear data, SVM uses kernel trick for classification. The kernel trick transforms data into another dimension to have a clear dividing margin between classes of data. After that a hyperplane can be drawn between the various classes of data.

SVM uses kernel function that systematically finds support vector classifiers in a higher dimension; for example, it can transfer data from 1-D to 2-D data. The polynomial kernel has a parameter *d*, which stands for the polynomial degree. When *d=1*, the polynomial kernel computes the relationships between each pair of observations in 1-dimension and these relationships are used to find a support vector classifier. When *d=2,* we get 2–dimensions. The polynomial kernel computes the 2-dimensional relationships between each pair of observations, and those relationships are used to find a support vector classifier. When *d=3,* we get the third dimension, and the polynomial kernel computes the 3-dimensional relationships between each pair of observations to find a support vector classifier. If *d=4* or more, then more dimensions to find a support vector classifier.

In summary, the polynomial kernel systematically increases dimensions by setting d. The polynomial degree and the relationships between each pair of observations are used to find a support vector classifier [53]. Good value for *d* with cross-validation can be found. Another commonly used kernel is the radial kernel, also known as the radial basis function (RBF) kernel. Radial kernel finds support vector classifiers in infinite dimensions. However, when using it on a new observation, the radial kernel behaves like a weighted nearest neighbour model. In other words, the closest observations (the nearest neighbours) have much influence on how we classify the new observation. The observations that further away have relatively little impact on the classification.

Kernel functions only calculate the relationships between every pair of points as if they are in the higher dimensions; they do not do the transformation. The approach of figuring out the high dimensional relationships without transforming the data to the higher dimension is called the kernel trick. The kernel trick reduces the amount of computation required for SVM by avoiding the maths that transform the data from low to high dimensions. It makes calculating relationships in the infinite dimensions used by the radial kernel possible. Regardless of how the correlations are calculated, the concepts are the same, when we have two categories but no obvious linear classifier that effectively separates them. SVM works by moving the data into relatively high dimensional space and finding a relatively high dimensional support vector classifier that can effectively classify the observations [54].

SVM has many advantages like working with high dimensional input space or avoiding the overfitting because of having a regularisation parameter. The parallel lines give us a sense of where all the other points are about the soft margin. Some observations would be outside the soft margin, and some observations are inside the soft margin and misclassified. In this case, cross-validation is used to determine this misclassification results in better classification in the long run. Fine Gaussian SVM is a model that has high flexibility as it decreases with kernel scale settings. It makes finely detailed distinctions between classes with kernel scale set to sqrt (P)/4. Medium Gaussian SVM has medium flexibility and medium distinctions, with kernel scale set to sqrt (p). Gaussian is a nonlinear SVM function (radial basis function) [55].

2.4.2 Decision Tree Algorithm

A data structure which comprises a root node then comprises some internal nodes (split nodes), then includes some terminal nodes (leaf nodes). Decision tree algorithm can represent data efficiently, which is hierarchical. The decision tree is mainly used for binary, multinomial, or continuous outcome types [56]. Decision tree gives all the possible solutions to a decision based on certain conditions. Entropy is the measure of randomness or unpredictability in the dataset.

If the entropy reaches zero at the end of the training, all objects are now classified with 100% accuracy. Information gain is the measure of the decrease in entropy after the data set is split, whereas the leaf node is the classification or the decision. The root node is the topmost decision node [57].

Random forest builds decision trees and merges them for more accurate and stable prediction. Random decision forests are correct for decision trees' habit of overfitting to their training set using the bagging method. Bagging method is based on combining learning methods to increase the overall result. Ultimately, we can measure the random forest's accuracy by the proportion of Out-Of-Bag samples that were correctly classified by the random forest. The ratio of Out-Of-Bag samples that were incorrectly classified is the Out-Of-Bag Error. In other words, a random forest is built then estimates the accuracy of the random forest and changes the number of variables used per step. This procedure is repeated to choose the most accurate one. Typically, we can start by using the square of the number of variables and then try a few settings above and below that value [58].

The decision tree has many advantages like it is simple to understand, interpret and visualise. There is no need for special preparation for the data in the decision tree method as it works for numerical and categorical data [59]. However, the decision tree has some disadvantages like overfitting. If there is noise in the data, it requires high variance as the model can get unstable due to small variations of data. The low biased tree is a highly complicated decision tree to have a little bias, making it difficult for the model to work with new data [60].

2.4.3 Ensemble Algorithm

Ensemble did not create a new algorithm but instead assembled several different algorithms or models to create an ensemble learner [61]. Ensemble model calculates the mean if regression or estimates the voting for better classification. The ensemble has lower errors than any of the algorithms, and it has less overfitting than other algorithms. The adaptive boosting model can combine several weak learners into a single keen learner. The vulnerable learners are almost always stumping which is a very short tree from the training data. Some stumps get more say in the classification than others and the amount of saying that the stump has on the final output based on how well it compensated for those previous errors. Each stump learns by taking the last stump's mistakes into account [62]. Adaptive boosting is mainly used for classification. **Figure 2.7** demonstrates the strategy of how the ensemble model works.

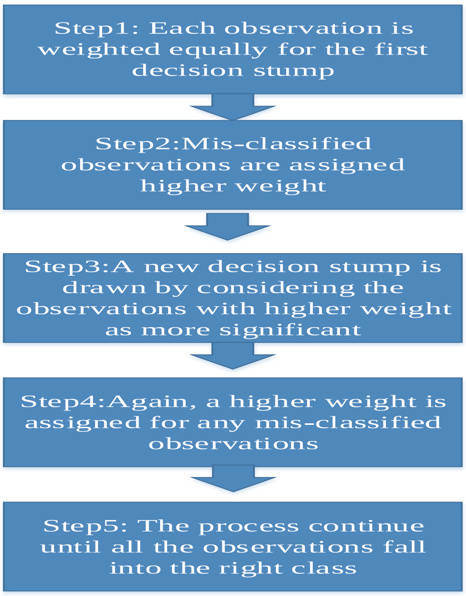


Figure 2.7 How the ensemble model works [61]

An ensemble model is used when a single model over fits results that need extra training and can be used for classification and regression. There are some conventional ensemble methods like Bootstrap Aggregation (Bagging). Bagging technique is based on providing a different dataset for every model; this technique is called row sampling with replacement. The models are trained on the given data then the test data is used for the prediction. Aggregation is the voting classifier that is applied to the model's predictions then combines the outputs to find the best outcome. Ensembles often have lower error than the individual methods by themselves. Ensemble learners have higher consistency by offering less overfitting. It also reduces bias and variance errors [61].

2.5 Big Data

The science of data has emerged as a new discipline of some importance in recent years. Data science can be considered a combination of the classic discipline of statistics with databases and data mining and distributed systems. There is a need for existing approaches to be amalgamated so that the plentiful, available data can be turned into more excellent value for organizations, individuals, and society. Furthermore, there have arisen new challenges, not solely about the size of the ‘big data’ but also concerning further questions that call for new answers/solutions.

The expression ‘big data’ has become a fashionable phrase these days. More than just a fad, however, big data represents the opportunity to change the design of business models and the associated, day-to-day decisions that go along with the emergent analysis of data. The combination of tools, applications and resources is increasing in magnitude. By way of example, big data is now being used to transform medical practice, the modernization of public policy, and better inform decision-making within the business [63]. Potentially, big data can radically change the dynamics involved with supply chains. Increasingly voluminous and diverse data has resulted in more massive data sets that cannot be managed by hands-on, conventional management tool forms. So that new and incredibly valuable datasets can be managed effectively, there has been the development of new data science methods and new types of application of analytics for prediction. Some data has backed up the widespread notion that data is a driver of improved decision-making and greater profitability.

Based on a large-scale study, it was found that companies of self-characterized as being driven by data, the better was their performance within respect to objective measures for results related to operations and finance. Companies placed in the uppermost third for their particular industry, with respect to use of decision-making that was data-driven, were, on average, 6% more profitable and 5% more productive than competitors [64]. There can be multiple forms of data, including structured and non-structured, including text files, financial data, genetic mappings and multimedia files. Unlike much of the analyses of traditional data that organizations perform, most big data is semi-structured or unstructured by nature; as such, different tools and techniques are required for processing and analysis [65]. Analyses of big data are successfully employed within a variety of industries, like insurance and banking. Understanding and personalization based upon the behaviour of online users and studies of the environment, as well as analyses by organizations of the national government to enhance ability in serving citizens while addressing challenges such as those about terrorism and natural disaster, healthcare, economy and job creation [66].

2.6 The Science of Data, Predictive Analytics and Big Data.

Data science is increasingly being given attention within academia and is growing more popular. There is a constant creation of data, and its production rate is ever-increasing. Social media, mobile phones, and technologies of imaging for the determination of medical diagnoses are all examples of sources for creating new data. That data must have a place of storage for future use. There is the automatic generation of diagnostic information by devices and sensors, and that information has to have storage and processing within real-time. It is difficult enough to keep on top of the enormous data influx; however, analysis of the vast volumes of data for identification of patterns that are meaningful, and the extraction of useful information is extremely challenging, mainly if it is not in conformity with more traditional ideas for the structure of data. Those data challenges do, however, present opportunities for transformation of science, government, business and, indeed, everyday life.

Numerous industries have been pioneers in the development of ability in gathering and exploiting data, as the examples below illustrate:

1- The calling patterns of subscribers are analysed by mobile phone companies for the determination, for instance, of whether the frequent contacts of a caller are upon one of the rival networks. If a rival network offers an attractive promotion that could lead to a subscriber's defection, an incentive may be provided proactively by the company to encourage the subscriber to stay within the contract.

2- Data is the main product for a company such as Facebook or LinkedIn in itself. Those companies have valuations that are derived heavily from the very data that they are gathering and hosting, and that intrinsic value contained therein continues to grow with the growth in data.

3- The company in question monitors all of the purchases made by customers on their credit cards. Fraudulent purchases can be identified to a high level of accuracy by using rules that have been derived through the processing of several billion transactions.

Three attributes can be considered definitive ones regarding the characteristics of big data. Firstly, there is a considerable amount of data. Instead of just thousands of rows and columns of data, or even millions, there may be billions of them with big data. Secondly, big data involves data structures and types that are complex. Big data reflects various new data sources and new structures and formats that include the digital kinds of traces that remain upon the web and other kinds of a digital repository for later analyses. Thirdly, big data involves speedy creation of new data growth; big data can describe data of high velocity with data ingestion that is rapid and analysis that is almost real-time [67]. There are multiple forms in which big data can be found as mentioned above, however, contrary to lots of data analyses that are traditionally performed within organizations, most big data is in a semi-structured or unstructured form, and different kinds of tools and techniques are needed for processing and analysing it. For such complex forms of data to be processed, there is a preference for distributed environments of computing and architectures of MPP (massively parallel processing) to enable the parallelized ingest of data and analysis. With that in mind, the section that follows looks more closely at data structures.

It is estimated that from 80% to 90% of future growth in data hail from non-structured types of data. Although they are distinctly different, there is commonly mixing up of the four types. The classic kind of database, the RDBMS (relational database management system), can store the logging of calls as software support for a call centre. An RDBMS can store support call characteristics in the form of typical data of a structured kind, with attributes associated to them such as machine type, time stamps, type of problem and the operating system. Usually, there is an unstructured, semi-structured or quasi-structured data in the system. Such as the history of customer chat, information of the call log in free-form such as that taken from a ticket from an e-mail in relation to the issue, a phone call transcript with a description of the problem in technical terms or the audio file of the telephone call conversation with a record of the provision of the solution. Indeed, many insights could be gleaned from the call centre's data, be it in the quasi or semi-structured or unstructured form [67]. In general, data science relates to applying either qualitative or quantitative methods for solving relevant problems and predicting outcomes. A salient revelation these days is that, as the vast volume of data continues to grow, there cannot be a separation of domain knowledge and its analysis.

Historically, the healthcare industry has generated huge volumes of data that drive patients' care, by the requirements of regulation and compliance and the keeping of records. Whilst there is a storage of most data in the form of hard copy, a current trend results in large volumes of data being rapidly digitized [68]. Across the world, the productivity and quality of systems for healthcare are vital concerns. For example, within the UK, there are many good projects and initiatives related to the usage of data within analyses in medical and health research [69]. Significant opportunities exist for UK-based data science capabilities with the emerging vision of accelerated access activities and review at the EU levels.

The healthcare sector does account for a considerable proportion of the GDP (gross domestic product) of the US; within 2011, healthcare was the largest US economy sector at around 17.9% of GDP [69]. Terrific opportunities exist for the analytics of big data for impacting upon healthcare sector quality and productivity within the UK and various other countries including Japan, the USA, South Korea, China, Malaysia and Thailand [70]. Analytical insights that are acquired by analysing healthcare data in a meaningful way have the potential of causing significant changes to clinical and business models, can bring about greater efficiency through smarter care delivery and can serve to guide rollout expected of purchasing based on value. It is often the case that the quality of data is somewhat taken for granted; in contrast to other sectors like manufacturing which have market-based expectations driving product quality, market forces of the industry of big data have not been imposing similar data quality standards within healthcare. Illustrations and examples from the real world are provided to show key sources of poor quality data [71]. **Figure *2.8*** captures a typical health data lifecycle. Different health data types are listed at the left side in **Figure *2.8***. Data can be made up of EHR (electronic health records), insurance claims, diagnostic/clinical laboratory data, pharmaceutical events, genetic information, associated geospatial statistics and various other potentially relevant information (even if the association may seem weak). There are various parameters for different Vs in healthcare big data. For a patient population of one million people, the data volume for healthcare claims may have the order of several terabytes and, for data that is genomic; the order can be in petabytes. Data related to claims within a transactional form that is structured may stream in with a rate of around twenty claims each minute (the velocity). Various data that are unstructured such as clinical image data and EHR may have velocities and volumes that are even higher than they are for claims data. Furthermore, variability in velocity, volume and type of big data in healthcare can all add to the difficulty and complexity in assuring the veracity of data analytics.

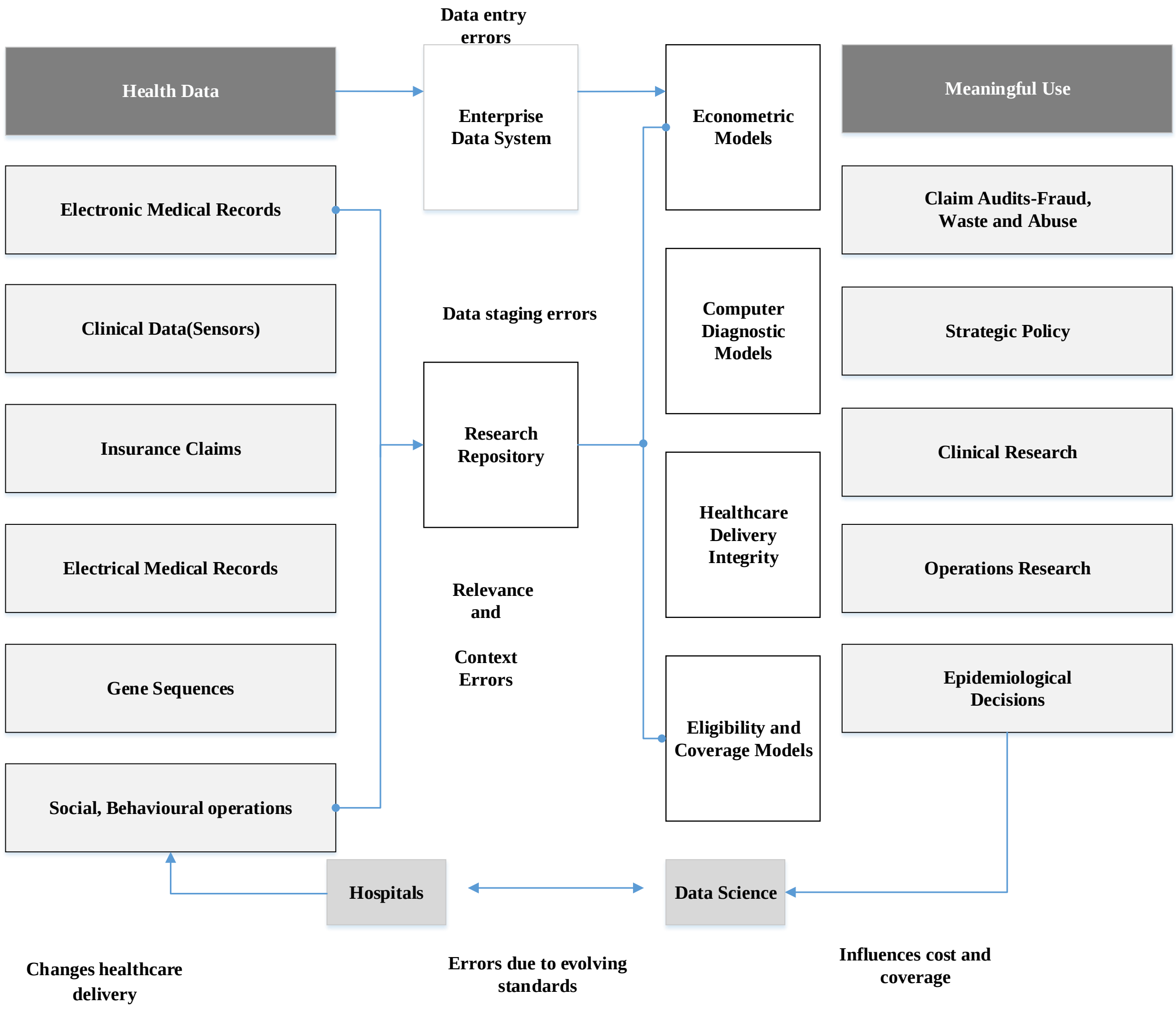


Figure 2.8 The typical lifecycle for health data and the use of it within the domain of health care [72]

There is leveraging of that centralized repository in order for business-specific models of analysis to be run that make recommendations of insights that are actionable. A centralized system that is an example resulting in those kinds of insights is the Japanese national clinical database [72]. Often, the actionable insights result in changes and improvements in outcomes related to the integrity and quality of the delivery of healthcare. In the majority of cases, it can mean further data collection, improvements to regulatory mechanisms or, perhaps, moves towards greater convenience through improved codebooks and standards. Issues of quality may arise at all stages from the collection of data, its integration and transformation and any inferences. There is also an increased chance that issues of data quality can be propagated and the quality deteriorating within the healthcare system that is controlled by feedback. The main sources of problems in data quality are as shown in **Figure *2.8***. Within the following section, there is discussion around the sources that contribute to low levels of veracity, as well as discussion of the consequences within the lifecycle of health data. The error sources that are discussed are not errors in statistics because of sampling. The focus taken is in relation to sources of errors that are non-sampling. It is difficult to quantify non-sampling errors within accuracy estimates and the -/+ kind of error margin.

The following are the advantages of involving data science in health care.

1. The early detection of disease

Early disease detection is facilitated by big data, with the help given to clinical objectives associated with the achievement of better treatments and improved patient outcomes; the authors discovered there to be great promise in those areas in relation to disease and illness that are age-related. As well as early detection, help may also be given by big data analytics to the prevention of a broad range of fatal illnesses and the personalized monitoring and management of disease. It helps providers track behaviours that are healthy and aids patients in the monitoring of their particular conditions; with the need to address worldwide issues for health, such as cardiology, or diseases that are age-related, those capabilities hold a great deal of potential.

2. Data quality and structure and its accessibility

The suggestion from the literature is that big data facilitates rapid data capture and conversion of raw, unstructured, and primary data into information that is meaningful. There is a generation of new knowledge from the high amounts of useful data, and potential data reuse.

The transparency and accessibility for the data are increased by the open-source technology. Finally, there can be the maintenance of data quality using analytics to shed information that is unnecessary; around 57% of the relevant literature did mention that particular opportunity.

3. Improved decision making

Big data facilitates suitable utilization of medicine that is evidence-based and aids the providers of healthcare in the making of decisions that are better informed; in turn, that leads to improvement in care quality provided for patients. Examples of other kinds of application that have an impact upon the process of decision-making are patient profile analytics, genomic analytics and remote monitoring. Processes of decision-making may be optimized greatly through availability of information that is up-to-date and accurate, since the making of decisions is impacted significantly by generation of new treatment guidelines and practices within clinical research. If big data is allowed to influence the making of decisions, it will facilitate processes that are simpler and faster through offering support to human decision making or replacing it.

4. Reduction in costs

The suggestion from the literature is that decreasing costs of computing elements, such as processing and storage, results in decreasing costs of tasks that are data-intensive. Passing on such savings will result in benefits to a broad medicine spectrum and to the workforce within healthcare. There will be the realization of savings through treatments being more cost-effective as well as more cost-effective monitoring to help bring about improved adherence to medication and to bring about reduction in expensive costs for transportation as the field of cardiology has experienced; this opportunity was mentioned within 36% of relevant literature.

5. Patient-centric care

Increased technology use is slowly bringing about a change of direction for the sector of healthcare from disease-centric forms of care, to care that is more patient-centric; a significant role is played in that transformation by big data. Big data facilitates direct delivery of information to patients and empowers them in playing a more active role within their care. If suitable information is provided to patients, there is an impact on their decision-making in that their decisions can be better informed. Increased levels of communication amongst providers, patients and the wider community also impacts upon informed decisions; that opportunity was mentioned by around 29% of the relevant literature.

6. Enhancement of personalized medicine

With big data use, there can be translation of personalized medicine objectives into the clinical practice. The access to and the processing of huge volumes of data ought to enable the recording of disease risk within specific, personalized patient records; the aim of applications of big data is for that process to be made more efficient. Recently, there has been greater usage of machine learning as an effective and practical approach to the handling of big data, founded upon both historical databases and artificial techniques of intelligence. Therefore, there is therefore a research theme that is attractive for application of approaches of machine-learning to the resolving of the task; indeed, current challenges for biomedical data indicate that algorithms of machine-learning look set to play a significant role within the handling of big data.

Summary

Hydrocephalus is a chronic and lifelong disease. It requires neurosurgical intervention and follow-up of these patients usually for life. In general, shunt failure continues to be a significant problem and threat to the patient’s health and wellbeing for the rest of their life. This chapter introduces the hydrocephalus disease, the ventriculoperitoneal shunt, and an overview of ICP signals. This chapter clarifies why hydrocephalus disease is series and why it need lifelong monitoring. It also demonstrated the current diagnose that followed by clinicians to follow up shunted patients. The real-world management of shunt malfunctions is more complicated than just that scenario. Patients often complain of subtle changes - behavioural change, change in sleep patterns, mild irritability. The chapter demonstrates the symptoms that patients may feel which are: irritability, nausea, fever, double vision, drowsiness, and weakness. In addition, the chapter clarifies different machine learning types which are supervised, unsupervised and reinforcement machine learning. Also, it demonstrates the following machine learning algorithms: Support Vector Machine Algorithm, Decision Tree algorithms and Ensemble Algorithm. The concept of big data and its impact on healthcare has been demonstrated. In addition, the chapter illustrates the typical lifecycle for health data and the use of it within the domain of health care. The health data lifecycle commences with various kinds of data, that hail from a variety of different sources, integrating together at a location that is centralized.

Also, the benefits of involving data science in health care have been demonstrated which are: The early detection of disease, data quality and structure and its accessibility, Improved decision making, reduction in costs, patient-centric care and enhancement of personalized medicine. The next chapter is about different literature review about machine learning, different machine learning classifiers and different research work that related to hydrocephalus and machine learning.

Chapter 3 Literature Review

3.1 Introduction

Machine learning (ML) has become an increasingly important science tool and is emerging as a potentially practice-changing analytical tool within healthcare. Machine learning is an application of Artificial Intelligence (AI). Machine learning is used to learn and improve from experience without being explicitly programmed automatically. Algorithms enable the software to improve performance over time as more data is obtained, this programming by input-output. Learning without any supervision requires identifying patterns in streams of inputs, whereas learning with adequate supervision involves classification and numerical regressions [73]. This chapter demonstrates different literature review and related work regrading machine learning techniques and its role in dealing with different diseases especially hydrocephalus disease.

3.2 The Role of Machine Learning Techniques in Diagnosing Cancer

Precision medicine is an initial approach for disease prevention and treatment that considers personalised patient information that includes genomics, environment, and lifestyle [74]. Artificial intelligence has recently played a significant role in medicine and health to provide advanced methodologies for analysing, generating, and propagating heterogeneous data. However, machine learning offers the ability to join existing knowledge to discover relationships and create computational models that improve care and quality of life [75]. Machine learning is used to develop predictive models within various ground fields of big data analysis by interpreting data beyond the mechanical fitting of input data/matrix of numbers into a given model depending on different methods such as Support Vector Machines, Random Forests, and Logistic Regression. Cancer biology is illustrative of the interplay between unsupervised and supervised learning. It introduces the concept of combination to improve predictive models, giving them plenty of learning algorithms that are targeted for particular problems [76]. Artificial Neural Networks (ANN) can provide accurate breast cancer diagnosis results when the data set is provided. ANN consists of different layers: the input layer, one or more hidden layer and output layer [77]. The data set is fed to the input layer which comprises of the age, Body mass index (BMI), the number of pregnancies, or post-menopausal, details of genetics analysis like GCPII C1561T, RFC1 G80Aand cSHMT C1420T, and different nutrients that are consumed regularly like folate, B2, B6 and B12. In this approach, the output variable is 0 if the patient does not have Cancer and one if the patient has Cancer. The data throw the hidden layers, and every layer takes the input from the previous layer, as the information moves between layers. It is multiplied by the random weight that is assigned to each of the connections that travel along. However, the individual weight indicates the strength of the relationship between layers as they are the crucial factors to convert the input layer to the output layer [78].

Consequently, bios and activation functions are added to the hidden layers during the data's move. The sigmoid function is used to place any output results between zero and one. The input data flow through the layers and arrive at the output layer with a value between zero and one. Backpropagation uses the algorithm's feedback by comparing the output just produced with the output it was meant to produce. However, weights are modified according to the difference between them and rerunning the network [79]. The goal is to run the network repeatedly, adjusting the weights and getting closer to the right output. Gradient Descent is the process that adjusts the weights to have the lowest possible error in the output. Gradient descent is considered the backbone of the network and the most used learning algorithm. Gradient descent uses cost function that measures how far the guessed output is from the actual output as well as measuring the number of errors in the network.

Moreover, the number of network errors are typically expressed as the difference between the predicted value and the actual value [80]. We can plot the error against the connection weight for a given data as it changes with each iteration. To get the best neural network, minimise the cost function by choosing the correct connection weight that allows having the lowest point of the cost function. The cost function's derivative is to know the direction it needs to move in to get the least error value. Means –Squared Error function is used to measure the number of errors in models that vary from the correct weight and give the direction to move to the correct cost.

Consequently, the learning rate estimates how much to move in the direction to get the least error value. This approach predicts whether the patient has Cancer or not [81]. Deep learning can provide a precise evaluation of intricate patterns observed in microscopic tissue images by using deep learning techniques that evaluate sets of digitised formalin-fixed paraffin-embedded hematoxylin-eosin stained tumour tissue microarray (TMA). Four hundred and twenty patients with colorectal Cancer were employed to provide samples for the research [82]. Using convolutional neural networks and Long Short-Term Memory networks, we validated the predictive power of the colorectal TMAs concerning the patient outcome.

The univariate Cox proportional hazard regression analysis showed that the deep learning algorithm's prognostic accuracy on TMAs (hazard ratio 2.3; CI 95% 1.79-3.03) outperforms visual histological grading. The univariate Cox hazard regression performed by a certified pathologist on a whole slide level (hazard ratio 1.65; CI 95% 1.30-2.15) [83]. K top-scoring (K-TSP) algorithm is successfully used in many cancer microarray datasets because it is based on relative expression ordering of gene pairs. Performance can be improved by separating its practical feature selection component and linking it with a robust classifier like support vector machine (SVM) [84]. An approach was developed to combine the K-TSP ranking algorithm with other machine learning methods like SVM to provide a well-organised, multivariate feature ranking of K-TSP. Consequently, SVM, combined with the K-TSP ranking algorithm, beats K-TSP and SVM alone in some Cancer prognosis datasets. Studies suggest that as a feature selector, it is better tuned to specific data characteristics such as correlations amongst informative genes, which is hypothetically remarkable as an alternative feature ranking method in pathway analysis [85].

3.3 Classifying Different Types of Headache Using Machine Learning Techniques

Migraine is a neurological disorder characterised by severe throbbing pain on one or both sides of the head. In some cases, head pain may be accompanied by other symptoms, including nausea, vomiting, and numbness or tingling in the face [86]. Patients may also experience sensitivity to light and sound and vision problems. Headache is widespread in the community; there are broad categories of headaches, primary headaches and secondary headaches. A primary headache is not related to any disorder, while a secondary headache is usually connected with other diseases. There are four main phases of migraine [87].

Phase 1: The prodromal, where there is a trigger inside or outside the body. It causes the abnormal firing of neurons in the brain. It can begin hours or days before the actual migraine starts [88].

Phase 2: The aura phase includes temporary visual or sensory disturbance that usually strikes before other migraine symptoms. Abnormal neuronal firing leads to a wave of electrical hyperactivity that moves across the brain that processes the signal from the senses. Once the electrical waves stop, the aura goes away. However, not everyone experiences an aura when having a migraine; only 30% of migraine suffers experience aura [89].

Phase 3: The attach phase, also known as the headache phase. Headache phase occurs when the actual headache strikes and can last for hours, up to several days, the abnormal firing neurons activate the trigeminal nerve, which surrounds the blood vessels in the head. This nerve is responsible for motor functions and sensation in the face [90]. The attach phase leads to the release of an inflammatory substance that causes the blood vessels to swell and increases blood flow around the brain.

Consequently, this is the cause of throbbing pulsing pain most people experience during migraines. Pain receptors are then activated to send pain signals to different parts of the brain. However, untreated migraine can last up to 72 hours before the nervous system response finally calms it [91].

Phase 4: The postdrome or recovery phase where non-headache symptoms like fatigue, weakness and impaired concentration can continue for 1-2 days [92].

The authors in [93] presented a decision support system that provides headache diagnoses and follow-up for primary headache patients. The decision support system has three essential parts: a mobile application for the patients, a web application to visualise the collected data and an automated diagnosis module. However, decision trees were used to automate the headache diagnoses.

Feature selection methods are commonly used to identify subsets of relevant features to facilitate models for classification. Election methods have been used in diffusion tensor images (DTIs). Many machine learning techniques have been used to automate the diagnosis of migraine. By using DTIs and questionnaire answers. 52 adults were employed to experiment. They were divided into three groups: 15 adults who focused on sporadic migraine, 19 adults subjects with chronic migraine, and overuse of medication. Eighteen adults focused on a magnetic resonance that relies on diffusion tensor to see white matter pathway integrity of the regions of interest involved in pain and emotion.

The test results and the DTI images were used as input for different election algorithms like Gradient Tree Boosting, L1-based, Random Forest and Univariate, whereas, Support Vector

Machine (SVM), Boosting and Naïve Bayes were used to producing a migraine classification. A committee method was implemented to provide classification accuracy. Based on this approach, there was an increment of accuracy from 90 to 95 % using support vector machine classifier. The accuracy increased from 67 to 93% when using Naïve Bayes classifier, 93 to 94% in boosting. The proposed system achieved 90% accuracy, performing a migraine diagnosis [94].

3.4 Extracted Morphological Features of ICP

Many methods have been proposed to measure and analyse ICP signals, including nonlinear methods and traditional spectral analysis. Nonlinear studies have discovered that ICP signals reveal the lowest sample values for entropy when pressure values are within the highest range [95]. Mentoring of ICP is a procedure that is common within NPH (normal pressure hydrocephalus); for NPH in the UK, several units do just lumbar puncture, and others do the test of a lumbar drain. With this study, NPH presence within ICP readings is investigated through WEKA classification software. The investigation employed fourteen ICP recordings from various patients who had undertaken the infusion test.

Furthermore, the software can extract twenty morphological features from the pulsed ICP wave. Nine determined statistical functions and one hundred and eighty features were used as input within the classification. It facilitates the accessible computing and deep analysis of the intracranial pressure—the pre-processed and filtered data for extraction of the morphological parameters and features. Then, the trends of the parameters are provided. The software creates twenty output vectors at a rate of one for each of the calculated movements. So, there is a determination of twenty trends by each of the recordings. For each of those, there is a computation of nine statistical functions, i.e., the value of the mean, the variance, the minimum, the maximum, the kurtosis (the difference between the minimum and maximum), the first quartile, the median (second quartile), the third quartile, and the skewness or interquartile range (third quartile – first quartile). Thus, the number of 180 (20 x 9) features was determined for each of the classified segments [96]. WEKA, the classification software that was utilised, has shown itself to be an essential, useful tool for analysing data sets of the real world. The analysis may be backward elimination (starting from a vector that contains all components and then prunes them down by worst through step by step). The analysis could be forward selection (commencing with a list that is empty and then inserting a new attribute at each step until there is the reaching of a threshold that has been pre-set) [97]. There was an achievement of correct classification of 85.7% in the results using three features. There was correct classification of 88.89% of the patients who had not been affected by NPH. The results showed that 80% of the patients affected by NPH were correctly identified [96].

3.5 The Monitoring of Intraparenchymal ICP of Hydrocephalus and Cerebrospinal Fluid

There has been an analysis of ICP and PA (pulse amplitude) recordings for all day and night within a study that aimed at utilising PCA (principal component analysis) for the diagnosis of doubted Hydrocephalus. A software package is used to record the PA and ICP; artefacts are eliminated, and data is recorded on a minute-by-minute basis. Consequently, there is analysis in the study of median ICP and PA (pulse amplitude) recordings in the neurosurgical naïve patients; the patients had been undergoing a kind of elective monitoring of ICP for doubted disorders of CSF. Furthermore, there was a measurement of the correlation between PA and ICP during the recording period. The investigation used 198 patients distributed within six distinct diagnostic kinds of the group (in each, n = 21 to 47); PA determined 61.4% of that data, and ICP determined 33%. The study showed a significant difference in PA and ICP for diagnosing. The PA analysis managed IH (idiopathic hydrocephalus), Chiari/ syrinx and NPH/LOVA (long-standing over ventriculomegaly of the adult). The ICP, however, managed low-pressure and IH. In total, there was the identification of 198 patients who had undergone first-time monitoring of ICP, during the period of study, who, before the neurosurgical intervention, was naïve. There was a splitting of the demographics of the population through diagnosis. The diagnoses were divided towards broad categories. There was diversity in the population concerning age, ranging from 16 years of age up to 85, with a good age group within each diagnostic subgroup. The study offers insights into hydrodynamic type disturbances within various diagnostic patient groups with CSF-type hydrodynamic disorders. The study highlights utility in analysing both recordings of median PA and ICP, stratified into recordings for the night and day times [98].

Fifty-eight patients were employed in the research, of whom 53% had surgery following the ICP monitoring. The study illustrates that no links were found between ICP scores/ICP waves and the ventricular size symptoms or age. The diagnosis of shunt-dependent hydrocephalus relies on 1.patient's histories 2. The results of clinical neurological examinations 3. Radiological assessment of the ventricular size. The basis for the indication of the preoperative kind of diagnostic ICP wave/monitoring of ICP, is through the observation of the issues. Clinicians should consider the following observations: 1. There is not a typical, shunt-dependent type patient history; 2. No clear evidence for shunt-dependent hydrocephalus is provided by clinical neurological examination. 3. No clear evidence for shunt-dependent hydrocephalus is provided by the imaging done of the cerebral ventricles. 4. Other potential causes for the patient situation have not been revealed by non-invasive assessment. In that situation, there is diagnostic ICP monitoring, which includes both assessments of ICP and ICP waves, to help select a further treatment. This study aimed to characterise ICP/ICP waves within those children who are hydrocephalic and who had clinically improved after surgery. Patients who were managed in non-surgical ways were used as a reference. The hypothesis expressed was that the degree of ICP scores changed within the surgery group compared with the patients used as a reference, and this could offer indirect information about the workings of shunts within paediatric hydrocephalus. Secondarily, the examination was undertaken of the ICP monitoring complication profile. The study gave proof that those children who had either non-communicating or communicating hydrocephalus, who had clinically improved following surgery, presented with mean ICP and wave amplitudes of ICP (MWA) that were elevated. The ICP wave amplitude levels had been lifted to a magnitude observed when there was a decrease to intracranial acquiescence. Therefore, the current observations could support the notion that improvement in intracranial compliance may be a mechanism that has importance for the working of shunts within paediatric hydrocephalus [37].

3.6 Use of Convolutional Neural Networks for ICP Waveform

A study looked into how CNN (convolutional neural networks) can be used which extract features, automatically within waveform morphology, that is connected within intracranial hypertension. Any hypertension characteristic properties are recognised by the system, which provides an unbiased waveform analysis. However, the feature set is defined by the system. There has been the use of CNN for the operation of training for labelled data in the creation of filters; there is labelled data to produce filters that then generate outputs that can detect proper classification of hypertension. Furthermore, those outputs may be utilised for further analysis for concluding the data pattern. This study is retrospectively related to patients being treated for various conditions related to intracranial pressure including Chiari syndrome, idiopathic intracranial hypertension and patients with slit ventricle with clamped shunts. For this study, 60 patients had been considered in total, and there was a continuous recording of the ECG (electrocardiogram) signals. The patient's record was distributed to normalised, average beats within segments of 30 seconds; each reading was given a labelling of low intracranial pressure or high intracranial pressure, i.e. over 15 mmHg. The aim of the study was the prediction of the presence of ICP at increased levels. There is accuracy for the algorithm of 92.05% plus or minus 2.25% in detecting intracranial hypertension within the data set.

This work's primary contribution is the provision of a framework for the detection of hypertension consisting of two key components, i.e., a convolutional type neural network and an auto encoder. An auto encoder is a type of unsupervised learning utilising neural networks to generate encoded data representations; if utilised as a pre-training kind of method, the auto encoder has been shown as leading to improvement in performance in deep networks. That type of pre-training comprises the auto encoder's training upon beat samples followed by the use of the layers generated for initialisation of a neural network, which facilitates its performance of supervised learning upon those encoded representations. The model's conducting was done with three layers, i.e. a dense type of output layer and two convolutional layers that each consisted of ten filters of size 5. The study determined the layer parameter combination for minimisation of training loss and discovered that there was little consequence for the accuracy of detection from a sizeable number of filters. The experiments have results that indicate deep neural networks' ability to detect intracranial hypertension within patients accurately with waveform morphology. Amongst the methods of deep learning, CNNs offer an ability unique in the extraction of features hailing from signals in translationally invariant ways, which allows us to analyse those data objectively. Whilst deep learning can generate complex functions that are fitting, even though the results have promise, a full evaluation of the performance of the model calls for a more extensive set of tests. Testing upon a set that is independent fails to ensure there is uncorrelated data and so there is a need for further analyses to understand to what degree the network is generalisable. Neural networks and CNN (convolutional neural networks) specifically have been shown as useful about the learning properties for ICP beat waveforms to detect intracranial hypertension presence. Methods for the characterisation of hypertension in a manner that is non-invasive have been researched extensively. However, they remain to be realised; the anticipation from this paper is that the model of deep learning described herein represents a significant stepping stone in achieving that goal [99].

3.7 The System of Computer-Aided Diagnosis for Patients with Hydrocephalus

NPH (normal pressure hydrocephalus) is a reversible type of dementia, one of just a few of such types. Because of their versatility and low cost, CT (computed tomography) scans have been utilised for many years to help with reversible kinds of dementia and help diagnose, for example, NPH, and other kinds of intracerebral anomalies. However, no adequate and well-defined protocols currently exist, for the analyses in the setting to scan the subarachnoid space volumes and the ventricular, cerebral mass. In the NPH setting, the Evans ratio approximates the ratio of the ventricle to the ventricular, cerebral mass and the volumes of subarachnoid space. It has been proposed to use the Evans ratio for approximating the ratio of the ventricle to the brain volume using just one two-dimensional scan slice; however, this is not sufficiently robust. The proposal within this study is to use an automated kind of method for calculating brain volumes so that there is, from the standpoint of radiology, better NPH recognition. Firstly, the method involves the alignment of the 3D volume of the subject CT to a space that is common by way of an affine transformation. A random kind of forest classifier is then used to mask the relevant types of tissue. The brain volume is partitioned by a 3D method of morphological segmentation and this, in turn, is utilised for the training of machine learning methods for the classification of subjects into NPH versus non-NPH based upon the volumetric information. Compared to the Evans ratio's thresholding method, there is increased sensitivity with the proposed algorithm. The SVM (support vector machine) and the random forest were utilised for training the volumetric information acquired from the algorithm for segmentation. As well as the ventricle, cerebral mass, and subarachnoid space, the classifiers were trained for brain size. The findings showed that the volumes of ventricles were more significant for NPH whilst there is mostly consistency for subarachnoid space in both NPH and non-NPH. For the ages of 69.5 plus or minus 4.8 years, ventricular volumes are stable for standard cases with average MRI (magnetic resonance image) derived for ventricular volumes [100].

Summary

The integration of artificial intelligence (AI) of tools and techniques into a digital healthcare system becomes an effective strategy to reduce healthcare costs, support clinical decision-making and manage chronic disease.

It is noticeable that there are preliminary studies that include machine learning techniques and their applications to analyse ICP readings for hydrocephalus follow up. There are many research studies about diagnosing the hydrocephalus disease using machine learning classifiers. This chapter demonstrates research studies to find the relation between ICP waveform and diagnosing hydrocephalus. It illustrates the role of machine learning in diagnosing headache. Headache is the main characteristic for hydrocephalus as patients feels in headache pain most of the times. Also, it demonstrates the role of machine learning to diagnose chronic diseases like cancer.

In this chapter, a comprehensive literature review is produced that motivates this research to go further and improve the currently available methods. This chapter achieve the research objective, which provide with a proper literature review about hydrocephalus, and the role of different types of machine learning in diagnosing and managing hydrocephalus disease. The chapter clarifies other types of machine learning like convolutional Neural Networks to analyse for ICP Waveform. In addition, the chapter demonstrates a study of monitoring of intraparenchymal ICP of hydrocephalus and cerebrospinal fluid. Another study clarifies the extracted morphological features of ICP.

Next chapter demonstrates the research framework. This chapter shows the flow of the whole work which employs the machine learning techniques to follow up shunted patients. In addition, a questionnaire of testing the user acceptance of using mobile health applications has been conducted.

Chapter 4: Research Framework

4.1 Introduction

As mentioned before the research goal is to employ the machine learning techniques to monitor and follow up hydrocephalus patients with implanted shunt. This chapter describes the research methodology layout including the steps of data collection including ICP analysis and collecting the patient’s feedback from the developed HydroApp, automation of the clinician’s way to follow up shunted patients. At the end of the chapter, it demonstrates the predictive models that used to produce the required risk assessments to monitor shunted patients.

4.2 Questionnaire Analysis

Studies shows that UK National Health Service (NHS) estimated that 4 out of 10 shunts would malfunction in the first year after shunt implant. The overall shunt failure rate was 46.3%, and most of the shunt revisions take place within the first few months after shunt placement. Hydrocephalus can arise at any age, even before birth. Some statistical estimations indicate that one out of every five hundred children are affected by hydrocephalus, and this rate is most likely on the rise.

The following data Analysis investigates the user's acceptance of healthcare technology, it discusses patient monitoring using M-health applications, and demonstrates an analysis for a questionnaire, which investigates the user's acceptance of healthcare technology. The development of IOS System (HydroApp) is illustrated in chapter 5.

The following figures (4.1 – 4.6) demonstrates the analysis of the questionnaire using SPSS software

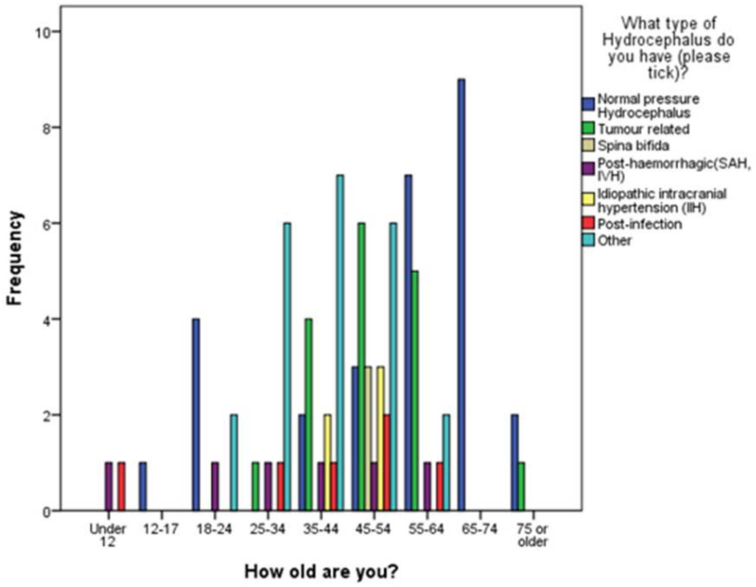


Figure 4.1 Analysing the relationship between hydrocephalus type and the patient's age.

The bar graph in **Figure *4.1*** illustrates the relationship between the patient's age and the type of hydrocephalus he has. Patients who were under 17 had Post-haemorrhagic (SAH, IVH) type, Post-infection type, and normal pressure hydrocephalus shared the frequency of one patient. However, most patients who have normal pressure hydrocephalus (NPH) were between 45 and 74 years old. Consequently, normal pressure type was a higher frequency than other types of hydrocephalus in age 45 to 55, while four patients were aged between 18 and 24 years old when they had NPH.

As for the tumour-related type, most patients were aged between 45 and 54 years old when they had the tumour related type, and four patients were between 35 and 44 years old. Patients who were 25 to 34 and who were older than 75 years old shared the frequency of one patient. The Post-haemorrhagic (SAH, IVH) type had a rate of one patient in most age categories as well as the Post-infection type. On the other hand, only three patients had Spine bifida type at the age of 45 to 54 years old. For the Idiopathic intracranial hypertension (IIH) type, patients were between 35 and 54 years old with the frequency of five patients. Patients who had other types of hydrocephalus had a high rate in different age categories. For example, seven patients had other types when they were between 35 to and years old, while six patients were aged 45 to 54 years old. Overall, the highest frequencies were distributed between NPH and the other types of hydrocephalus disease. Mainly NPH patients were aged between 55 and 74 years old. Tumour-related hydrocephalus type had the second-highest frequency for patients who were aged between 35 and 55 years old. **Figure *4.2*** illustrates the relationship between the hydrocephalus disease type and the patient's age when he had the first shunt.

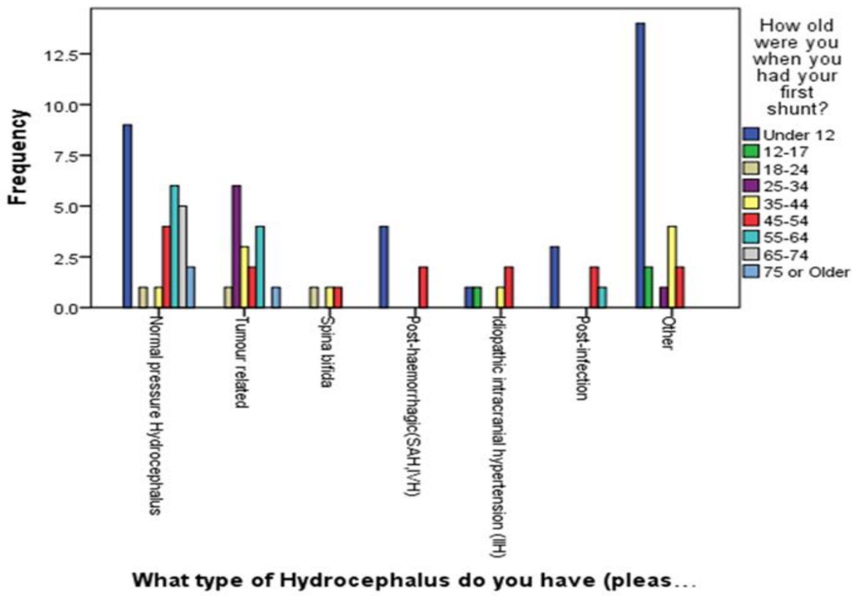


Figure 4.2 Analysing the relationship between hydrocephalus type and the patient's age at the first shunt

The chart shows information about the patient's age when they had their first shunt and the type of hydrocephalus. According to the bar chart, most patients had their first shunt when they were under 12. Nine patients who had NPH had the first shunt operation when they were under 12 years old; however, it was noticed that six (NPH) patients were between 55 and 64 years old when they had the first shunt. Five patients were between 65 and 74 years old when they had the first shunt. Only four patients had NPH when they were between 45 and 54 years old. The least frequency was for patients who were older than 75 and had NPH. The age categories 18 -24 and older than 75 years old shared the frequency of one patient with a tumour related hydrocephalus. As for the other age categories, the rate is more in the age category 25 to 34 years old, which is six tumour related hydrocephalus patients, while four patients were between 55 and 64 years old when they had their first shunt. The following age categories 18 to 24, 35 to 44 and 45 to 54 years old shared the frequency of one patient who had Spina bifida when they had their first shunt. However, four patients who had Post-haemorrhagic (SAH, IVH) type were under twelve years old. We can see from the chart that one patient with idiopathic intracranial hypertension (IIH) was under 12 and one patient was 12 to 17 years old and one patient was between 35 and 44 years old at the first shunt operation. Two patients who had Idiopathic intracranial hypertension (IIH) were 45 to 54 years old at the first shunt. Lastly, three patients who had Post-infection were under 12 years old at the first shunt, while the other three patients were between 45 and 64 years old.

Overall, most patients who had NPH and other types of hydrocephalus had the first shunt when they were children. Consequently, NPH is a common hydrocephalus type in childhood. There are some other types of hydrocephalus that have frequency in in most age categories. Therefore, patients who had different types of hydrocephalus were mostly under 12 years old when they had their first shunt. However, patients with Spina bifida type were the lowest frequency.

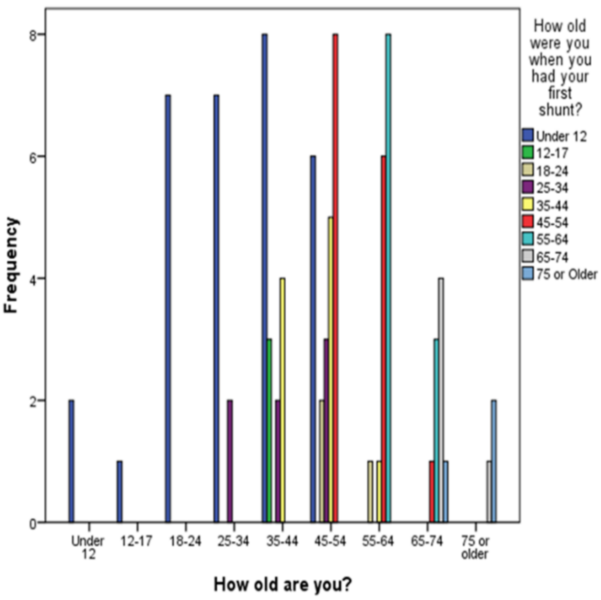


Figure 4.3 Analysing the relationship the patient's age and his age when he had the first shunt

The bar graph in **Figure *4.3*** illustrates the relationship between the patient's age and age of the first shunt operation. Around 6.5 % of patients who were under 12 years old, had the first shunt operation. However, one patient who was between 12 and 17 years old had the first shunt when he was under 12 years old. The age categories 18 to 24 and 25 to 25 to 34, shared the same frequency, which is seven patients, which is 22.6%. Six patients aged 45 to 54 years old had the first shunt when they were children under 12 years old.

Only three patients were between 12 and 17 years old and had the shunt when they were under 12 years old. However, two patients were between 45 and 54 years old and had the first shunt when they were 18 to 24 years old. Following that, 42.9% of patients who were 45 to 54 had the operation when they were 25 to 34 years old. However, five patients had their shunt at age 45 to 54 years old. Most patients who were aged between 55 and 64 years old, had their first shunt at the same age represented in the percentage of 72.7%. Six patients were between 45 and 54 years old. Patients who had hydrocephalus disease in the adulthood, had the shunt at the same age or a few years before. Based on the previous analysis, patients who had the disease in middle age had the first shunt operation at an early age of their life. It has been found that patients who had their first shunt operation when they were children had NPH, which means that patients with NPH had more shunt operations than the other types. Most patients with a tumour related type were between 25 and 34 years old and had the first shunt at the same age or under 12 years old.

Consequently, patients with a tumour related type had a high number of shunt operations. On the other hand, patients who were between 45 and 54 year old had had different types of hydrocephalus disease and the first shunt operation usually was at the same age. Patients aged between 55 and 64 years old, were diagnosed with NPH or a tumour related or post-infection type and started to have the shunt operations at the same age or ten years before. Moreover, patients who had NPH and tumour related had a more significant number of shunt operations than the other hydrocephalus types.

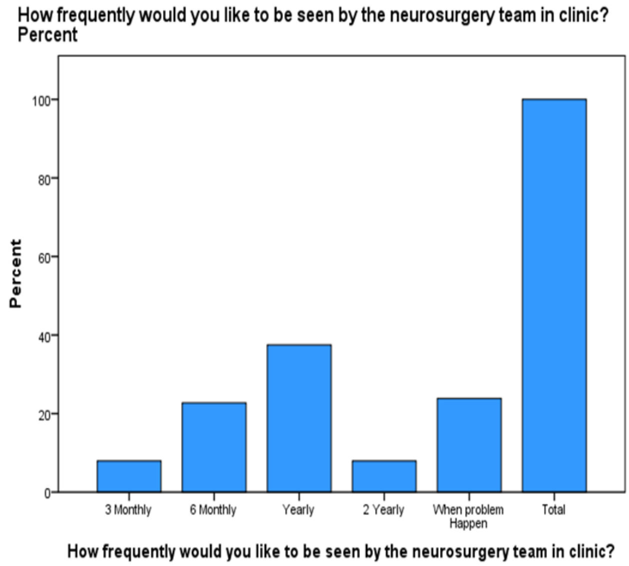


Figure 4.4 Analysing how frequently patients would like to visit the clinic

Figure *4.4* illustrates how frequently the patients would like to be seen in the clinic. Patients who wanted to be seen every three months or every two years shared a percentage of 8%. 22.7% preferred to be seen every six months. Most patients would like to visit the clinic once a year while 23.9 % of patients did not prefer regular visits; they would like to come to the clinic when a problem happens. Patients would like to decrease the number of regular clinic appointments despite having the need to be followed up continuously. **Figure *4.5*** illustrates the biggest worries for patients about their shunt. The graph shows that 75% of patients were worried about the shunt blockage or the shunt not functioning well. Moreover, 6.8% of patients were concerned about a headache that the shunt may cause for different reasons. 4.5% of patients were worried about the infection that can happen because of the shunt. However, patients who did not have concerns shared the same percentage as patients who were afraid of the shunt infection. Shunt blockage is the primary concern that may affect their health. As a result, patients have to have a regular follow-up to avoid the shunt blockage and discover any infections early then avoid pain and headache that may happen to the patient.

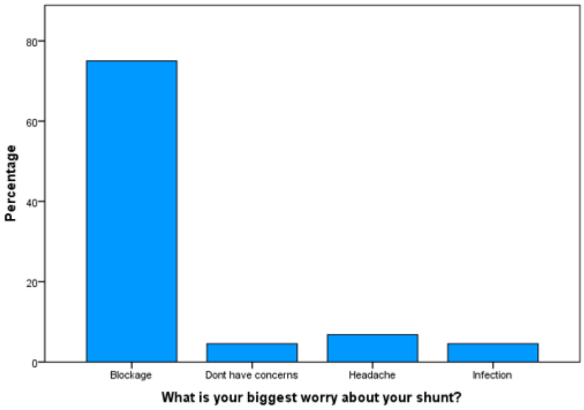


Figure 4.5 Analysing the biggest worries of shunted patients.

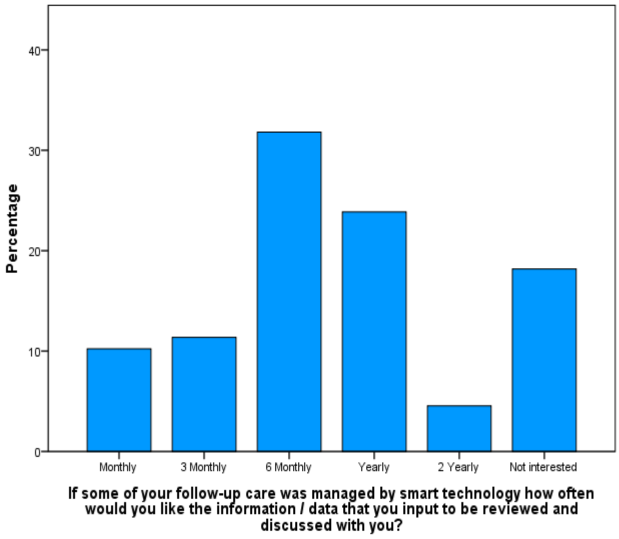


Figure 4.6 Analysing how often patients would like to be reviewed using smartphone technology

Figure *4.6* shows how patients would like to be reviewed in case of using smart technology to record their pain events. 10.2 % of patients prefer to be reviewed monthly. 11.4 % of patients wanted to be reviewed every three months to ensure the functionality of their shunt and treating any series of pain events. Most patients preferred to be reviewed every six months, which represented 31.8%.Consequently, 23.9 % of patients wanted to be reviewed yearly. Moreover, only 4.5 % of patients preferred to be reviewed and discussed every two years. On the other hand, 18.2 % of patients were not interested in this type of monitoring. Overall, the graph percentages indicate that hydrocephalus patients prefer to be monitored electronically using smartphone technology. Monitoring patients electronically will save their time, and at the same time, they feel comfortable and safe because they can record any pain episodes at any time.

Healthcare technology has a significant impact on patients' lives; it allows patients to record their daily health status and feel safe that they will be called when something serious is around. On the other hand, clinicians have time and flexibility to check their patient's records. The analysis showed that patients are ready to use health care technology, especially with a chronic disease like hydrocephalus. However, patients who have normal pressure hydrocephalus, usually implant the shunt within their childhood. Moreover, hydrocephalus disease needs to be followed regularly to protect the patient from the shunt blockage or infections that the shunt may cause it. Overall, using healthcare technology to follow up and specify risk assessment will improve patient experience, safety, and quality of life utilizing proper prognosis together with lowering the potential for the occurrence of medical errors. As a result, using healthcare technology has a significant impact on NHS, patients, and clinicians.

Based on the analysis of the user acceptance of M- health, which is very high. It was a strong motivation to carry on this research.

The next section shows the implemented methodology to monitor shunted patients using machine learning techniques, ICP analysis and the use of M-health technology.

4.3 Methodology Flow Chart

This research is going through several procedures including data analysis and getting it ready for machine learning classifiers. In addition, HydrApp system has been developed to record the patient's feedback.

The following **Figure** ***4.7*** shows the flowchart of the research framework. The following sections is clarifying each step.

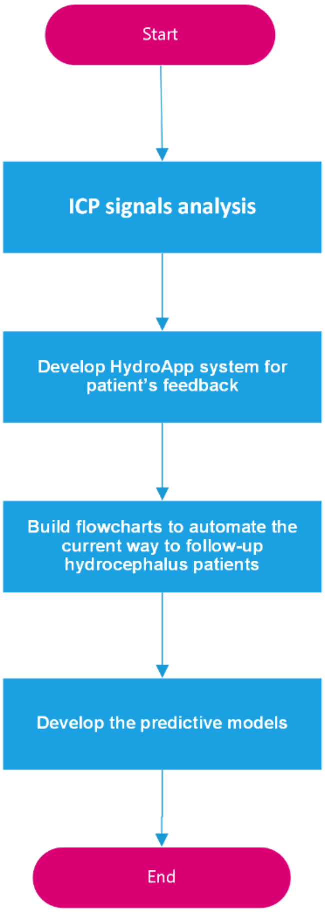


Figure 4.7 Methodology research framework

4.4 ICP Signal Analysis

In this stage, the ICP signals are converted from signals to numeric to be ready as an input for the chosen classifiers. It is also explaining feature extraction and how it is used for preparing the ICP data set for the purpose of selecting a ready to use ICP data set.

The proposed methodology framework and experimental set-up for ICP signals have also been presented in this section. It discusses the data preparation process. In this scenario, this step focuses on addressing the missing values, oversampling, identifying outliers, and data normalisation technique. The ICP signals are processed and converted to numeric to be a sufficient input to the chosen machine learning classifiers. The ICP signals are converted to eight blocks of averages based on the clinician's recommendations that allow them to effectively monitor shunted patients. The Dataset consist of analysed ICP signals and the patient's feedback that extracted from HydrpApp system which is the next step of the research framework.

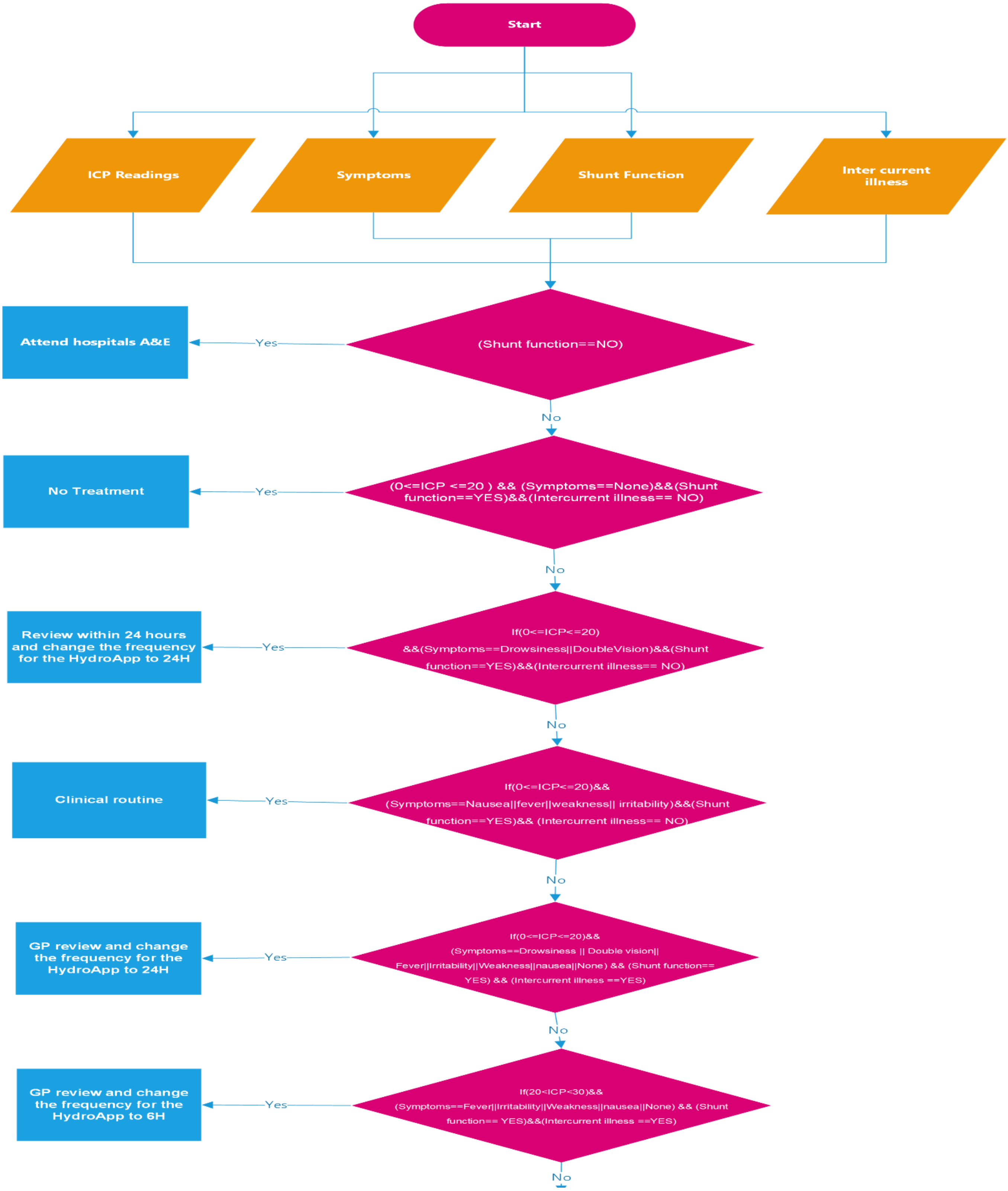
4.5 Develop HydroApp System for Patient's Feedback

Patients with long-term conditions such as hydrocephalus are usually asked to complete traditional paper-based diaries and regularly, which enables specialists to monitor and evaluate their status. However, within a publicly funded healthcare system such as the UK's National Health Service (NHS), long-term follow-up in neurology clinics appears not to be possible for all shunted patients due to the continued decline in funding over the past decade. Consequently, ensuring the continuity of care for shunted patients requires a switch from a classical model of care to a new model, in which shunted patients are encouraged to track their conditions and to play a vital role in managing their care. In this context, a questionnaire was conducted to investigate the user's acceptance of healthcare technology and to test the patient's ability to transfer from the traditional follow-up method to the use of mobile health applications. Eighty-eight hydrocephalus patients have been picked randomly and asked to complete the questionnaire. Most patients were adults within different age categories and have the shunt. The graphs were extracted using SPSS, which is a statistical software used in various sciences like the business world, social sciences and natural sciences [19–24]. The following analysis demonstrates how far patients can accept the idea of electronic follow–up by using m-Health applications.

4.6 Flowcharts to Automate the Patient's Follow-up

This section presents the automation of clinical approach in following up hydrocephalus patients.

The flow charts show the automation of the process of combining the signs and the ICP readings by taking the right decision based on the given scenario from clinicians. Clinicians can take their decisions by relying on the ICP readings for the patient and the symptoms that he feels at this time. **Figure *4.8*** show a flowchart that automates the current method of monitoring shunted patients. Detailed flowcharts is demonstrated in chapter 4 for clearer vision.



Start
ICP Readings
Symptoms
Shunt Function
Inter current illness
(Shunt function==NO)
Yes
Attend hospitals A&E
No
(0<=ICP <=20) && (Symptoms==None)&&(Shunt function==YES)&&(Intercurrent illness== NO)
Yes
No Treatment
No
If(0<=ICP<=20) &&(Symptoms==Drowsiness||DoubleVision)&&(Shunt function==YES)&&(Intercurrent illness== NO)
Yes
Review within 24 hours and change the frequency for the HydroApp to 24H
No
If(0<=ICP<=20)&& (Symptoms==Nausea||fever||weakness|| irritability)&&(Shunt function==YES)&& (Intercurrent illness== NO)
Yes
Clinical routine
No
If(0<=ICP<=20)&& (Symptoms==Drowsiness || Double vision|| Fever||Irritability||Weakness||nausea||None) && (Shunt function== YES) && (Intercurrent illness ==YES)
Yes
GP review and change the frequency for the HydroApp to 24H
No
If(20<ICP<30)&& (Symptoms==Fever||Irritability||Weakness||nausea||None) && (Shunt function== YES)&&(Intercurrent illness ==YES)
Yes
GP review and change the frequency for the HydroApp to 6H
No

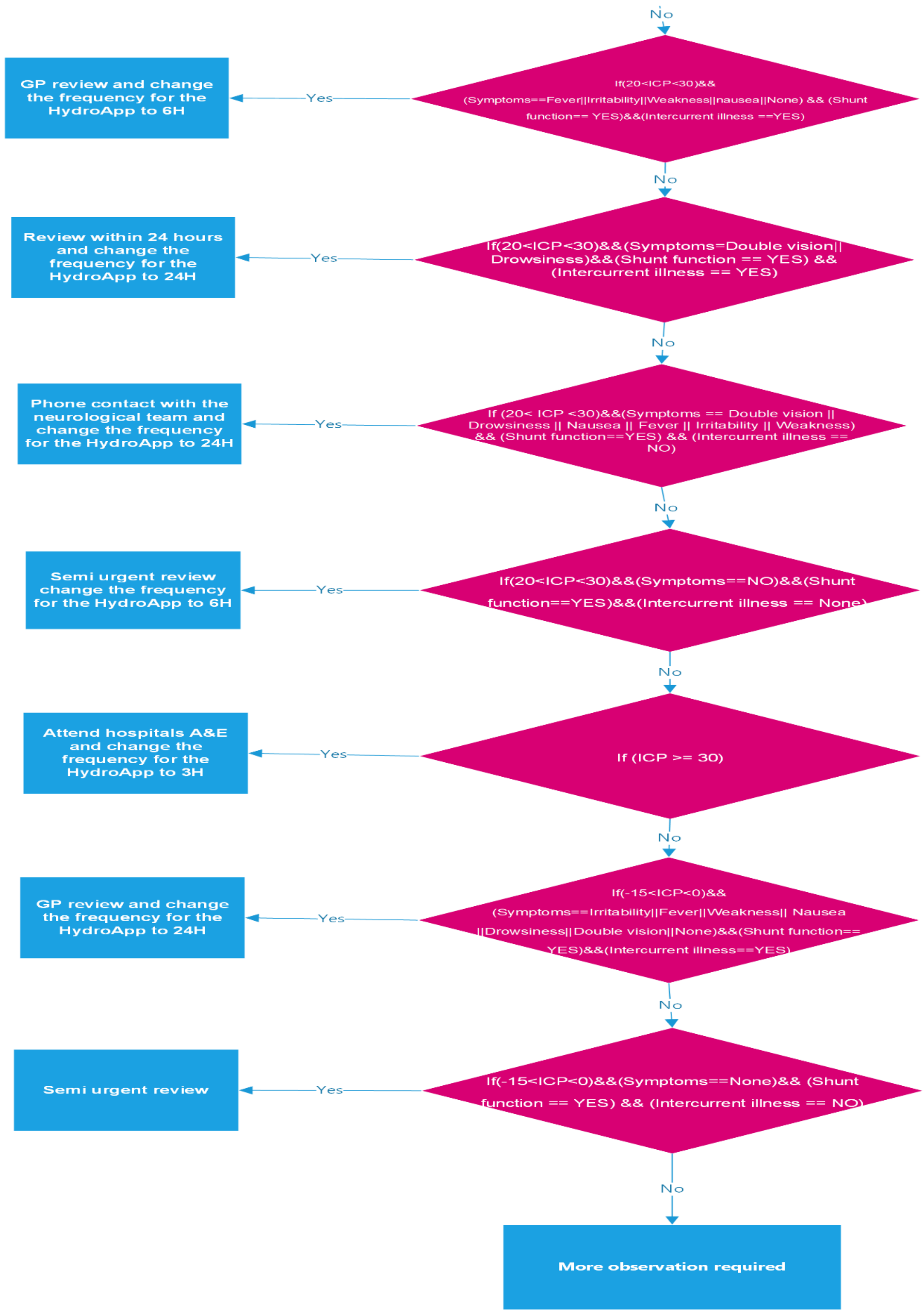


Figure 4.8 Flowchart to automate the monitoring procedure for shunted patients

4.7 Predictive Models and Results

This step demonstrates the performance metrics and simulation results. In addition, it demonstrates the analysis for the various machine-learning models that have been selected in this research work. It elaborates more in further discussion about each of the used classifier based on the performance evaluation metric techniques (Sensitivity, Specificity, precision, accuracy). A Computation of the confusion matrix was also performed in this step.

Summary

There is potential for machine learning and the employment of advanced forms of analytics for advancing the manner in which technology is leveraged by providers in the making of more informed types of clinical decision. However, the huge volumes of data that are generated each year in the healthcare field have to be compartmentalized and organized in such a way that it enables there to be transparency and universal accessibility between different healthcare organizations. This chapter demonstrates the research workflow and clarifies the steps that employs different machine learning techniques achieve high results to monitor shunted patients.

It is expected that there will be further studies showing consideration for patient characteristics through use of customized forms of medicine and diagnostics that are computer aided. It is crucial to have a data set that contains ICP readings for hydrocephalus patients to improve the currently available methods. The next chapter will include a discussion about the available data set and data features extraction and selection. HydroApp system is demonstrated to retrieve the other features for the study to start developing our dataset, which contains many properties and features to help in achieving the required result.

Chapter 5: The Intracranial Pressure Dataset

5.1 Introduction

Intracranial pressure (ICP) could be an indicator of a neurological disorder known as hydrocephalus, which is currently managed by the shunting procedure. This chapter provides an overview of ICP readings interpretation from a medical point of view concerning Alder Hey Children's Hospital NHS Foundation Trust in Liverpool, UK. Moreover, it helps to express ICP readings using an advanced data science approach and prepares for implementing intelligent strategies as an alternative pathway to improve the use of ICP within the current medical system. It is assumed that would help specialists and non-specialists in an informative way to comprehend ICP readings. It also allows combining ICP readings with other parameters to derive a proper action concerning patients with hydrocephalus.

A Swift programming language has been used for the IOS platform to implement the application. Users can use the HydroApp as long as the internet connection is provided. Users can use the HydroApp to record their pain episodes. This chapter demonstrates the dataset developed in this research.

5.2 Selection and Extraction Features

The general approach to machine learning, which captures many existing learning algorithms, is the modelling approach allowing systems to automatically enhance their performance of a task by spotting relevant data. Machine learning techniques are based on recognizing patterns in data by discovering ways to categorize a required subject based on the existing variances between issues [101]. The process of reducing the number of variables and features is called dimensionality reduction. Dimensionality reduction can be divided into subcategories which are feature selection and feature extraction. There are many advantages for feature selection like shortening the training time, more accessible to interpret the model, reduce the overfitting and improve accuracy [102]. There are many types of feature selection; forward selection, backward elimination (recursive feature elimination) and stepwise selection. Forward selection can identify the best variables (e.g., based on model accuracy). Forward selection can add the next best variable into the model and so on until some predefined criteria are satisfied. Back elimination can start with all variables. Backward elimination drops the least useful variable (e.g., based on the smallest drop in model accuracy) and so on until some predefined criteria are satisfied. Stepwise selection is similar to the forward selection process, but a variable can also be dropped if it has been deemed as not useful any more after a certain number of steps.

5.2.1 ICP Signals Feature Selection Methodology

Compared to other topics in computer vision, little formal or analytical work has been published to guide the creation of ground truth data [103]. There is some guidance provided by the machine learning community for measuring the quality of ground truth data used for training and test data sets, but this tends to revolve only around the size of the data set [104]. To address this issue, we propose a novel method to assess ground truth quality, through calculating its confidence and consistency levels to measure its accuracy and variability, respectively. Ideally, Hydrocephalus patients should be ICP monitored continuously to confirm that ICP remains within the normal range. The raw data were obtained using the Raumedic device, which is a portable ICP device. A patient's feedback is extracted from the HydroApp, which includes the current symptoms and inter current illnesses. **Algorithm 1** presents the process that is used to explain the methodology that followed in the ICP feature selection. The data set includes ICP signals, collected from patients who are shunt dependent. However, the patient's feedback from the HydroApp is also used as an input for the classification algorithms. Matlab software is used to analyse the ICP signals. **Figure *5.1*** shows the flow chart of the signal-processing phase.

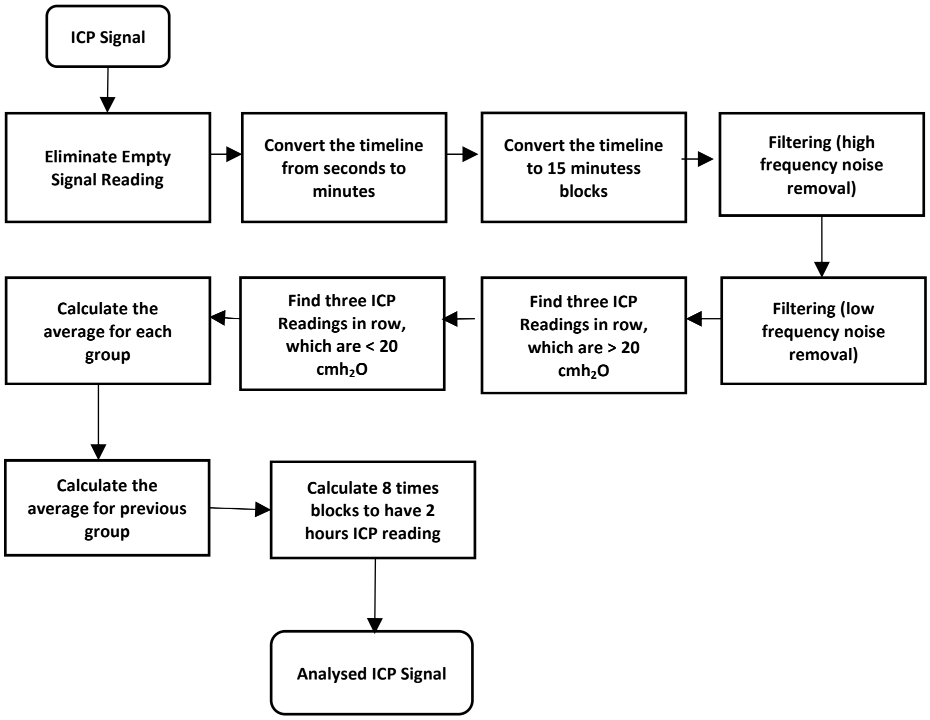


Figure 5.1 Methodology of features selection of ICP signals

5.2.1.1 Data Cleansing

Missing data can happen for several reasons, such as unexpected difficulty in getting some vital readings. Missing values or null values are common in the medical data set. Data cleansing tasks are performed to reduce noise like gaps or empty values as well as increasing the consistency of the data. Some ICP signals have meaningless readings, which means null values at different times, as highlighted in **Figure *5.2***.The algorithm eliminates all the null values from the ICP readings to prepare the data for the next step by having a consistent and continuous stream of input data to our model.

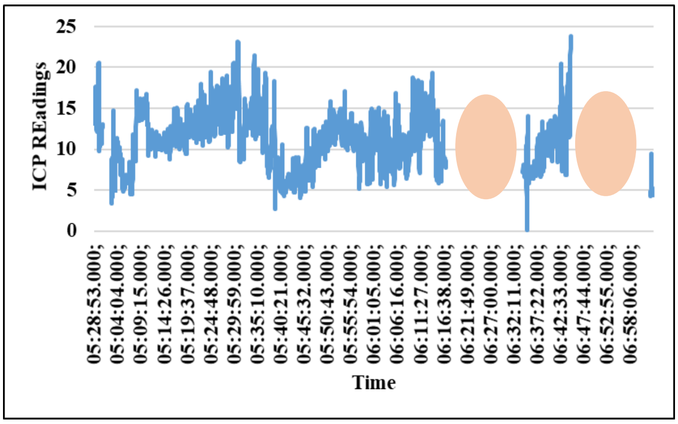


Figure 5.2 ICP signals with empty readings

5.2.1.2 Converting the ICP Signals from Seconds to Minutes

Usually, clinicians only consider a change in ICP signal when it is seen continuously for several minutes. However, the Raumedic ICP device registers the signals in seconds. Consequently, to avoid this problem, the algorithm converts the timeline from seconds to minutes. **Figure *5.3*** shows the ICP signals in minutes, so it is easier to detect the concerning signals that indicate the patient's case.

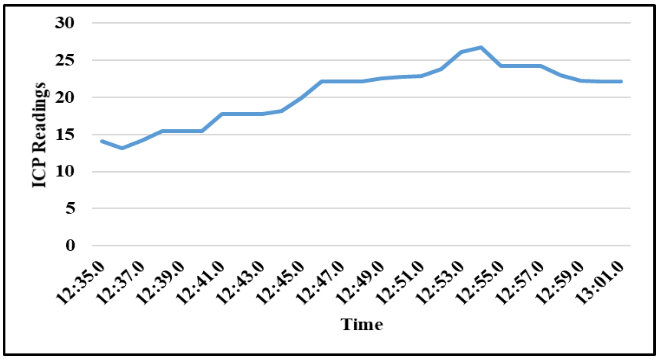


Figure 5.3 ICP signals in minutes

5.2.1.3 Data Grouping

Based on the expert's recommendations, the algorithm divides the timeline into 15 minutes blocks because doctors consider at least 15-30 minutes of continuous high or low ICP readings to be significant. However, they keep observing the patient for at least two hours to evaluate any ongoing shunt issue better. The multiple chunks of data are grouped by the ICP number like ICP1, ICP 2 …, ICP8. As seen in **Algorithm 1,** the sums of every 15 minutes been processed to produce eight columns of 15 minutes of ICP readings for two hours which indicates eight columns of 15 minutes blocks of ICP readings.

Let us assume that X is a matrix of t and r where t is the time in minutes and r is the ICP readings, r is the number of ICP blocks. The algorithms will group the reading in 15 minutes' blocks. Moreover, the algorithm defines the average pressure as ICP readings between 0 and 20 if 0<=r<=20 where a>=3.

Algorithm 1: Data Preparing

$Intitilase$

$X \leftarrow input\ matrix$

$Y \leftarrow output\ matrix$

$t \leftarrow Timestamp\ in\ second$

$r \leftarrow ICP\ reading$

$Read\ new\ file\ as$

$$x \leftarrow \begin{pmatrix} t1 & r1 \\ t2 & r2 \\ t3 & r3 \\ . & . \\ . & . \\ . & . \\ tn & rn \end{pmatrix}$$

$Perform\ Processing$

$\forall X\ if\ Length\ X >= 7200\ then$

$Drop\ empty\ value\ from\ X$

$Transform\ X\ to\ minutes\ interval$

$\forall r \; in \; X$

$Find \; consigative \; 3 \; or \; ablove \; r \; calculate \; the \; average$

$$r' \leftarrow 1/a \sum_{n=1}^{a} \mathrm{rn} \qquad \text{Where} \quad \mathrm{r} < 0 \,, \qquad \mathrm{a} \geq 3$$

$$r' \leftarrow 1/a \sum_{n=1}^{a} \mathrm{rn} \qquad \text{Where} \quad 0 \leq \mathrm{r} \leq 20 \,, \qquad \mathrm{a} \geq 3$$

$$r' \leftarrow 1/a \sum_{n=1}^{a} \mathrm{rn} \qquad \text{Where} \quad \mathrm{r} > 20 \,, \qquad \mathrm{a} \geq 3$$

$$Y \leftarrow \begin{pmatrix} r'1 \\ r'2 \\ r'3 \\ . \\ . \\ r'n \end{pmatrix}$$

$Reshape \; Y \; into \; multiple \; of \; 8$

$$Y = \begin{pmatrix} r'_{1,1} & r'_{1,2} & \ldots r'_{1,8} \\ r'_{2,1} & r'_{2,2} & \ldots r'_{2,8} \\ & & \vdots \\ r'_{n,1} & r'_{n,2} & \ldots r'_{n,8} \end{pmatrix}$$

$End \; For$

$Else$

$No \; Action$

$End \; If$

$End \; Procedure$

5.2.1.4 High -Frequency Noise

Figure *5.4* shows ICP signals with individual values of high ICP readings. High individual values happen when the patient has a sudden movement or response like yelling, crying, being extremely happy and many other examples of human reactions and does not affect the patient clinically. The red arrow represents high ICP readings. The figure shows that the patient had an ICP reading of 22 cmH_2O at a specific time.

On the other hand, the graph shows a normal ICP signal throughout the baseline. The ICP data preparing algorithm checks for high-frequency noise which is higher than 20cmH_2O for a short period. Then the algorithm removes it.

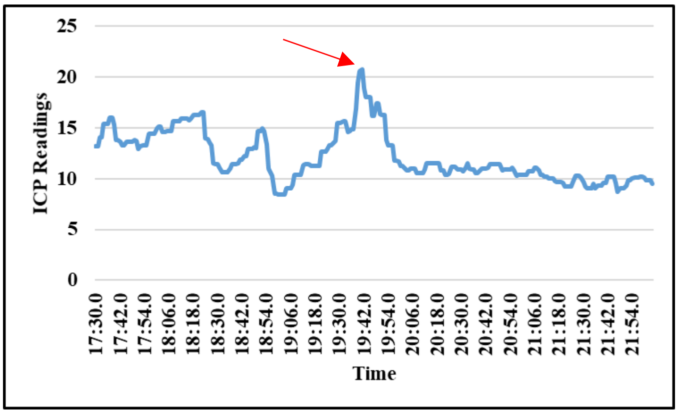


Figure 5.4 Example of high-frequency noise

5.2.1.5 Low-Frequency Noise

Usually, doctors do not consider the low-frequency signals which occur once or twice at different times. The algorithm in **Figure *5.5*** removes the low-frequency noise from the ICP readings. **Figure *5.5*** shows some low-frequency noise that will be eliminated to prepare the data for the analysis. The red arrow indicates the low-frequency noise in the graph. The algorithm uses the same strategy for disposing of the high and low-frequency noise.

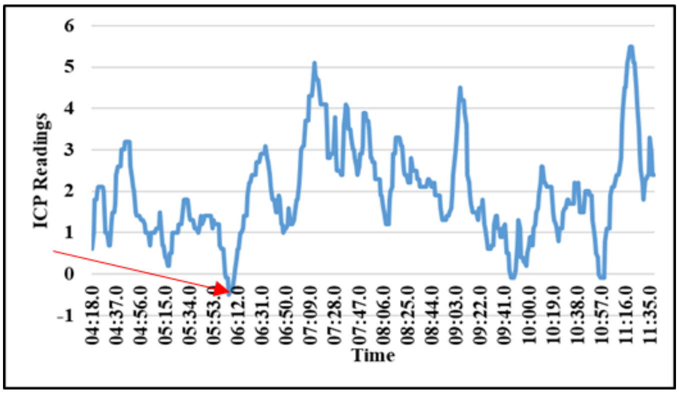


Figure 5.5 Example of low-frequency noise

5.2.1.6 Converting the ICP ≥ 20 From Signals to Numeric Data.

Figure ***5.6*** shows more than three consecutive readings which are higher than 20; the algorithm in **Algorithm 1** detects at least three peaks in a row and finds the average for these readings. This process will convert the data from signals to understandable numeric that enables the clinicians to read the ICP readings in an efficient way with minimum time consuming.

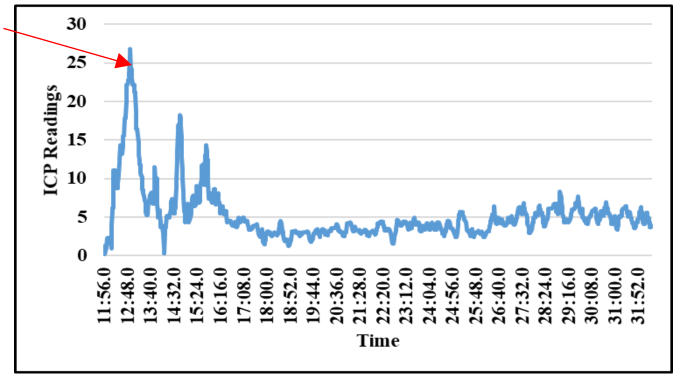


Figure 5.6 More than three consecutive readings of>20

5.2.1.7 Converting the ICP Readings < 20 From Signals to Numeric Data.

For over drainage cases, doctors consider at least three continuous peaks of ICP signals which are under 0 cmH_2O. **Figure** ***5.7*** shows that the following readings have at least three peaks under 0 cmH_2O within 15 minutes. The red arrow shows three peaks under 0 cmH_2O.

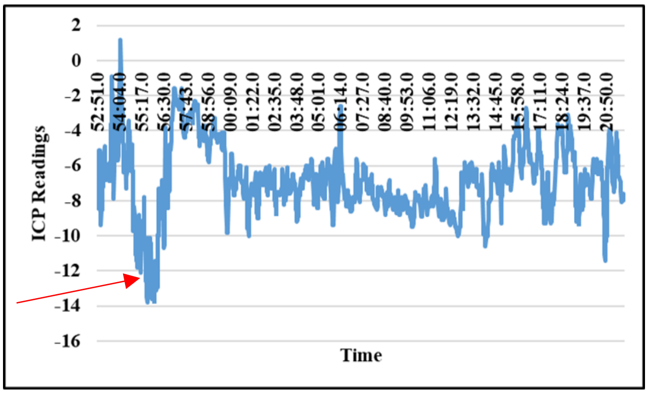


Figure 5.7 Readings have at least three peaks under 0 cmH_2O within 15 minutes.

5.2.1.8 Calculating the Average for ICP Groups

For every group, if there are three peak readings, we have to calculate the average of the readings to have one value to more easily estimate the patient’s status within a particular time as well as condensing data to a usable state for training and testing.

5.2.1.9 Calculating the Average for Previous Averages

This step unifies the averages for all the ICP signals to generate a new data set for all previous readings. **Table *5.1*** and **Table *5.2*** shows the normalized data set that is ready for training and testing.

5.2.1.10 Combining 8-time Blocks to Have 2-Hour ICP Readings.

Algorithm 1 demonstrates the process used to analyse the data set. Based on the clinician's recommendations, the patient’s case is considered as having high or low ICP signal when there are at least three high /low readings within fifteen minutes. Continued ICP monitoring establishes whether it is high /low-frequency noise. **Table *5.1*** shows a sample data of combined eight blocks of fifteen-minute averages to compose two hours for ICP signals with calculated averages. Whereas **Table *5.2*** demonstrates a sample of the data input obtained from the HydroApp system.

Table 5.1 ICP readings in 15 minutes blocks

ICP1	ICP2	ICP3	ICP4	ICP5	ICP6	ICP7	ICP8
0.891389	1.177937	2.905407	2.272444	2.411444	3.93763	4.632704	2.264963
3.093296	4.024111	3.853111	4.473778	4.802704	4.832333	4.976778	7.501629
3.955852	5.925296	7.967556	7.006889	8.152	5.642259	8.289296	10.62674
14.48144	19.81993	22.50759	18.80355	18.25744	15.78385	11.42337	9.244111
12.0233	12.46907	18.16535	18.15718	17.59496	15.32167	14.57405	9.847704

Table 5.2 Sample of the input data

Symptoms	Shunt Function	Intercurrent illness
None	Yes	Yes
Irritability	No	No
Drowsiness	Yes	Yes
Drowsiness	Yes	No
Drowsiness	No	No
Nausea	Yes	Yes
Nausea	No	Yes
Nausea	No	No
Double vision	Yes	Yes
Double vision	No	Yes
Double vision	No	No
Fever	Yes	Yes
Fever	No	Yes
Fever	No	No
Weakness	Yes	Yes
Weakness	No	No

5.3 Development of HydroApp

The phone market is one of the broadest and most competitive sectors in the modern time. Phone companies try to attract and build a strong relationship with customers by delivering better service and better quality [105][106]. As a result of the growth of the phone market and social media usage, there are ever-increasing numbers of mobile owners downloading applications for every aspect of life [107]. Therefore, smartphones support many sectors in the economy, such as business, transportation, and especially health care [108][109].

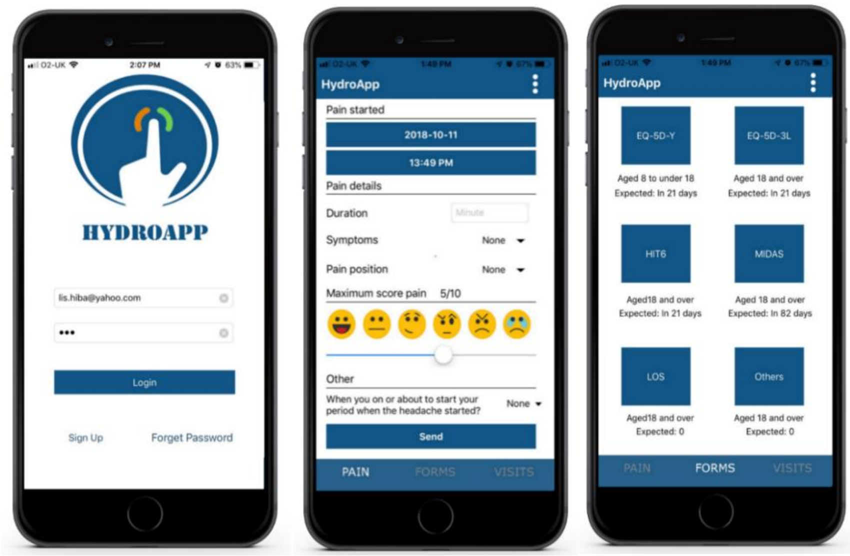
Mobile–health applications (M-health applications) have an increasingly integral role in people's lives. Mobile health is part of the broader "eHealth" global movement, which is using technology such as computers, mobile phones, mobile health devices and mobile health apps to monitor patients and provide them with health services and the necessary lifestyle advice. A study in 2014 that compared the average usage of health applications with the previous year showed that 19% of mobile owners downloaded health apps while 27% of users looked for enhancement of health-related motivation (fitness applications). This study also showed that downloading apps for environmental monitoring and tracking increased by 38% [110]. Both mobile health and eHealth providers gather information required to improve healthcare outcomes.

M-health applications have the potential to reduce the cost to the NHS by reducing the number of regular follow-up appointments as well as phone calls. M-health may change the need for regular follow–ups. This experience provides patients and clinicians mobile, personalized records for every patient.

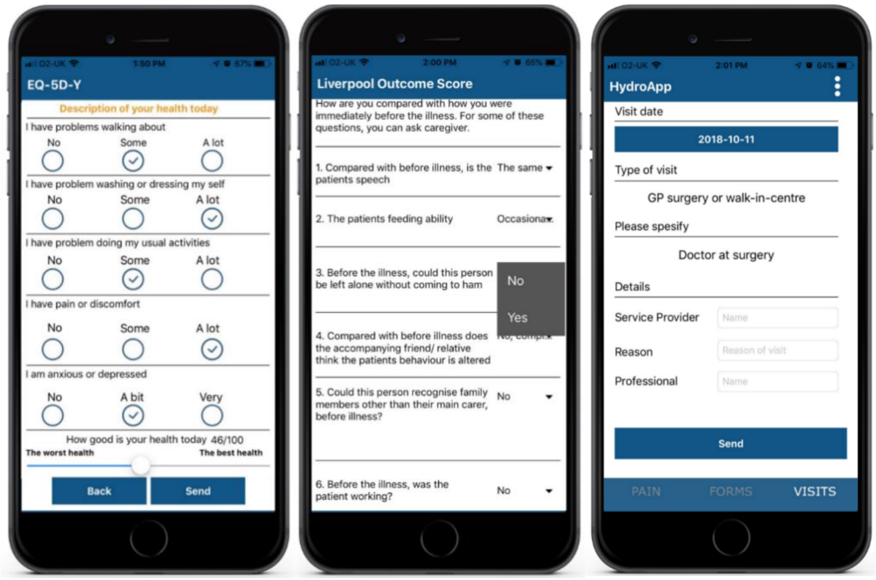
More than 15 million people in England have a long-term health condition [111]. These people use a large proportion of health care resources. Patients with long-term conditions such as hydrocephalus are often asked to complete paper-based diaries and outcome measure forms regularly, to enable specialists to monitor and evaluate their status. Ensuring long-term continuity of care for shunted patients requires a switch from a classical model of care to a new model, in which shunted patients are encouraged to track their conditions and to play a vital role in managing their care.

There are many types of research trying to reduce medical costs by automating the diagnosis of disease, especially chronic diseases. Research in machine learning and health care makes it possible to drive innovative medical practice using the enormous volume of data (evidence). Moreover, physicians, nurses and clinical staff may be helped to make decisions and decrease the incidence of medical errors by analysing all available data; presenting it clearly and suggesting a course of action [112].

Over the last few years, we have started to work with our partners in Alder Hey Children's Hospital NHS Foundation Trust to improve the monitoring of patients with hydrocephalus using intelligent mobile applications. We have successfully developed the HydroApp system for remote control of patients with hydrocephalus, which is currently in the process of feasibility testing in Alder Hey Hospital. The HydroApp allows patients to send their diaries and outcome measures anytime/anywhere. It enables specialists to monitor and evaluate their status. We have also investigated patients' acceptance of using such technology to manage their conditions. Enormous interest was found amongst patients with hydrocephalus to adopt the HydroApp. The developed system is a web-based system. HydroApp can be used to manage, communicate and provide the required follow-up for patients with hydrocephalus +/- headache. This App gives both patients and clinicians the ability to keep track of pain. HydroApp system allows patients to record all the symptoms related to headache. Questions related to the patient health need to be answered by the patients, which can be used with the recorded data from the system to help the clinician to make the decision, based on the graphical representation for the system analysed data. As shown in **Figure *5.8Figure 5.8*** , the application has been implemented and is already in use. The clinical dashboard displays a graphical representation of the data provided by the patient and analysed by the App.



A. Login activity **B. Pain tab** **C. Forms tab**



D. EQ-5D-Y tab **E. LOS tab** **F. Visits tab**

Figure 5.8 (A-E) Regular user tabs on the application

We worked on the management of the users' accounts, of which managing passwords are the most crucial part. We used the salted password hashing method which converts the password to fixed–a length that cannot be reversed and it will be different from the original password. Ideally, we used hash functions because it could not return the unique password, which provides adequate security for the password. On the other hand, Hackers and malicious software may try to know passwords, so we used "salting" which is a function that can add random numbers, that are called salt, to the password before hashing the password. Consequently, in the implemented application, the server application will receive the user's login information, which is username and password when the user submits his login information, which is a standard method of authentication. The server application will investigate whether the login information was right and query the table that has the ID for the authorized users. If the user's data is matching with one of the authorized users, the server application will send patient_id to the client app to start a session and enter the necessary information.

5.4 Automating the Clinical Approach in Following Up Hydrocephalus Patients

The current methodology followed by clinicians to follow up the hydrocephalus patients, is based on combining a set of symptoms with ICP readings. The symptoms include drowsiness, nausea, double vision, fever, irritability, weakness, which are collected manually by patients in addition to the collected ICP reading for each patient. The symptoms are demonstrated in chapter 2.

The following flow charts are the automated process of clinician's methodology of monitoring shunted patients using ICP readings and the patient's feedback through HydroApp. Moreover, intercurrent illness plays an essential role in taking the decision as well. All the following figures of flow charts demonstrate the scenarios have been reviewed and accepted by clinicians.

1. Shunt function is very important factor for shunted patients to keep them stable and continue with their daily life normally. Shunt malfunction leads to several problems that must be fixed; shunt malfunction has been discussed in chapter 2. **Figure *5.9*** shows that the patient should attend the hospital's A&E if the shunt is not functioning well regardless the other data.

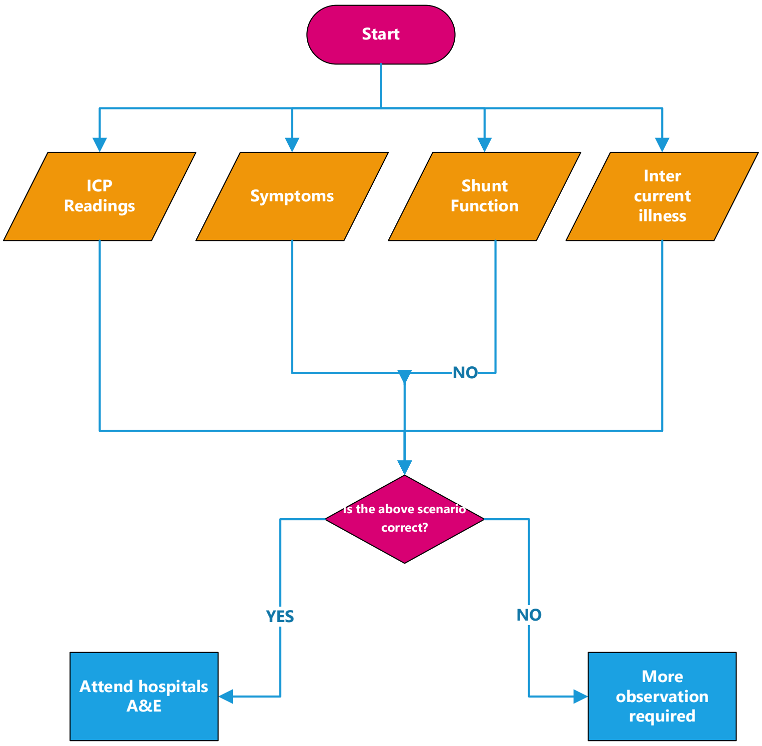


Figure 5.9 Flow chart of Attend hospitals A&E

2. No treatment action is taken when the ICP reading is at the regular and stable, and the patient feels well and there no symptoms to be recorded in the HydroApp. At the same time, there are no other illnesses, so the patients require no treatment. **Figure *5.10*** shows a flow chart to take no treatment action.

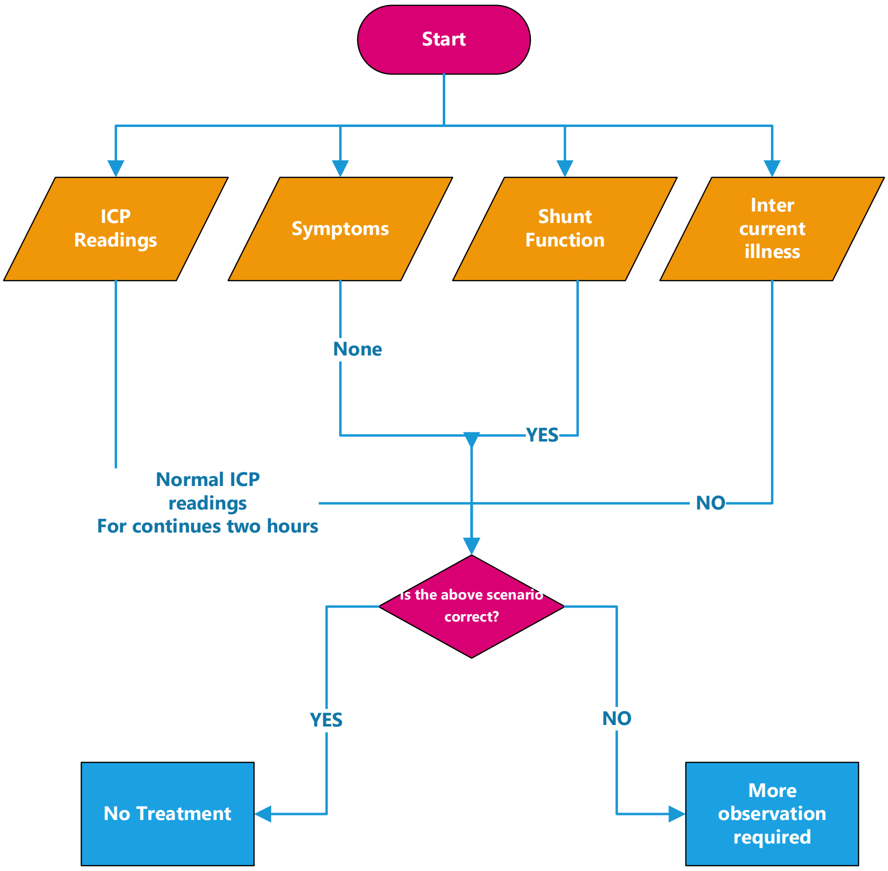


Figure 5.10 Flow chart of no treatment action

3. Drowsiness and double vision are considered as critical symptoms for shunted patients.

If the patient has regular ICP but double vision and drowsiness; the patient must be observed and reviewed within 24 hours to check his ventricles and the shunt functionality. The clinicians contact the patient and check his case. **Figure *5.11*** shows that if the patient has drowsiness or double vision with regular ICP, and the shunt is functioning well the patient should be reviewed and observed within twenty-four hours.

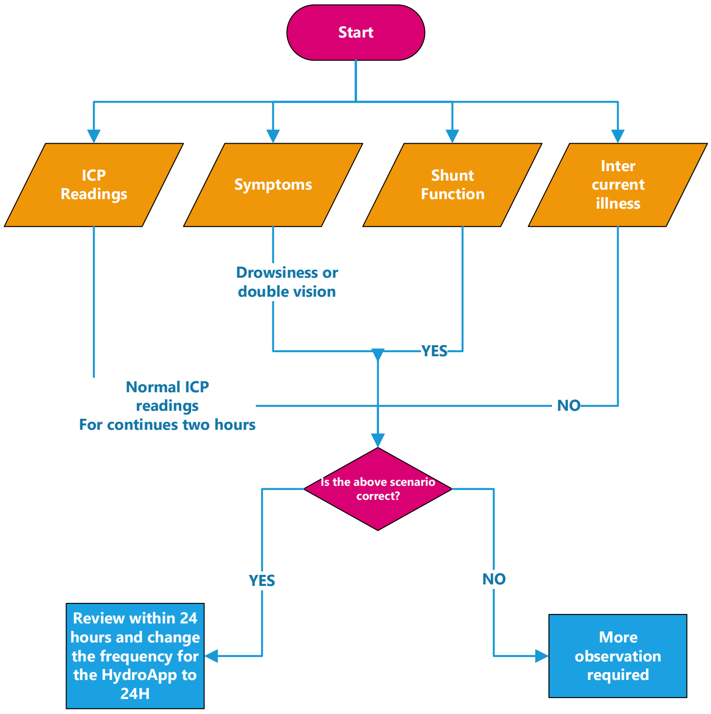


Figure 5.11 Flow chart to review patients within 24 hours

4. When the patient is feeling tired or not feeling well like having weakness, irritability, nausea or fever, however, their shunt is functioning well and their ICP is in its regular bases, and there are no other illnesses, in this case, the HydroApp sends notification of the following clinical routine. **Figure *5.12*** shows the flow chart of the clinical routine action.

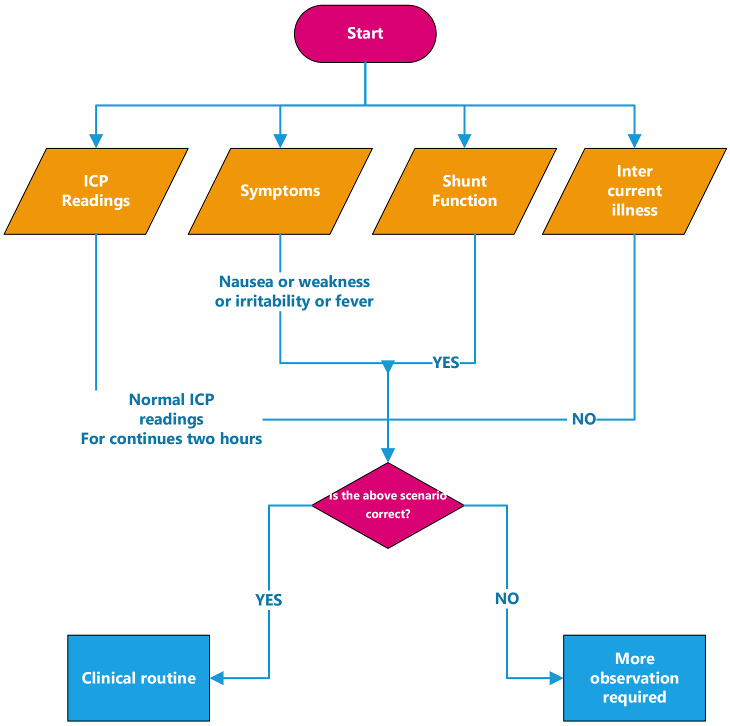


Figure 5.12 Flow chart to review patients in their clinical routine

5. When the patient has another illness that may cause symptoms like drowsiness, nausea, double vision, fever, irritability, weakness, the patient will receive a notification from the HydroApp to review GP. In this case, the ICP is stable, and the shunt is functioning well. **Figure *5.13*** demonstrates the flow chart of the GP review with regular ICP.

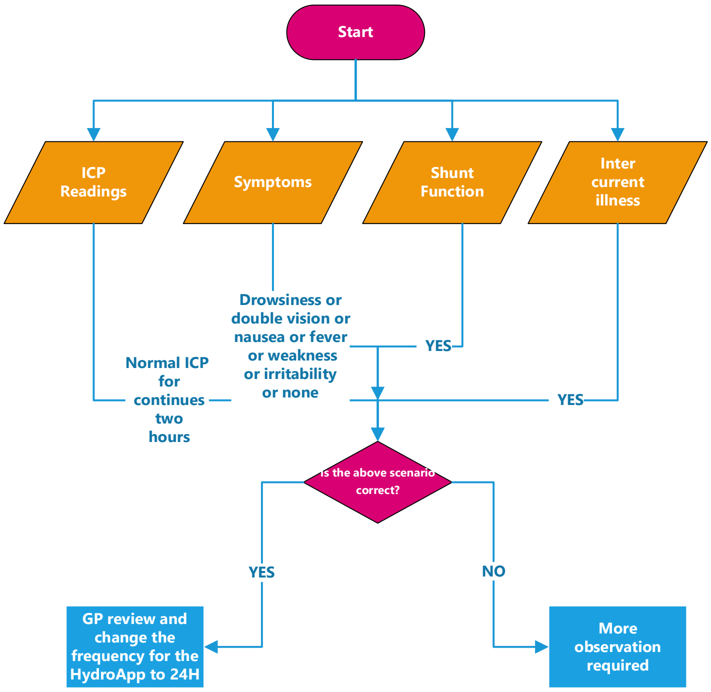


Figure 5.13 Flow chart for GP review with normal ICP

6. GP review is required, as shown in **Figure *5.14*** during the case of intercurrent illness. If the patient has high ICP for thirty minutes with or without symptoms, the GP still has to review because he has an intercurrent illness, so the GP review is required to figure out whether the patient needs more observation or just needs treatment for the sickness he has.

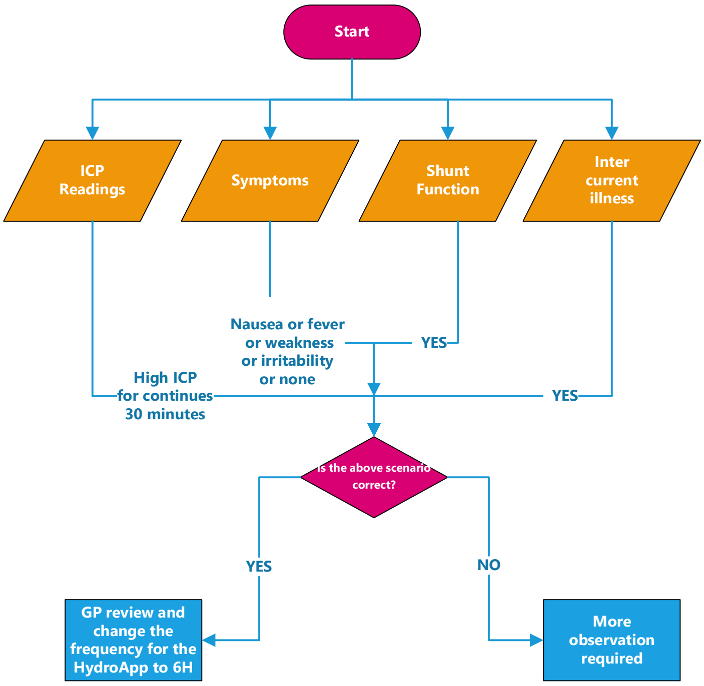


Figure 5.14 Flow chart for GP review with high ICP

7. Drowsiness and double vision are considered as critical symptoms for a shunted patient, especially when he has high ICP for at least 30 minutes. **Figure *5.15*** shows that the patient should be reviewed within 24 hours if he has double vision or drowsiness, or if he has another illness. The clinicians should consider the patient within 24 hours; even if he has another disease.

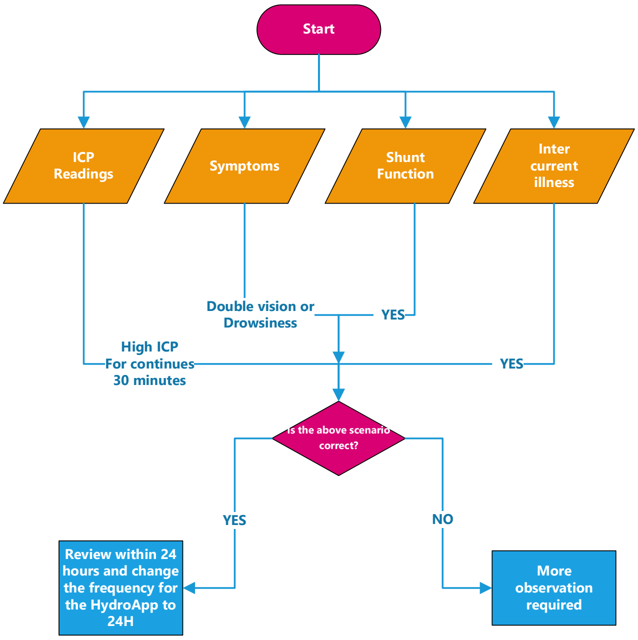


Figure 5.15 Flow chart for review within 24 hours

8. If the patient has high ICP readings for at least 30 minutes and he has one of the symptoms that were mentioned earlier, the neurological team will contact the patient by phone to have more feedback about the case and decide the correct action for the patient as shown in **Figure *5.16*** .

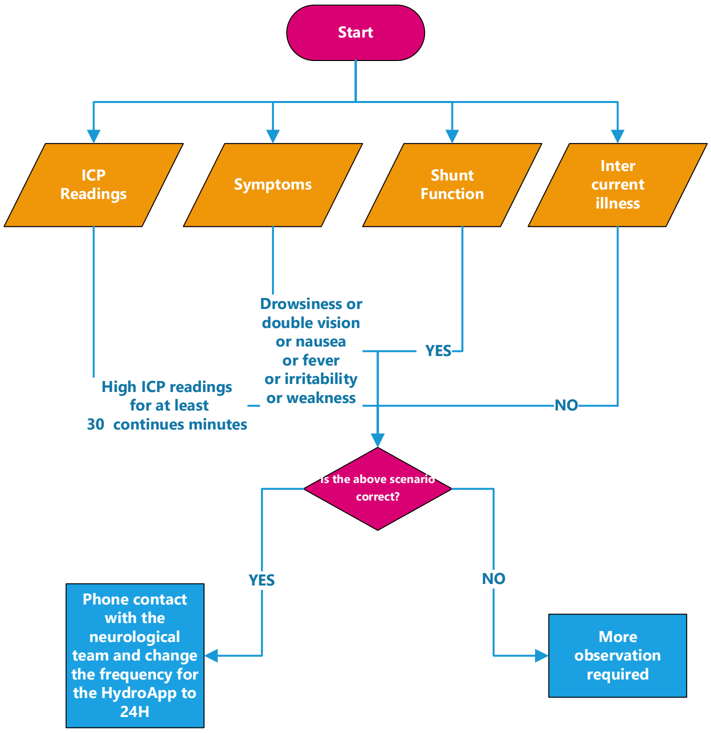


Figure 5.16 Flow chart for review patients by phone contact

9. As mentioned earlier in chapter 2, the normal ICP is considered from 0 mmH_2O to 20 cm H_2O. If the patient has high ICP from 25 – 30 mm H_2O, the clinicians keep an eye on the patient and go for the semi-urgent review. **Figure *5.17*** shows that the patient in this scenario has no symptoms and no intercurrent illness.

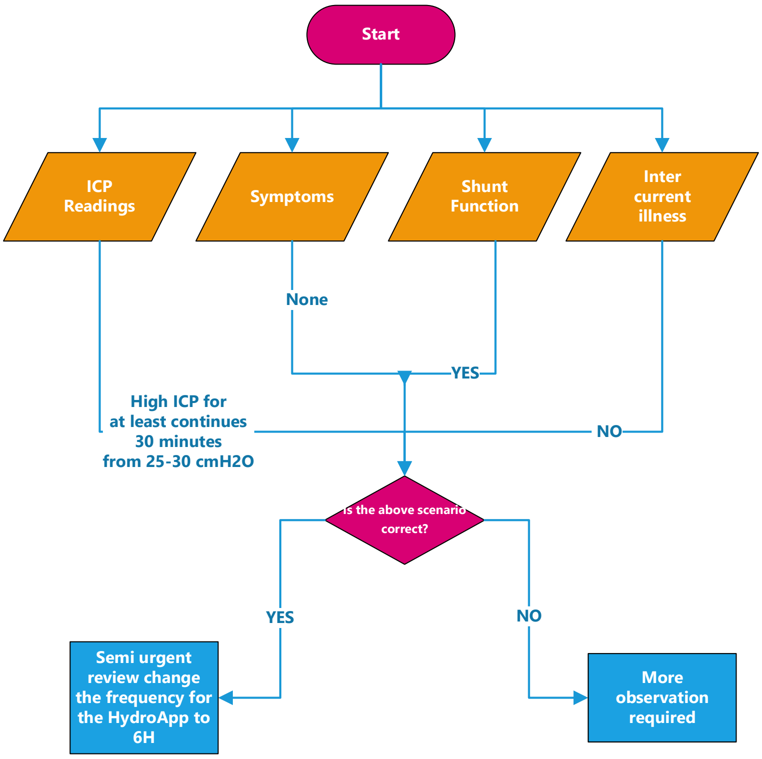


Figure 5.17 Flow chart for semi-urgent review

10. **Figure *5.18*** shows that the clinicians in the neurological department should contact the patient and find out the reason for the raised ICP that reached over 30 mm H2O. However, this decision is taken regardless of whether there is intercurrent illness or symptoms.

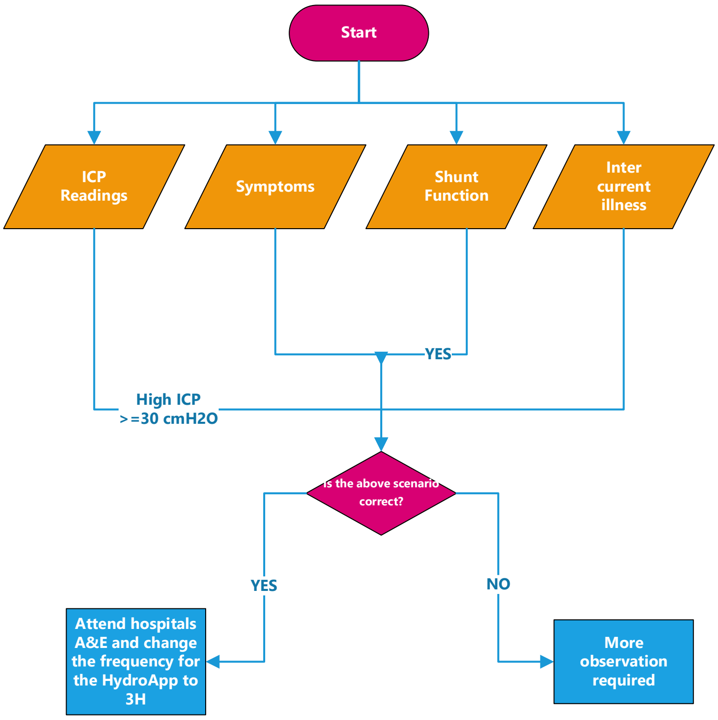


Figure 5.18 Flow chart for ICP over 30 mm H2O

11. As mentioned in Chapter 2, low ICP over drainage happens when it is over drainage for CSF. As mentioned in **Figure *5.19***, if the patient has another illness, the GP must review even though the ICP signals show low readings, or he is symptomatic.

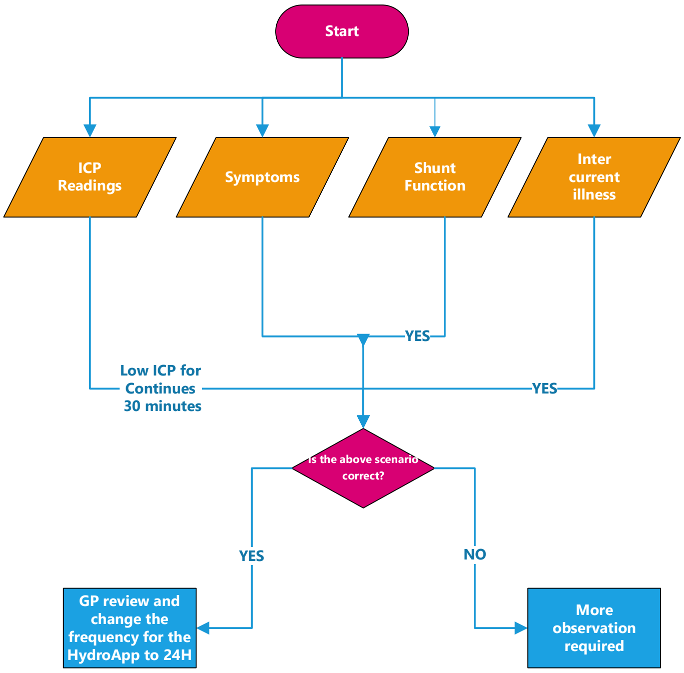


Figure 5.19 Flow chart for GP review with low ICP

12. **Figure** ***5.20*** illustrates that the patient should be reviewed within 24 hours in case he has low ICP readings between 0 and -15 and having symptoms like drowsiness, nausea, double vision, fever, irritability, weakness. In this scenario, the patient doesn't have another illness.

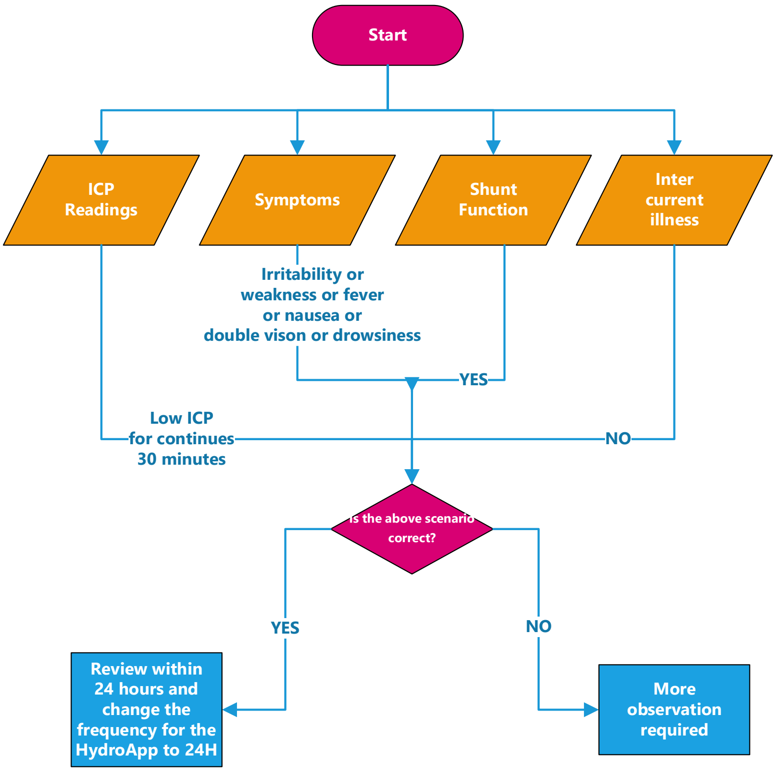


Figure 5.20 Flow chart for review within 24 hours with low ICP

13. A semi-urgent review is required when the patient has low ICP between 0 and -15 mmH2O for at least 30 minutes. The flow chart in **Figure *5.21***, shows that the patient doesn't have symptoms or other illnesses.

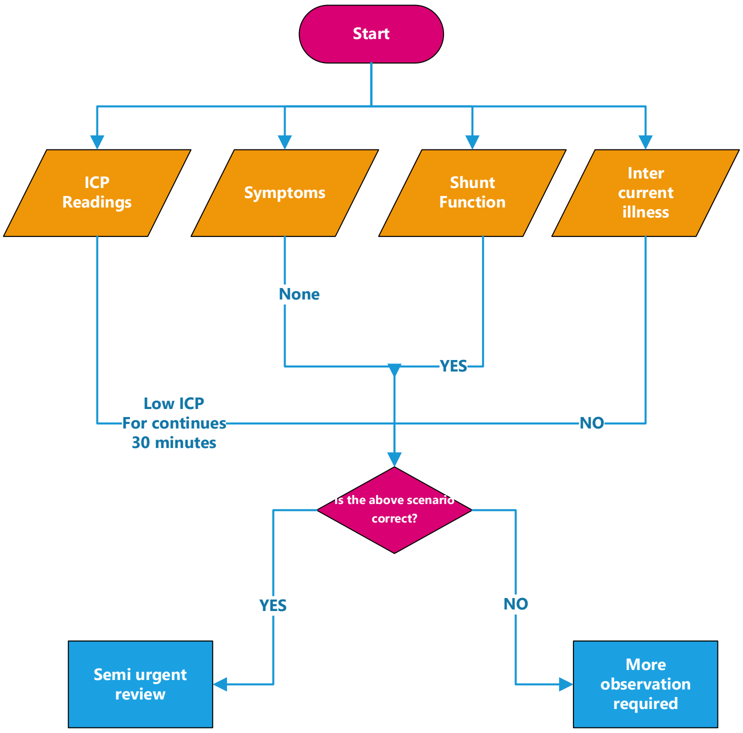


Figure 5.21 Flow chart for semi-urgent review with low ICP

14. The patient should attend the hospital's A&E if he has very low ICP, which is under -15 mmH_2O as this may cause bleeding in ventricles. The flow chart in **Figure *5.22*** shows that the patient should attend the hospital's A&E regardless of whether he may have symptoms or other illnesses.

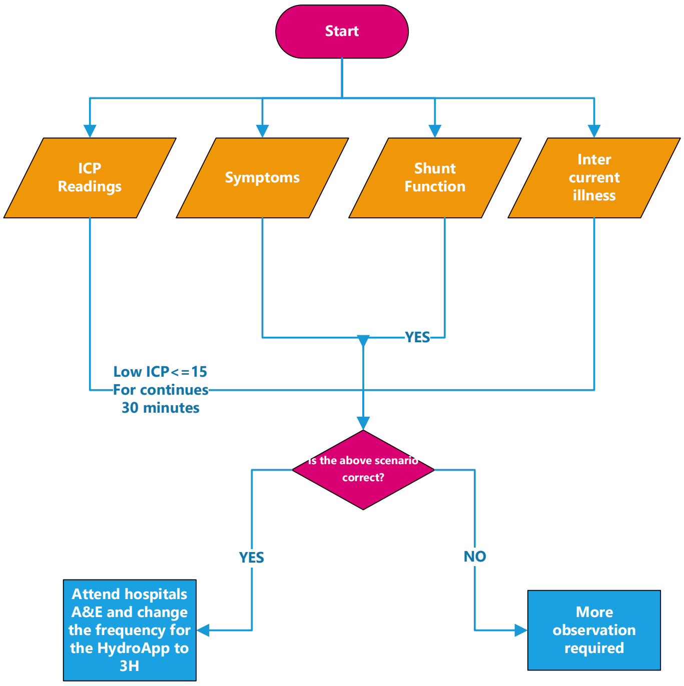


Figure 5.22 Flow chart for attending hospitals A&E with low ICP

Summary

Comprehensive processing stages have been conducted in this chapter. We start the chapter by describing the ICP signals feature selection methodology. Detecting and processing the data set was the first step of the data processing journey, in which we have employed the method for modifying processed ICP that is ready for automation. The process was in eight stages, which started with eliminating the gaps and ended up with two continuous averages for two hours of processed ICP. In addition, we demonstrated the HydroApp system, which helps patients with long-term conditions such hydrocephalus. This chapter illustrates the advantages of using the HydroApp system for patients' follow-up. By the end of this chapter a defined method to select the ICP signals and convert it to numeric data has been implemented as well as develop an improved follow-up platform by including more parameters required by neurologists and according to patients' willingness.

Chapter 6 Results and Evaluation

6.1 Introduction

As discussed in chapter 5, using feature extraction for ICP signals, can help in monitoring hydrocephalus patients. In this chapter, the methodology and the result of using the six classifiers will be discussed. The methodology used is derived from the main machine learning framework. This chapter describes the techniques and classifiers in machine learning that were used to develop a prediction model to monitor hydrocephalus patients.

6.2 Predictive Models

The dataset was collected from shunted patients from Alder Hey hospital. The patients have Raumedic devices to record ICP signals continuously. Details about the training and testing data set are given in **Table *6.1*** . In this research, the ICP signals have been analysed within two or more continuous hours of reading, with the patient lying down, to ensure that any observed change in the ICP reading is significant and genuine. However, the data set is randomly shuffled. When training the ICP signals, different ratios of training were tested for ICP signals, namely 20:80, 40:60, 50:50, 60:40, 70:30, 75:25, and 80:20. For convenience, we use the first ratio, which is 20:80 (i.e., training data percentage) to represent the ratio and refer to the parameter as a Percentage of Training Data (PTD). By evaluating the output of the experiment when it is trained using varying values of PTD, so we will be able to evaluate how well increasing training data ratio improves the quality of the experiment result performance.

Table 6.1 Distribution of the data set

	Training	Testing	Total
ICP signals	2610(80%)	652(20%)	3262

Six algorithms have been used for the experiment; Cubic support vector machine (SVM), Ensemble boosted tree, Medium Gaussian SVM, Quadratic SVM, Ensemble bagged tree' and the Fine Tree. The data used for the experiment is the combination of the prepared ICP signals and the data collected from the IOS system. In this study, the number of classes is 11, which is represented in **Table *6.2*** with an assigned code for more accessible presentation.

Table 6.2 Predicted classes

Classes for the confusion matrix	Code
Attend hospitals A&E	1
No treatment required	2
Review within 24H&change the HydroApp notification frequency to 24H	3
Clinical routine	4
GP review and change the HydroApp to 24H	5
GP review and change the HydroApp to 6H	6
Phone contact with the neuro team & HydroApp notification frequency to 24H	7
Semi-urgent review and HydroApp notification frequency to 6H	8
Attend hospitals A&E HydroApp notification frequency to 3H	9
Semi-urgent review	10
More observations required	11

The results from our experimental procedure are presented and organised for each respective classifier for the experiment in tables 6-11 when the data source was 652 patients' ICP readings.

Table *6.3* demonstrates the model classifiers that have been used for the experiment. The following model classifiers have been used for the experiment: Fine Tree, Ensemble Boosted, Tree, Ensemble Bagged Tree, Cubic SVM, Quadratic SVM, Medium Gaussian SVM.

Table 6.3 Trained models

The Trained Models
Fine Tree
Ensemble Boosted Tree
Ensemble Bagged Tree
Cubic SVM
Quadratic SVM
Medium Gaussian SVM

6.3 Performance Metrics

Statistical metrics can measure the overall capability and performance of predictive models. In this section, some performance metrics like sensitivity, specificity, precision and classification will be demonstrated. Sensitivity is called the true positive rate (TPR). Sensitivity is a performance metric, which identifies the classifier's ability to predict the class of interest correctly. Specificity refers to the true negative rate (TNR). Specificity indicates the classifier's ability in excluding the other class correctly. Classification accuracy is the overall correctness of the predictive model. Accuracy is calculated by adding the correct predictions (both true positives and true negatives), divided by the total number of predictions made [118]. Classification accuracy is usually the first step in evaluating the quality of predictive models. These metrics are calculated based on the terms listed in the confusion matrix (table 16-21). **Table *6.4*** demonstrates the computation of the performance metrics used in this experiment.

Table 6.4 Performance metrics

Metrics	Abbreviation	Computation
Sensitivity	TPR	TP/(TP+FN)
Specificity	TNR	TN/(TN+FP)
Accuracy	ACC	(TP+TN)/(TP+TN+FP+FN)
Precision	PPV	TP/(TP+FP)

Going back to the ICP readings that were used in the experiment; these were extracted from the ICP signals, which were prepared to be ready for the experiment. The other features were extracted from the HydroApp system. We tried to use the maximum possible amount of data for the training after many trials. The predictive model achieves high classification accuracy which means that the predictive models usually predict the value of the majority class.

6.4 Performance Accuracy

In our experiment, we concentrate on the classifiers' accuracy. **Figure *6.1*** shows the classifier accuracy for the algorithms used. The accuracy represents the most general correct classification proportion. The performance model has been conducted for the assigned classifiers. The best accuracy is 98.90% for Ensemble bagged Tree, whereas Ensemble boosted tree classifier has achieved 93.90% of accuracy. The cubic SVM and fine tree classifiers obtained approximately the same accuracy, which is 97%. Quadratic SVM and Medium Gaussian SVM obtained the following accuracy results, respectively 95.7% and 94.8%.

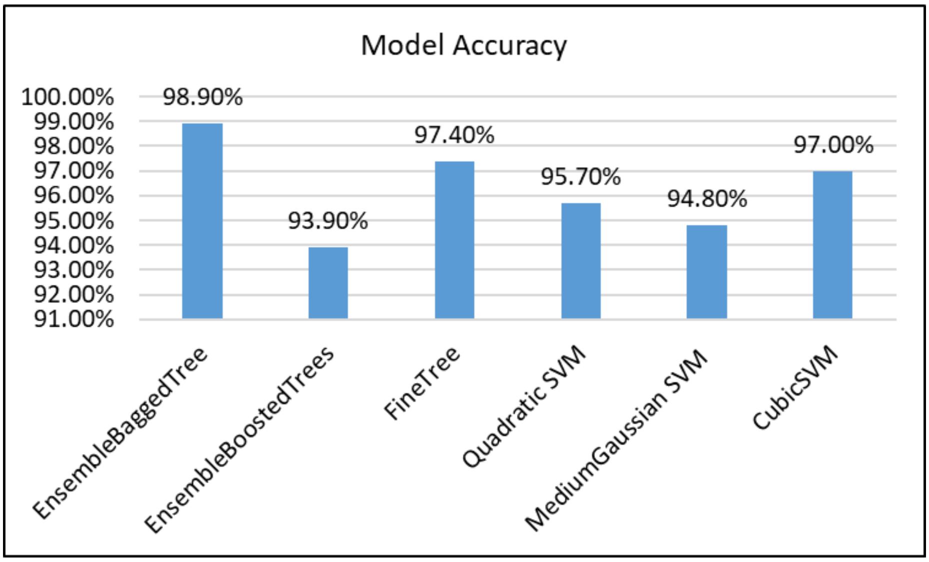


Figure 6.1 Model accuracy for the required classifier

Figure *6.1* shows that the Ensemble bagged tree model produces the highest accuracy compared to the other classifiers. The results from our experimental procedure are presented and organised for each individual classifier for the 11 classes, mentioned in **Table *6.2***. Meanwhile, performance metrics for the six classifiers were demonstrated. The data source was for 652 ICP signals. We then proceeded to present our evaluation of the classifiers according to the classifier accuracy. We have experimented with all the available classifiers in Matlab software, and there were 15 classifiers. Nevertheless, only the best six classifiers with the highest accuracy have been discussed. According to the accuracy results the selected model for the experiment is Ensemble Bagged Tree because it has the highest accuracy as well as it has the highest rate for the performance metrics as explained in the following sections. Ensemble bagged tree algorithm combines different tree models. It trains each learner on different data. The data is grabbed randomly for each bagging area then trained in several decision tree models. Ensemble Bagged Tree train different set of data using decision tree algorithm every time then take the mean of the outputs to have a final output, this explains why this model yields the highest accuracy.

6.5 True Positive Rate

In our experiments, we concentrate on the right prediction of the eleven classes to help clinicians for better monitoring for the patients; that is why a positive value has been given when the classifier predicts the right class. However, if the classifier has correctly predicted the right action, either one of the eleven actions, a true value is given for this case, and a false value is given for the incorrect prediction. The following scenario explains how to measure the true positive rate of the test results: Assume that we have scenario 1 to be tested by the system to produce the correct action, the system will verify the scenario for the first action if the response is correct and predicted correctly, so the system succeeded in classifying the situation as true positive. If the action is wrong, the system will test the next action, so the system succeeded in classifying the action as true negative. If the system classified the scenario as wrong while it is correct, it classified the scenario as false positive. False-negative has been classified if the system moved to the next action.

4- TP: Correctly classified action; the action is classified as the correct action
5- TN: Correctly classified as incorrect action; the system recognised that the action is wrong and transferred to the next action successfully, so it correctly classified the wrong action.
6- FP: incorrect action classified as correct; the system classifies the scenario for action one as a proper action for the scenario.
7- FN: actions are considered as incorrect while it is correct.

Tables 6.5-6.11 illustrate the experimental results for Cubic SVM, Medium Gaussian SVM, Quadratic SVM, Ensemble Bagged Tree, Ensemble Bagged Tree, Ensemble Boosted Trees and Fine Tree models respectively. The data source was for 652 ICP signals in all models. It is noticeable that class one has an equal true positive and true negative rate for all classifiers.

These results could be explained as classifiers test the first action, which is class 1 if it's the correct prediction, so it's included in the true-positive rate. If the prediction is not class 1, the classifier automatically transfers the data set to be tested for class 2.

6.6 Support Vector Classifier

Support vector machines are one of the binary model types which takes a set of variables as input and then classify each variable (input) into two categories. The goal is to build a linear approach by mapping the n-dimensional sample values space into a higher dimensional attribute space, and then the new instance is classified through this linear approach. In the SVM model, a data point is shown as a p-dimensional vector and SVM can be separated using p-1-dimensional hyperplane procedure. The main idea of this study is to identify geometrical patterns with 11 classes of actions that could be used generally through several models, like SVM. This study focused on several classifiers that are related to SVM to calculate the classification performance metrics. In this research, the classification outcomes were conducted using Medium Gaussian SVM, Quadratic SVM model and cubic SVM. The main target is to demonstrate the SVM models with different types of optimisation settings which have provided acceptable outcomes in terms of accuracy and performance.

Table 6.5 Cubic SVM model test results

Model	True Positive Rate (%)	False Positive Rate(%)	False Negative Rate (%)	True Negative rate (%)
Class 1	41.56	0.00	0.00	58.43
Class 2	1.07	0.15	0.00	98.77
Class 3	9.66	0.31	0.31	89.72
Class 4	4.75	0.00	0.15	95.09
Class 5	14.72	0.00	0.76	84.50
Class 6	7.20	0.15	0.00	92.63

Class 7	7.51	0.00	0.00	92.48
Class 8	1.68	0.00	0.00	98.31
Class 9	2.91	0.00	0.00	97.08
Class 10	0.61	0.00	0.15	99.23
Class 11	6.59	1.07	0.31	92.02

Table *6.5* shows that the cubic SVM classifier succeeded in predicting all class 1 correctly. For class 2, there is a 15 % false-positive rate, while the majority of the prediction was 98.77% classified as true negative. Cubic SVM had an equal percentage of false negative and false positive of 31% for class 3. Whereas it achieved a high true negative rate with 89.72%. When the classifier has a high percentage of true negative rate, this means that the classifier recognises that the first prediction is not the true one and the algorithm moves to the next prediction and tests whether it's the right decision or it has to move to the next. Cubic SVM achieved an impressive rate for classes 6, 7, 8, and 9 with 0% of the false-positive and false-negative rate. The true negative rate was higher than the true positive rate for these classes. The true negative rate varied between 92.48 and 97.08%. Class 4 and 10 has only 15% false-negative rate while the higher rate goes to true negative. Class 10 has 15%.

Table 6.6 Medium Gaussian SVM model test results

Model	True Positive Rate (%)	False Positive Rate(%)	False Negative Rate(%)	True Negative rate(%)
Class 1	41.56	0.00	0.00	58.43
Class 2	1.07	0.00	0.00	98.92
Class 3	9.66	1.07	0.31	88.95
Class 4	4.75	0.00	0.15	95.09
Class 5	15.49	2.30	0.00	82.20
Class 6	7.20	0.00	0.00	92.79
Class 7	7.36	0.31	0.15	92.17

Class 8	1.38	0.00	0.31	98.31
Class 9	2.91	0.31	0.00	96.77
Class 10	0.46	0.00	0.31	99.23
Class 11	3.68	0.46	3.22	92.63

Medium Gaussian SVM model test results are illustrated in **Table *6.6*** classes 1and 2 have no false predictions. Classes 3,7 and 11 have both false positive and false negative rates. These classes have a true-negative rate of 88.95%, 92.48%, and 92.48%, respectively. The false-negative rate of 0.15%, was acquired by class 4, whereas class 10 has 0.31%false negative rate.

Table 6.7 Quadratic SVM model test results

Model	True Positive Rate (%)	False Positive Rate(%)	False Negative Rate(%)	True Negative rate(%)
Class 1	41.56	0.00	0.00	58.43
Class 2	1.07	0.15	0.00	98.77
Class 3	9.81	1.07	0.15	88.95
Class 4	4.75	0.15	0.15	94.93
Class 5	15.18	1.38	0.31	83.12
Class 6	7.20	0.00	0.00	92.79
Class 7	7.51	0.00	0.00	92.48
Class 8	1.68	0.00	0.00	98.31
Class 9	2.76	0.00	0.15	97.08
Class 10	0.61	0.00	0.15	99.23
Class 11	4.44	0.61	2.45	92.48

Table *6.7* shows the true-negative rate for quadratic SVM classifier. The quadratic SVM classifier succeeded in classifying the classes 1, 6, 7 and 8 without false prediction. Classes 3, 4, 9 and 10 have 0.15% of the false-negative rate, while classes 2 and 4 have the same rate of false-positive rate. Class 11 has the highest rate of false-negative, which is 2.45%. Whereas, class 5 has the highest false-positive rate, which is 1.38%.

6.7 Ensemble Classifier

The ensemble model technique relies on combining two or more classifiers to improve the classification performance and accuracy as well as augmenting strength from any of the fundamental models. This method is considered adequate and produces good results, mainly when using the accurate classifiers to be combined. In this research, the ensemble classifier was able to learn precisely the ICP readings combined with the other features from the HydroApp and produced successful classification outcomes against the other models. Ensemble model demonstrates the abilities of the optimal performing models and estimates the overall classification accuracy and performance that improved with better predictions. This technique is designed based on the pattern recognition system in association with the bootstrap aggregating approach to enhance the accuracy and stability of the selected algorithms.

Table 6.8 Ensemble Bagged Tree model test results

Model	True Positive Rate (%)	False Positive Rate(%)	False Negative Rate(%)	True Negative rate(%)
Class 1	41.56	0.00	0.00	58.43
Class 2	1.07	0.00	0.00	98.92
Class 3	9.96	0.00	0.00	90.03
Class 4	4.90	0.00	0.00	95.09
Class 5	15.49	0.15	0.00	84.35
Class 6	7.20	0.00	0.00	92.79
Class 7	7.51	0.00	0.00	92.48
Class 8	1.68	0.00	0.00	98.31
Class 9	2.91	0.00	0.00	97.08
Class 10	0.61	0.00	0.15	99.23

Class 11	6.90	0.00	0.00	93.09

Table *6.8* illustrates the performance metrics for ensemble bagged tree classifier; It is evident that the classifier succeeded in most predictions of the classes. Almost all classes do not have false negative or false positive rate except for classes 5 and 10. These results indicate that the Ensemble bagged tree classifier had the highest performance in all classes.

Table 6.9 Ensemble Boosted Trees model test results

Model	True Positive Rate (%)	False Positive Rate(%)	False Negative Rate(%)	True Negative rate(%)
Class 1	41.56	0.00	0.00	58.43
Class 2	1.07	0.46	0.00	98.46
Class 3	9.96	1.68	0.00	88.34
Class 4	4.75	0.46	0.15	94.63
Class 5	15.03	0.15	0.46	84.35
Class 6	7.20	0.46	0.00	92.33
Class 7	7.51	0.00	0.00	92.48
Class 8	1.68	0.00	0.00	98.31
Class 9	2.30	0.00	0.61	97.08
Class 10	0.61	0.00	0.15	99.23
Class 11	4.90	0.15	1.99	92.94

Table *6.9* demonstrates the Ensemble boosted tree model test results. The classifier accomplished high prediction rate for classes 1,7 and 8. Class 3 has the highest false-positive rate, with 1.68%, followed by Classes 4 and 6 with .46%. On the other hand, class 11 was considered as incorrect while it's correct with the rate of 1.99%. As mentioned earlier, the reason for having a higher true-negative rate than true positive is because the classifier tests the input data for every class and moves to the next class to be tested.

6.8 Tree Classifier

Decision tree algorithms are known as they are relatively fast to train. Decision tree algorithms are prevalent due to the algorithm characteristics, such as they are fast to train and produce transparent models. The decision tree can classify the labelled data into a tree. The Tree is derived in the learning phase, which obtains the accuracy of a classifier test data that is taken randomly from training data. After that, unlabelled data is classified using the Tree or rules derived from the learning phase. The structure of a decision tree relies on a root node, a left subtree and right subtree. The leaf nodes in a tree characterise a class label. The arcs from one node to another node denote the conditions on the attributes. In our research, decision tree represented in fine tree model achieved high accuracy outcomes. As the data have to be tested with certain conditions like shunt functionality, if the patient has a shunt malfunction, the outcome is to attend the hospital's A&E. Tree classifier is easy to understand and interpret, handles categorical and numeric attributes, and is robust to outliers and missing values. Decision tree classifiers are used extensively for diagnosis of diseases as they can obtain good accuracy in medical data.

Table 6.10 Fine Tree model test results

Model	True Positive Rate (%)	False Positive Rate(%)	False Negative Rate(%)	True Negative rate(%)
Class 1	41.56	0.00	0.00	58.43
Class 2	0.92	0.00	0.15	98.92
Class 3	9.35	0.00	0.61	90.03
Class 4	4.75	0.00	0.15	95.09
Class 5	15.49	0.00	0.00	84.50
Class 6	7.20	0.00	0.00	92.79
Class 7	7.51	0.00	0.00	92.48
Class 8	1.68	0.00	0.00	98.31

Class 9	2.91	0.31	0.00	96.77
Class 10	0.61	0.00	0.15	99.23
Class 11	6.90	0.76	0.00	92.33

As shown in **Table *6.10***, Fine Tree model test results of classes 1, 5, 6, 7, and 8 were without false predictions. The true negative rate varies between 58.43 and 98.31%. The true positive rate varies between 1.38 and 41.56 for these classes. Class 2, 4, and 10 has a false negative rate of 0.15%. Only classes 9 and 10 have a false positive rate with 0.31, 0.76, respectively.

6.9 Sensitivity and Specificity

There are other Scalar Metrics to characterise the capability of the classifiers simulated in the experiment. Sensitivity and specificity have been calculated. Sensitivity = True positive divided by the number of all positive predictions. Whereas, the specificity = True negative divided by the number of all negative predictions [119]. **Table *6.11*** shows the sensitivity and specificity of the classifiers, in the experiment, the algorithm with the highest accuracy has been selected, which is Ensemble Bagged Tree, achieving the optimum sensitivity of 100% for the whole classes except class 10 (Semi-urgent review) which achieved 80%. Ensemble bagged Tree achieved a specificity of 100% in all classes. Boosted tree classifier obtained a specificity of 100% sensitivity for all classes except for class 3. In contrast, it obtained 100% sensitivity in classes 1,2,3,6,7 and 8. The other classes varied from 71 to 97%. Also, Cubic SVM classifier achieved high specificity for all classes of 100%. Classes 10 and 11 achieved 96% and 99% respectively.

Moreover, fine tree classifier acquired 100% specificity except for class 11 while the sensitivity was 100% for classes 1, 5, 6, 7, 8, 9 and 11. Medium Gaussian SVM obtained higher specificity in most classes than sensitivity, which was 100% in all classes except for classes 5 and 3, which have 97 and 99% respectively. Quadratic SVM also achieved high specificity in most classes as well, only classes 3 and 11 got 99%, and class 5 got 98%. In general, the classifiers obtained impressive results of specificity and sensitivity. As mentioned earlier, the classifier tests the data set for class 1 and moves to class 2 to be tested if class 1 is the wrong prediction. This technique explains why the specificity is higher than the sensitivity as the specificity is the True negative divided by the number of all negative predictions.

Table 6.11 Sensitivity and metric specificity measures

Class Name	Cubic SVM(%)		Ensemble Bagged Tree (%)		Boosted Trees (%)	
	Sensitivity	Specificity	Sensitivity	Specificity	Sensitivity	Specificity
1	100	100	100	100	100	100
2	100	100	100	100	100	100
3	97	100	100	100	100	98
4	97	100	100	100	097	100
5	95	100	100	100	097	100
6	100	100	100	100	100	100
7	100	100	100	100	100	100
8	100	100	100	100	100	100
9	100	100	100	100	79	100
10	80	096	80	100	80	100
11	100	099	100	100	71	100
Class Name	Fine Tree		Medium Gaussian SVM		Quadratic SVM	
	Sensitivity	Specificity	Sensitivity	Specificity	Sensitivity	Specificity
1	100	100	100	100	100	100
2	86	100	100	100	100	100
3	94	100	97	99	98	99
4	97	100	97	100	97	100
5	100	100	100	97	98	98
6	100	100	100	100	100	100
7	100	100	98	100	100	100
8	100	100	82	100	100	100
9	100	100	100	100	95	100
10	80	100	60	100	80	100
11	100	99	53	100	64	99

6.10 Evaluation Using Precision

Some more metrics were calculated, such as precision, to provide an objective performance evaluation of their predictive power. Precision or also called positive predictive value (PPV) which is the number of true positive predictions divided by the total number of true and false positives. Precision metrics show how a particular case that been predicted as positive is, in fact, a positive [118]. Low precision can expose a multitude of false positives; precision can be considered as a measure of a classifier's perfection. **Table *6.12*** shows the precision metric measures Class 1, which is "attend hospital's A&E" achieved a precision of 1 in all classifiers. This result indicates that the classifiers impressively achieved high prediction performance for class 1. For class 2 the following classifiers achieved high precision of 100%; Ensemble bagged Tree, Fine Tree and Medium Gaussian SVM. In contrast, the classifiers Cubic SVM and Quadratic SVM achieved a precision of 88%. The least precision for class 2 is Boosted trees classifier with 70%. Ensemble Bagged Tree, and Fine Tree has made the highest precision of 100% for class 3. Next, Cubic SVM with 0.97, followed by Medium Gaussian SVM and Quadratic SVM with 90%, finally, Boosted Trees achieved 86%. For class 4, Cubic SVM, Ensemble bagged Tree, Fine Tree and Medium Gaussian SVM had a precision of 100% followed by Quadratic SVM with 0.97 then Boosted Trees classifier with a precision of 91%. Cubic SVM and Fine Trees had a precision of 100% for class 5. Ensemble Bagged Tree and Boosted Trees achieved 99% of precision followed by Quadratic SVM of 92% precision. Medium Gaussian SVM had the lowest precision of class 5, which is 87%. Ensemble Bagged Tree, Fine Tree, medium Gaussian SVM and Quadratic SVM. In class 6; the following classifiers made a precision of 100%; Ensemble Bagged Tree, Fine Tree, Medium Gaussian SVM and Quadratic SVM. Cubic SVM achieved a precision of 98% and Boosted Trees with 94%. Cubic SVM, Ensemble Bagged Tree, Boosted Trees, Fine Tree and Quadratic SVM had a precision of 100% for class 7, whereas Medium Gaussian SVM had a precision of 96%. Class

8 has an impressive precision, which is 100% in all classes. This result indicates that the classifiers had 100% perfect prediction for classes 8 and 10. For class 9, the classifiers Cubic SVM, Ensemble Bagged Tree, Boosted Trees, and Quadratic SVM had a precision of 100% and 90% for the other classifiers. Classifiers also achieved an excellent precision for class 9. In class 11, only Ensemble Bagged Tree classifier achieved 100% whereas Boosted Tree and Fine Tree had a precision of 97% and 90% respectively. Cubic SVM, Medium Gaussian SVM and Quadratic SVM had a precision of 0.86,0.89 and 0.88% respectively. In general, **Table *6.12*** shows that Ensemble Bagged Tree has the highest precision as all the classes have a precision of 100% except for class 5; has 99% precision. Moreover, Fine Tree classifier has a high precision of 100%, except for classes 9 and 11. The other classifiers were varying between 100 and 70%.

Table 6.12 Precision metric measures

Class Name	Cubic SVM	Ensemble Bagged Tree	Boosted Trees
	Precision (%)	Precision (%)	Precision (%)
1	100	100	100
2	88	100	70
3	97	100	86
4	100	100	91
5	100	99	99
6	98	100	94
7	100	100	100
8	100	100	100
9	100	100	100
10	100	100	100
11	86	100	97
Class Name	Fine Tree	Medium Gaussian SVM	Quadratic SVM
	Precision (%)	Precision (%)	Precision (%)
1	100	100	100
2	100	100	88
3	100	90	90
4	100	100	97
5	100	87	92
6	100	100	100
7	100	96	100
8	100	100	100

9	90	90	100
10	100	100	100
11	90	89	88

In general, all classifiers have achieved an impressive overall result with more than 97% using ICP signals and features from HydroApp system. Ensemble Bagged Tree was the leading classifier followed by Fine Tree, after that Cubic SVM, Quadratic SVM, Medium Gaussian SVM and finally Ensemble Boosted Tree. The disparity rate among their overall performance was about 2%. The overall performance of Ensemble Bagged Tree classifier has overcome Fine Tree classifier by 1%, whereas it overcomes Cubic SVM by 2%, Quadratic SVM by 3%, Medium Gaussian SVM by 4%, while Ensemble Boosted Tree has come at the end of the list with a difference of 5%. This might indicate that DT classifier can achieve much better overall performance than others using highly hierarchical correlated attributes.

6.11 Classifier Training Result

The confusion matrix is a machine learning concept that helps researchers by providing information about the predicted and actual classifications that are done by the classification system. The confusion matrix has two dimensions, one for the actual data class and the other for the predicted class [51]. The confusion matrix has two dimensions x-by-x matrix, where x is the number of classes in the output variable. **Figure *6.2*** to **6.7** demonstrate the confusion matrix training results for the used classifiers.

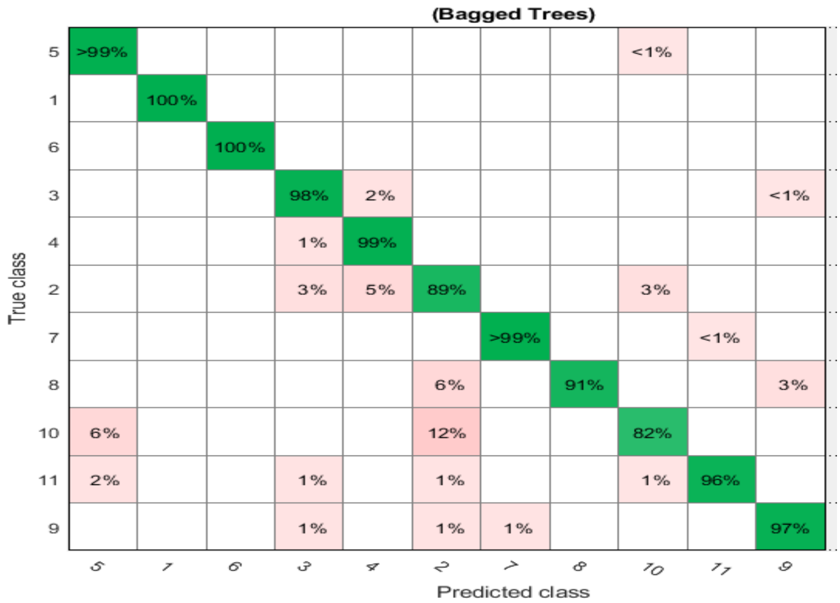


Figure 6.2 Bagged Tree confusion matrix

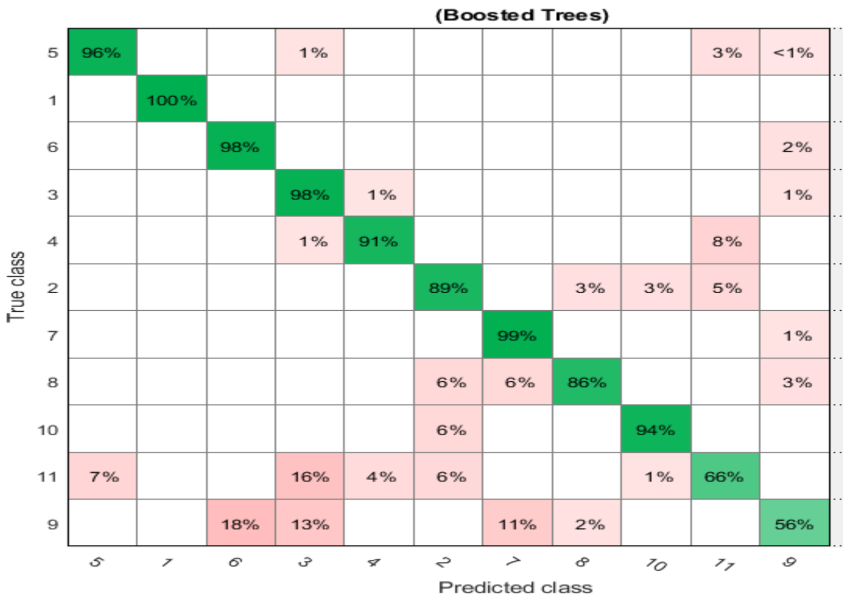


Figure 6.3 Boosted Tree confusion matrix

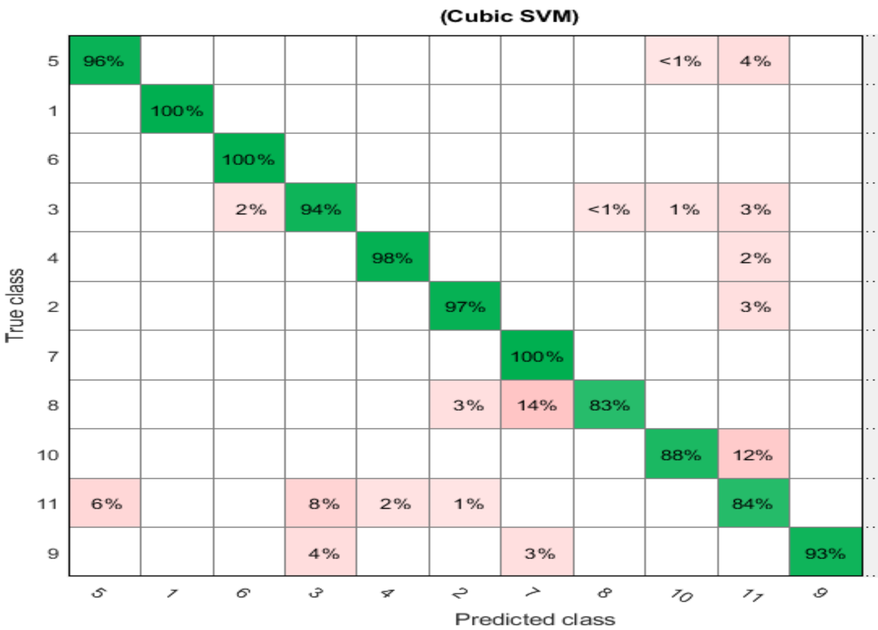


Figure 6.4 Cubic SVM confusion matrix

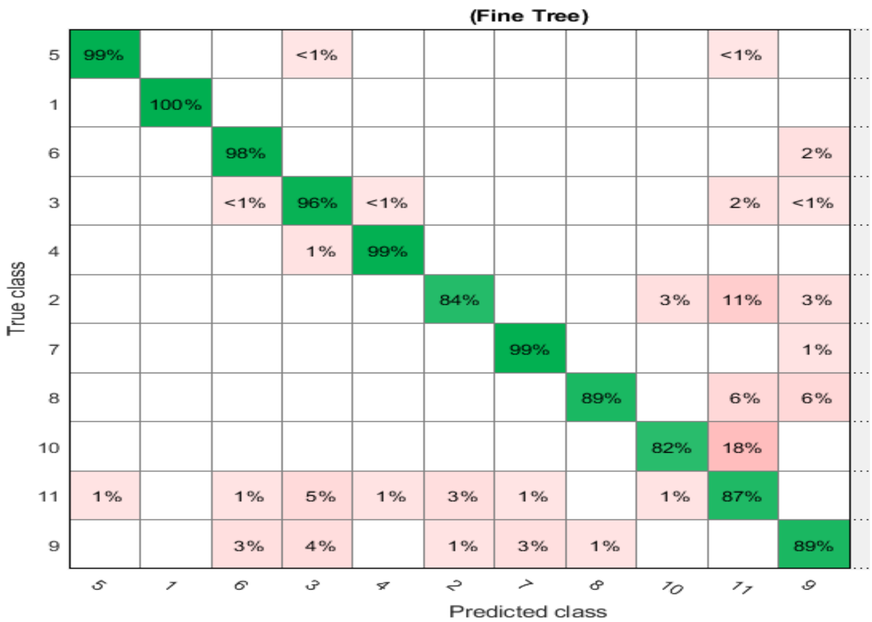


Figure 6.5 Fine Tree confusion matrix

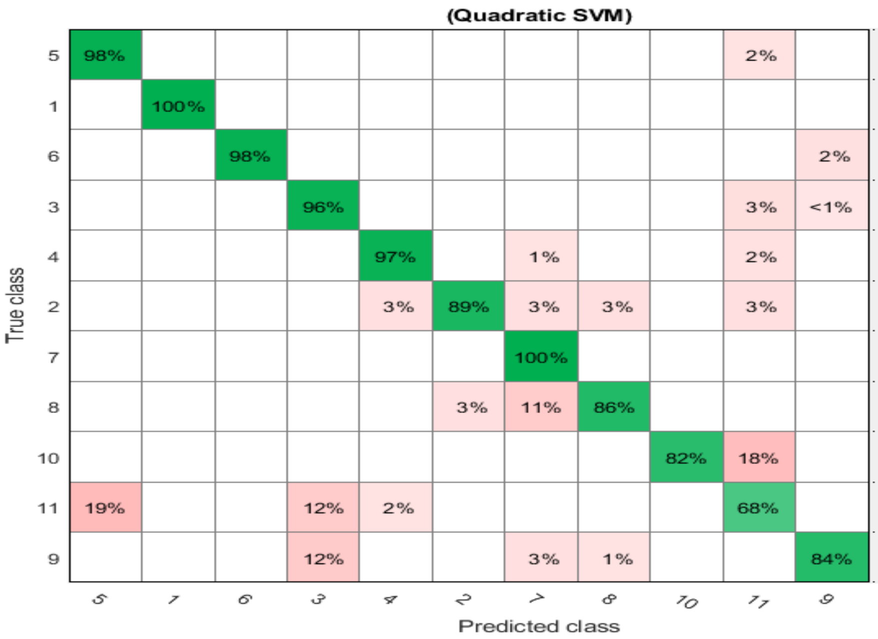


Figure 6.6 Quadratic SVM

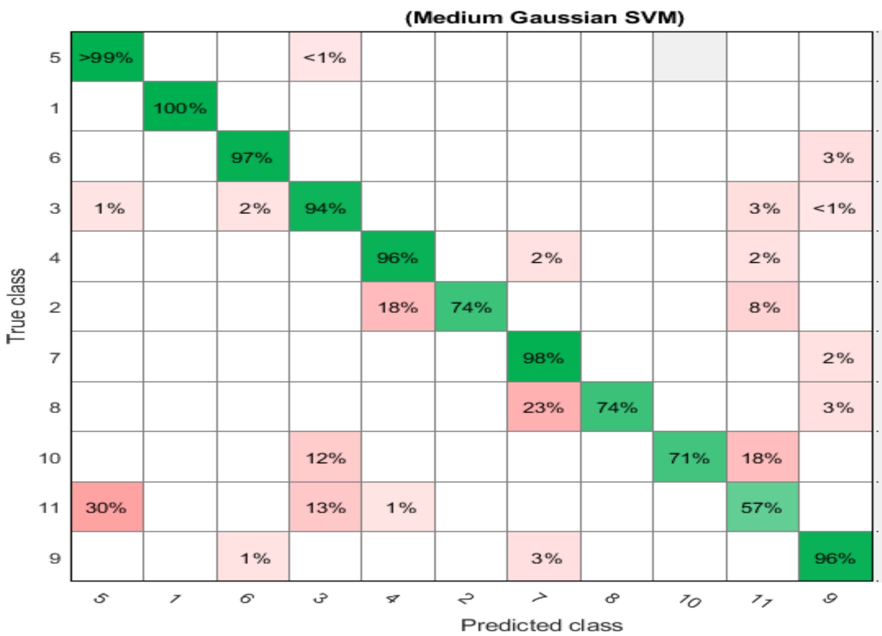


Figure 6.7 Medium Gaussian confusion matrix

6.12 Validation

This section demonstrates a comparison between the traditional method and the proposed method. As mentioned before, shunted patients should be monitored and followed as implanting the shunt can cause some problems like infection, blockage or shunt malfunction. Sometimes, the patient does not feel well with no apparent reason. Usually, clinicians ask the patient to keep records of specific questions they need for their decision like, what they feel, how long has the patient felt tired. In Alder Hey Hospital, the neurological team relies on the ICP readings that are extracted from the portable device with patients, the Raumedic device. Ordinarily, the clinicians' team import the readings to be visually analysed. The clinicians make their decisions based on the patient's feedback and ICP readings. However, the patient should wait for his regular appointment or book a new one. This process takes time and effort from the patients and the clinician team. In addition to that, it is difficult for patients to record all the details, especially if it is a long time of feeling unwell.

Our proposed methodology provides accurate predictions of the proper actions that should be taken by clinicians based on the analysed ICP signals using machine learning classifiers and the patient's input through the HydroApp system. This method enables clinicians to access the patient's feedback through the application at any time. Moreover, clinicians can take a quick decision for the patient's benefits, and they can change the notification of the HydroApp for patients according to their medical status. For example, clinicians can change the notification for the patient's HydroApp system so they can respond and fill their episodes according to the updates. A new sample of data has been used to validate the methodology. **Table *6.13*** represents a random sample of ICP readings for two hours.**Table *6.14*** shows the patient's input through the HydroApp system. **Table *6.15*** represents the outcome of the decision taken by the model and by clinicians for the same data set, after comparing the model results and the clinician's decisions for 50 random data set samples. The validation yields that 90% of the results are matching between the model results and the clinician's decisions.

Table 6.13 Random ICP readings for the validation process

	ICP 1	ICP 2	ICP 3	ICP 4	ICP 5	ICP 6	ICP 7	ICP 8
1	10.82982	10.44917	11.48177	10.46382	15.8645	22.53323	21.80053	22.69403
2	10.82982	10.44917	11.48177	10.46382	15.8645	22.53323	21.80053	22.69403
3	10.82982	10.44917	11.48177	10.46382	15.8645	22.53323	21.80053	22.69403
4	10.82982	10.44917	11.48177	10.46382	15.8645	22.53323	21.80053	22.69403
5	10.82982	10.44917	11.48177	10.46382	15.8645	22.53323	21.80053	22.69403
6	10.82982	10.44917	11.48177	10.46382	15.8645	22.53323	21.80053	22.69403
7	12.06121	12.00324	10.25976	18.24102	27.26542	24.49781	27.88922	28.69167
8	12.06121	12.00324	10.25976	18.24102	27.26542	24.49781	27.88922	28.69167
9	12.06121	12.00324	10.25976	18.24102	27.26542	24.49781	27.88922	28.69167
10	12.06121	12.00324	10.25976	18.24102	27.26542	24.49781	27.88922	28.69167
11	12.06121	12.00324	10.25976	18.24102	27.26542	24.49781	27.88922	28.69167
12	12.06121	12.00324	10.25976	18.24102	27.26542	24.49781	27.88922	28.69167
13	12.06121	12.00324	10.25976	18.24102	27.26542	24.49781	27.88922	28.69167
14	12.06121	12.00324	10.25976	18.24102	27.26542	24.49781	27.88922	28.69167
15	12.06121	12.00324	10.25976	18.24102	27.26542	24.49781	27.88922	28.69167
16	12.06121	12.00324	10.25976	18.24102	27.26542	24.49781	27.88922	28.69167
17	16.52056	16.63033	20.22022	14.31578	13.68622	28.92856	25.10476	22.41178
18	16.52056	16.63033	20.22022	14.31578	13.68622	28.92856	25.10476	22.41178
19	16.52056	16.63033	20.22022	14.31578	13.68622	28.92856	25.10476	22.41178
20	16.52056	16.63033	20.22022	14.31578	13.68622	28.92856	25.10476	22.41178

Table 6.14 Patients input from HydroApp system

	Symptoms	Intercurrent illness	Shunt functionality
1	Fever	Yes	No
2	Fever	No	No
3	Weakness	Yes	Yes
4	Weakness	Yes	No
5	Weakness	No	Yes
6	Weakness	No	No
7	None	Yes	Yes
8	None	Yes	No
9	None	No	Yes
10	None	No	No
11	Irritability	Yes	Yes
12	Fever	No	Yes
13	Fever	No	No
14	Weakness	Yes	No
15	Weakness	No	Yes
16	Weakness	No	No
17	None	Yes	Yes
18	None	Yes	No
19	Irritability	Yes	Yes
20	Irritability	Yes	No

Table 6.15 Comparison between clinicians' decision and the model decision

	Model's decision	Clinician's Decisions
1	Phone contact with the neurological team GP review and change the frequency for the HydroApp to 24H	Phone contact with the neurological team GP review and change the frequency for the HydroApp to 24H
2	Attend hospital's A&E	Attend hospital's A&E
3	Semi urgent review	GP review and change the frequency for the HydroApp to 6H
4	Phone contact with the neurological team GP review and change the frequency for the HydroApp to 24H	Phone contact with the neurological team GP review and change the frequency for the HydroApp to 24H
5	Attend hospital's A&E	Attend hospital's A&E
6	Attend hospital's A&E	Attend hospital's A&E
7	GP review and change the frequency for the HydroApp to 6H	GP review and change the frequency for the HydroApp to 6H
8	Semi urgent review and change the frequency for the HydroApp to 6H	Semi urgent review and change the frequency for the HydroApp to 6H
9	Attend hospital's A&E	Attend hospital's A&E
10	Attend hospital's A&E	Attend hospital's A&E
11	GP review and change the frequency for the HydroApp to 6H	GP review and change the frequency for the HydroApp to 6H
12	Attend hospital's A&E	Attend hospital's A&E
13	Attend hospital's A&E	Attend hospital's A&E
14	Phone contact with the neurological team GP review and change the frequency for the HydroApp to 24H	Phone contact with the neurological team GP review and change the frequency for the HydroApp to 24H
15	Attend hospital's A&E	Attend hospital's A&E
16	Attend hospital's A&E	Attend hospital's A&E
17	GP review and change the frequency for the HydroApp to 6H	GP review and change the frequency for the HydroApp to 6H
18	Semi urgent review and change the frequency for the HydroApp to 6H	Semi urgent review and change the frequency for the HydroApp to 6H
19	GP review and change the frequency for the HydroApp to 6H	GP review and change the frequency for the HydroApp to 6H
20	Phone contact with the neurological team and change the frequency for the HydroApp to 24H	Phone contact with the neurological team and change the frequency for the HydroApp to 24H

6.13 Discussion

In this study, a data science methodology is used that combines 10 features extracted from 2,610 ICP signals in addition to patients' input extracted from the HydroApp system. The methodology aim is to predict the correct action to monitor shunted patients. The main reason that the classifiers used in the methodology are powerful is due to the achievement made during the training and testing phase. The accuracy outcomes of the best ensemble classifier (Ensemble Bagged Tree) produced 100% for all classes except for class 10 in the training sets as shown in **Table *6.16***, while testing sets produced 100% accuracy for classes 1,2 5,6,7,8,9, and 11 using Fine Tree classifier while classes 3, 4, and 10 obtained 93, 96.4 and 75% respectively. The main reason that Ensemble and Decision Trees produced the best results was due to the highest outcome received by other classifiers. For instance, the training set of Ensemble Bagged Tree received 98.9%, Fine Tree received 97.4%. In terms of the testing set, the accuracy results are demonstrated in detail as it presents the accuracy for each class. Cubic SVM obtained 100% for classes 1, 2, 6, 7, 8 and 9, and Cubic SVM obtained around 96% for classes 3, 4, and 5. All classifiers yielded 75 % accuracy for class 10. Ensemble Boosted Tree yielded 100% accuracy for classes 1,2,3,6,7, and 8 while classes 4,5,9,10,1 and 11 obtained 96.4, 96.3, 81.3, 75 and 69.4% respectively. A 100% accuracy was achieved in classes 1,2,6,7, and 8 using Quadratic SVM classifier. Classes 3,4 and 9 results varied between 93.8 and 98.8% while the least accurate result is 61.6% for class 1. Medium Gaussian SVM classifier yielded the least accurate average results. However, it obtained 100% accuracy in classes 1,2,5,6 and 9. Classes 3, 4, and 7 varied from 96.5 to 97.4%. The lowest accuracy is for class 11, which is 50%. The best predictions in this study received during the training and testing phase show that the Ensemble Bagged Tree outperformed other classifiers. The experiment produced statistical methods. In addition to that, this methodology offers better performance to follow up shunted patients.

Overall, the body of results that were obtained highlight the potential of ICP signals for the classification of predicting the required actions to monitor shunted patients. The choice of model is crucial in obtaining a satisfactory result, as is evident in the variation of the performance between the models used in our experiment. The classifiers used reacted adequately to the ICP signals and are therefore of potential use in the medical field.

Furthermore, the performance evaluations are for data drawn from a number of probability distributions, particularly for distributions that are not standard. Ensemble Bagged Tree, and Fine Tree are powerful models for the analysis of the ICP data set as has been proven for this domain to offer vital prediction accuracy and performance in comparison with other classifiers. A good relationship between input features and target actions is discovered during the development process. The data sets were moderate in size, with 80% for training and 20% of the input features randomly selected for testing. With the integration of accuracy and efficiency in addition to the useful analytical techniques, the Ensemble and Decision Tree algorithms constitute a practical and effective technique for the ICP signals data sets, where no suitable statistical algorithms are available. The results gained from the practical examination into the use of various types of machine learning models show that the chosen data sets exhibit significant outcomes for the test models.

Table 6.16 The prediction accuracy for the testing data set

Classifier / Classes	Ensemble Boosted Tree (%)	Ensemble Bagged Tree (%)	Cubic SVM (%)	Fine Tree (%)	Medium Gaussian SVM (%)	Quadratic SVM (%)
Class 1	100.0	100.0	100.0	100.0	100.0	100.0
Class 2	100.0	100.0	100.0	100.0	100.0	100.0
Class 3	100.0	100.0	96.5	93.0	96.5	98.2
Class 4	96.4	100.0	96.4	96.4	96.4	96.4
Class 5	96.3	100.0	96.3	100.0	100.0	98.8
Class 6	100.0	100.0	100.0	100.0	100.0	100.0
Class 7	100.0	100.0	100.0	100.0	97.4	100.0
Class 8	100.0	100.0	100.0	100.0	80.0	100.0
Class 9	81.3	100.0	100.0	100.0	100.0	93.8
Class 10	75.0	75.0	75.0	75.0	75.0	75.0
Class 11	69.4	100.0	97.2	100.0	50.0	61.1

6.14 Summary

The methodology of giving the right action to follow up shunted patients worked well, after preparing the ICP data set to be chunks of two hours. The methodology results yielded high accuracy and good prediction of taking the right actions to monitor shunted patients. The next chapter discusses the conclusion and future work. This study conducted an empirical investigation into the use of various types of machine learning models for predicting the r actions that were required to follow up shunted patients. This research has introduced various types of machine learning algorithms for analysing ICP signals as well as medical data obtained from the HydroApp system. In contrast with traditional medical solutions, this research investigates the effectiveness of the machine learning approach in managing and monitoring shunted patients. It was discovered through experimental investigation, comprising the usage of patient input through the HydroApp system and approaches such as the Ensemble classifiers, SVMs, and decision tree models, that the analysis of ICP signals is viable and yields precise results. The results obtained from a range of models during our experiments have shown that the combined classifiers, Ensemble bagged Tree, and Fine Tree produced significantly better outcomes over the range of other classifiers.

Chapter 7 Conclusion and Future Work

7.1 Conclusion

This study proposes the employment of artificial intelligence systems to enhance the environment of the medical domain presented to patients who suffer from hydrocephalus disease. For improving the quality of care for patients and clinicians, the research focused on two essential perspectives. Firstly, this study used machine-learning algorithms based on real ICP signals data sets for shunted patients. The main goal of doing this is to improve the classification process to monitor those patients. Secondly, this study designed a user-friendly platform which is the HydroApp system to construct secure communication and follow-up between patients and healthcare providers. The research is proposed by the Alder Hey Children’s Hospital to develop the patient’s quality of life and reduce time for the NHS which include phone calls and clinical appointments, and acquire precise results depending on the patient’s ICP readings and patient’s episodes through the HydroApp system. Moreover, building a machine learning model could help healthcare providers by reducing the need for medical expert’s assessment. Also, junior clinicians can learn from data that has been analysed previously. This type of model can help specialist nurses and the junior clinicians to improve their decision-making process. This research supports the urgent need for a new pathway that reduces the load on the NHS, as well as enhancing patients’ quality of life. The use of machine-learning methods as a monitoring model could reduce the need for specialist assessment. This machine-learning model can be used to train non-specialist doctors to improve their decision-making procedure. In this research, a comprehensive different research studies and proposal projects has been reviewed and explored. This aim to improve follow-up and management of patients with hydrocephalus.

Extensive research indicates that machine learning models produce a good enhancement with clinical data sets and have helped in achieving high accuracy prediction results. The main aim of this research is to provide a model to distinguish applications of machine learning approaches for medically related problems. This study attempts to follow up with the shunted patients of hydrocephalus by predicting the right action required. This research uses different architectures in terms of examining performance for each model within this study. The motivation for the classification approach used in this study is to support medical sectors to provide proper therapy advice depending on the former data set. Expert systems and various Artificial Intelligence methods and techniques have been used and developed to improve decision support tools for medical purposes. Machine Learning models are considered as a powerful technique in the field of scientific research that enables computers to learn from data. There are several machine learning techniques for classification including the Artificial Neural Network, the Random Forest model, and the Support Vector Machine. In this research, the application of machine learning approaches provided a methodology of following shunted patients. As mentioned in chapter 2, hydrocephalus patients need long term/lifetime follow-up, as most are shunt dependent for life. Therefore, better follow-up information, in terms of resources used, time spent in primary and secondary care, health professionals consulted, total in-patient stay, will lead to a better understanding of the natural history and future effective planning. Eventually, this could guide future follow-up management and resource utilisation. In this study, a novel machine learning approach has been demonstrated to predict the required actions in the management of hydrocephalus patients. In this research, a

7.2 Research Contributions

The significance and the research contribution can be described as developing a machine learning approach that helps clinicians to follow up hydrocephalus patients, and developing follow-up using M-health technology can promote the quality of care given to this category of patients. It has revealed further novelties in the domain of machine learning models, pre-processing medical data sets, classification tasks, and performance evaluation techniques metrics. The data set includes 2,610 records for training and 652 for testing. As mentioned in chapter 5, an algorithm was developed to prepare the data according to the specialist's advice to avoid inaccurate or biased data sets. Six popular machine-learning classifiers were used for the experimental procedure undertaken in this study for training. These machine learning classifiers can establish intelligent diagnostic models. The classifiers used are Fine Tree, Ensemble Boosted Tree, Ensemble Bagged Tree, Cubic SVM, Quadratic SVM and Medium Gaussian SVM. The results show that assembling models obtained high sensitivity, specificity, precision and accuracy. The results provide optimal classification with a high rate, as illustrated in chapter 6. In this aspect, Decision Tree classifiers obtain an impressively high rate of performance and accuracy. This Ensemble Bagged Tree classifier received better results during the training set process including; sensitivity 100%, specificity 100%, Precision 100%, Accuracy 98.90%. Where the Ensemble Bagged Tree achieved the highest rate of accuracy during the test process including the detailed accuracy of each class, the Ensemble Bagged Tree classifier obtained 100% accuracy for all classes and 75% accuracy for class 10.

Moreover, Fine Tree and Cubic SVM received high and close results of accuracy during the testing set process. This study used visualisation methods and statistical techniques to present our results. Statistical techniques have assisted us to make a comparison on the outcomes from different aspects and finally to choose the best classifiers that can be proper to provide the best prediction that helps clinicians to monitor shunted patients. A confusion matrix was computed. This research aimed to have an automatic observation and follow-up plan for shunted patients as well as predicting the right action for every patient event (i.e. Raised/lowered ICP with symptoms). Machine learning has been used to assess and process the ICP signals to help manage hydrocephalus follow-up in the long term. This methodology helps to increase the capacity of the current service model in neurosurgery clinics, decreases the pressure of unnecessary visits, and minimises the risk of complication and errors through intelligent assessment and decision support of the medical team.

In summary, the results reveal that intelligent systems, i.e. machine learning-based diagnostic models, represent a promising approach for the classification of monitoring shunted patients who have hydrocephalus disease, and are likely to hold significant visions to develop traditional models of monitoring and follow –up delivery.

Clinicians need to investigate through patients' outcomes, which include their pain episodes. A user-friendly software which is the HydroApp system was developed to help patients to record their pain episodes, at the same time, clinicians can access the patients' feedback at any time and send them the necessary notification based on their feedback from the HydroApp system and their automatically analysed ICP signals. The main target of this system is to provide a user-friendly web-based system capable of making an on-demand, decision support system and recommendations that could lead to functional improvements.

This research revealed that the potential of such a HydroApp system is a practical and useful tool for healthcare providers to recommend therapy. Moreover, the clinician's platform system sends timely notifications to the patients based on their analysed ICP signals and their pain episodes through the HydroApp system. This methodology can lead to development in their health condition. In aggregate, machine learning-based monitoring models in combination with the HydroApp system for long-term follow-up are likely to hold a significant potential to improve the quality of healthcare provided to patients with hydrocephalus. In addition to that, this methodology can reduce avoidable expenses for the NHS by reducing unnecessary visits as well as enabling clinicians to work faster and more efficiently in managing their patients. In short, it is the start of personalised healthcare.

7.3 Summary and Future Work

Hydrocephalus patients need long-term/lifetime follow-up, as most are shunt dependent for life. Therefore, better follow-up information, in terms of resources used, time spent in primary and secondary care, health professionals consulted, total in-patient stay, will lead to a better understanding of the natural history and future effective planning. Eventually, this could guide future follow-up management and resource utilisation. In this study, a novel machine learning approach has been demonstrated to predict the required actions in the management of hydrocephalus patients. With the success of our experimental study, this study considers further work directions, including improvements to the proposed machine learning along with the HydroApp system and extending its proposed techniques for better prediction. The data set is composed of 3,262 samples to obtain better accuracy. Further research is recommended to make a confirmation on the experiment outcomes, where a large number of data could also be utilised to advance the performance of the results. In this part, the possible extensions are highlighted to medical applications as discussed below.

- As future work, understanding and analysing the ICP signals will be the key to more investigations of intelligent systems to help hydrocephalus patients and their clinical management. Deep learning could be used for more investigations and more prediction systems for ICP signals.
- The proposed methodology framework is used with the machine learning algorithms, with the target values (classes) provided by the neurological team at the Alder Hey Children's Foundation Hospital Trust. Moreover, the proposed model could serve different domains within medical environments.
- The predictive models can be applied to another available medical data set. Consequently, the proposed model can be tested on another data set. The automated data recording through the HydroApp system could be extended to broader usage.

This research aims to collect a data set containing ICP signals features as input data to the classifiers. As an example, implanting a sensor in a patient could provide more datasets that can be linked to the HydroApp system and help clinicians to be always informed about the patient’s condition.

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