Smart Monitoring: An Intelligent System to Facilitate Health Care across an Ageing Population

Carl Chalmers, William Hurst, Michael Mackay, Paul Fergus
School of Computing and Mathematical Sciences
Liverpool John Moores University
Byrom Street
Liverpool, L3 3AF, UK
{C.Chalmers, W.Hurst, M.I.Mackay, P.Fergus}@ljmu.ac.uk

***Abstract*— In the UK, the number of people living with self-limiting conditions, such as Dementia, Parkinson's disease and depression, is increasing. The resulting strain on national healthcare resources means that providing 24-hour monitoring for patients is a challenge. As this problem escalates, caring for an ageing population will become more demanding over the next decade. Our research directly proposes an alternative and cost effective method for supporting independent living that offers enhancements for Early Intervention Practices (EIP). In the UK, a national roll out of smart meters is underway, which enable detailed around-the-clock monitoring of energy usage. This granular data captures detailed habits and routines through the users' interactions with electrical devices. Our approach utilises this valuable data to provide an innovative remote patient monitoring system. The system interfaces directly with a patient's smart meter, enabling it to distinguish reliably between subtle changes in energy usage in real-time. The data collected can be used to identify any behavioural anomalies in a patient's habit or routine, using a machine learning approach. Our system utilises trained models, which are deployed as web services using cloud infrastructures, to provide a comprehensive monitoring service. The research outlined in this paper demonstrates that it is possible to classify successfully both normal and abnormal behaviours using the Bayes Point Machine binary classifier.**

Keywords*— Smart Meters, Profiling, Early Intervention Practice (EIP), Data Analysis, Patient Monitoring, Anomaly Detection, Assistive Technologies.

I. INTRODUCTION

Smart meters are the foundation of any smart electricity grid, used for balancing grid load and demand. They also provide consumers with highly reliable and accurate metering services. Energy usage readings are taken at 10 second intervals [1] and monitor the electrical usage of appliances in the home; specifically, their operation time and duration of use. All data is produced to a granular level. Their introduction has brought about new technological opportunities, which can be applied to a health care environment.

In the UK, around one in five adults are registered disabled. More than one million of those is currently living alone [2]. Providing a safe and secure living environment places a considerable strain on social and healthcare resources. Effective around the clock monitoring of these conditions is a significant challenge and affects the level of care provided. Consequently, a safe independent living environment is hard to achieve. Current public policy enables sufferers to live independently in their homes for as long as possible. However, it faces significant challenges. For example, current monitoring services are expensive and are met, often, with patient resistance, as the equipment is intrusive and complex. Substantial research gaps in non-invasive and cost effective monitoring technology exist [3]. Specifically, for safe and effective monitoring solutions, that are beneficial to the patient and healthcare providers alike. Any remote monitoring system must facilitate EIP, enabling front line services in the community to intervene much earlier.

As such, the method put forward in this paper presents the concept of smart meter analytics for the detection of anomalies in a patient's electricity usage. Using the Bayes Point Machine binary classifier, we demonstrate how the identification of abnormal behaviour provides an accurate solution for patient monitoring. The remainder of this paper is as follows. Section 2 provides a comprehensive assessment of current assistive living technologies while highlighting the significant caps in each of the methods. In addition, the different components that are used to facilitate the profiling of patients using smart meters is discussed. Section 3 discusses the proposed system methodology. Section 4 presents a detailed patient monitoring case study utilising the system. The paper in concluded in Section 5.

II. BACKGROUND

The use of smart technologies in primary care delivery is significantly increasing. In recent years, there has been rapid developments in monitoring technologies for independent living, early intervention services and condition management. In this section, an overview of these technologies, along with their feasibility, is provided.

A. Assistive Technologies and limitations

The term assistive technology covers a wide range of applications and tasks [4]. Assistive technology refers to devices or systems that support a person to maintain or improve their independence, safety and wellbeing. Typically, existing monitoring technologies can be divided into two categories. Firstly, physical aids, which assist the sufferer in performing specific tasks. Secondly, monitoring and surveillance, whereby electronic devices keep track of a person's medical condition and automatically alert health care staff when required. Although no official standardisations exist for assistive technologies, it is widely agreed that technology should be personalised, adaptive and non-intrusive. Current assistive living technologies involve the deployment of various sensors around the home [5]. These include motion sensors, cameras, fall detectors and communication hubs. However, installing, maintaining and monitoring these devices can be costly and a technical challenge [6].

In addition, diverse wearable technology exists. These include personal emergency response systems, wearable body networks, ECG, pulse oximeter, blood pressure and accelerometers. The main objective of these sensors is to obtain essential medical data to assist in the overall assessment of a patient's wellbeing. These readings enable clinical staff to assess remotely, while determining if there is a requirement for intervention.

There are many limitations and challenges with existing solutions, as many of them are impractical. Affordability and associated costs with existing technologies mean they cannot be implemented on a large scale. This leaves many solutions inaccessible to health care trusts, councils and social services. In addition, the use of sensors and cameras around the living environment raise many privacy and protection concerns [7]. This leads to a general reluctance to use the technology. Often technical solutions are tailored to a specific application and do not meet the ongoing changing requirements of a patient. Many solutions fail to adequately identify tends in behaviour, which may indicate health problems. This inhibits early intervention.

B. Deploying Cloud Computing for Patient Monitoring

One of the most significant limitations in existing solutions is the absence of personalisation. The inability to learn the unique characteristics of each individual and condition degrades the effectiveness of any solution. A person's habits and routines are clear indicators of their wellbeing. The ability to model routines and understand them is imperative for any patient monitoring system.

With the emergence of cloud infrastructures, the ability to analyse large data and model behaviour in real-time has become feasible. Smart meters like many other sensors generate large amounts of data [8]. Being able to extract and analyse useful information is an imperative requirement for any system. In order to achieve this requirement, the use of smart and scalable analytics services are needed. Big data is often unstructured and is often difficult to process using conventional tools. Cloud based analytics utilise complex and demanding algorithms which require vast computational power [9].

Using a cloud infrastructure removes the historical constraints associated with data analysis, as vast storage and flexible computational resources is offered. Using cloud services enables the real-time interpretation of data intelligence through the integration of front-end applications. This can be achieved by deploying analytical services, such as ready-to-use web services. These web services enable the integration of apps, which can be utilised to provide critical information to the patients support network. Our solution takes advantage of the cloud infrastructure and big data analytics, to provide a personalised patient monitoring system. The following section introduces our dataset and discusses the system methodology.

III. METHODOLOGY

In this section, the components of the system and their specific roles are highlighted. A case study is presented, along with the data analytics being used.

A. End to End Processing

The system directly interfaces with a patient's smart meter to learn and detect changes in routine. It operates in two separate modes. Firstly, mode one, which is used for training and, secondly, mode two which is used for the prediction of health deterioration. The method has a modular design in order to cater for different circumstances of healthcare monitoring. Smart meter data is collected in an unstructured way. Therefore, the data is processed by collecting energy usage readings that represent a specific behaviour. Figure 1 shows this overall process.

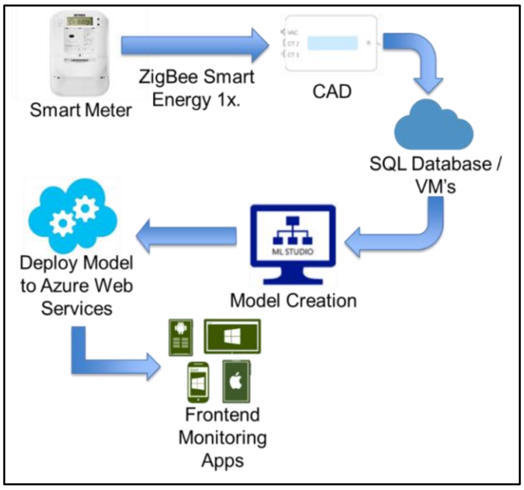

Figure 1. End-to-End Process.

The process starts with the smart meter, which resides within the patient's home. The main function of this device is to record accurately and store electricity consumption information for defined times (to a minimum of 10 seconds). Table 1 shows example readings obtained from a smart meter at 10 second intervals. The date time column illustrates the date and time of the reading, while the reading column displays the amount of electrical load in watts.

TABLE 1. DATA SAMPLE

Date Time	Reading
01/03/2016 21:25	1217
01/03/2016 21:25	1224

In order to collect the energy usage readings from the smart meter a Consumer Access Device (CAD) is required. Smart meters utilise ZigBee smart energy. The UK Department of Energy & Climate Change (DECC) has announced Smart Metering Equipment Technical Specifications (SMETS) 2, which cites the use of ZigBee Smart Energy 1.x.

Smart meters establish a wireless Home Area Network in a consumer's home. This is a local ZigBee wireless network (the SM HAN), which gas and electricity smart meters and in-home displays use to exchange data. Consumers are also able to pair other devices that operate the ZigBee Smart Energy Profile (SEP) to the network. Once a consumer has paired the device to their HAN, a CAD is able to access updated consumption and tariff information directly from their smart meter; a CAD can request updates of electricity information every 10 seconds and gas information every 30 minutes.

All of the obtained data from the CAD is logged remotely to a cloud SQL database. Here the data is used to create, test and deploy the classification models. Once the model is generated the classification models need to be accessible to the end user applications to provide real-time monitoring. This is achieved by deploying trained models, as ready-to-use web services. Once the web service is deployed, data from the SQL database can be directly sent to the service for active monitoring. The generated monitoring applications interface with the service API key to receive real-time monitoring alerts about the patient's wellbeing.

To further support individual health monitoring, a mobile application is provided to the patient. The patient is asked to log any unplanned interactions with medical services, such as visits to GPs, A and E and Walk-in Centres. The app records the visit type and date; this is undertaken so the patient's energy reading can be assessed prior to the visit and to highlight any noteworthy changes in behaviour directly to the medical practitioner. Figure 2 displays a screen shot of the mobile application.

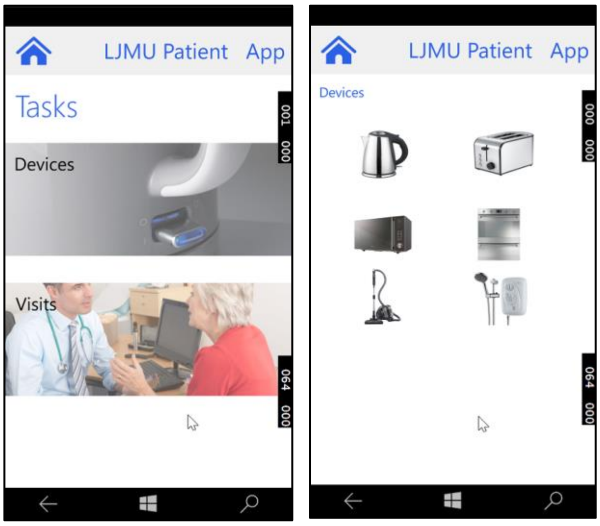

Figure 2. Application Screenshot.

B. Data Case Study

In this sub section, a case study presents the real-time data gathering capabilities of a smart meter. An energy monitor is installed in a person's home to perform the collection of real-time energy usage data. The installation is used to model a person's daily routine and to identify any noteworthy trends in device utilisation. Figure 3 shows the patient's energy usage taken at ten second intervals. The y-axis shows the amount of energy being consumed in Watts, while the x-axis shows a snap shot of the time. Each individual colour represents one week's electricity usage, which has been overlaid to show correlation over a three-week period.

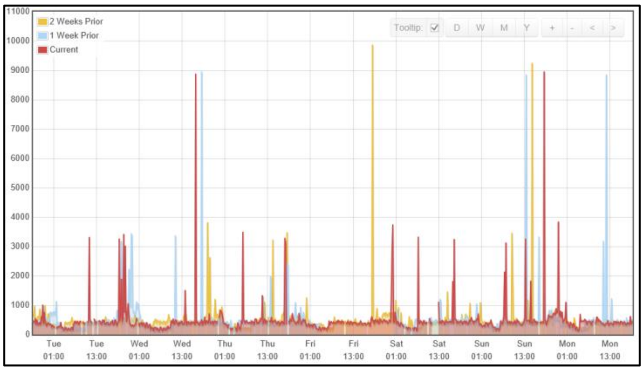

Figure 3. Energy Usage over a 3 Week Period.

Obtaining energy readings at 1 to 10 second intervals provides energy signatures for each device. Figure 4 displays the amount of electricity being consumed for a kettle and its duration of use. Identifying the use of specific electrical devices enables the assessment of a patient's wellbeing.

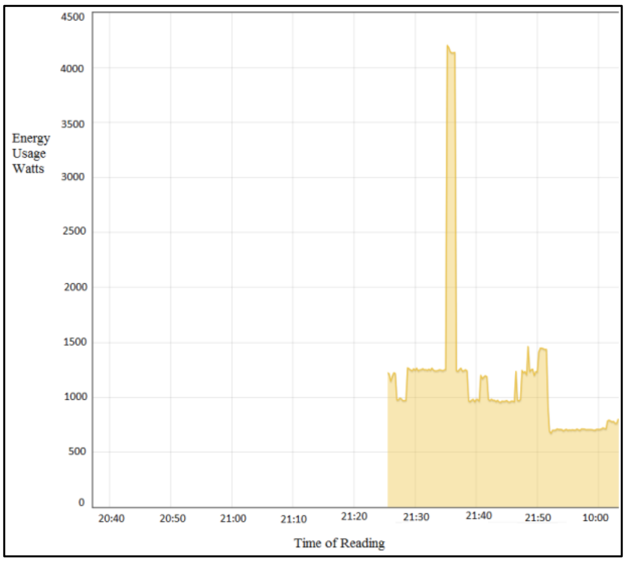

Figure 4. Kettle Usage.

C. Behavioural Analysis

Knowledge about a person's ability to undertake normal Activities of Daily Living (ADL) is an essential part for the overall assessment [10]. This is imperative in determining the diagnosis. The following list highlights the main ADL's that can be detected through a patient's interaction with their electrical devices:

- Eating patterns – for the purposes of detecting abnormal or altering changes in eating habits. These types of behavioural changes provide key indicators regarding the general health of the patient.
- Sleep patterns – changes in sleep patterns can provide insights into a patient's mental and physical wellbeing. Sleep disturbances are often key indicators for various mental health problems.
- Behavioural changes – provide impotent indicators for the detection of new conditions while providing information about the progression of existing medical problems.
- Changes in activity – can highlight possible periods of inactivity. These types of changes would require intervention to prevent additional complications and worsening of a patient's condition.
- Routine alteration – is vital for detecting changes in a patient behaviour and forms a key part in our system for the purposes of facilitating independent living. The identification of a route change especially in more serious conditions such as dementia can indicate the need for immediate intervention.
- The effects of social interaction on consumers and if the benefits are short or long lasting. This is important for assessing the mental wellbeing of a patient.

Being able to detect subtle changes early and predict future cognitive and non-cognitive changes facilitate much earlier intervention. Often, dementia sufferers in hospital are admitted due to other poor health caused by other illnesses [11]. These illnesses are often a result of immobility in the patient. Most commonly infections cause additional complications and can also speed up the progression of dementia [12]. Additionally, immobility leads to pressure sores, which can easily become infected, other serious infections and blood clots, which can be fatal. With any of these complications early intervention for both preventative care and early treatment is vital to ensure a good prognosis and safe independent living.

D. Mode One

When the system is in training mode, learning a user's personalised behaviour, features are extracted from the collected data. Features represent the dataset's characteristics as a whole and are needed for training the classifiers. While in the training mode, the information clearing component runs a set of SQL queries against the data store for the specific condition or application. Each query returns a balanced data set for both normal and abnormal behaviours. A balanced dataset is required for the classification process as it removes the possibility of a bias prediction and misleading accuracies.

The period and type of energy usage data collected varies. Each training iteration is application specific. A high-level view of the data collection process is shown in figure 5.

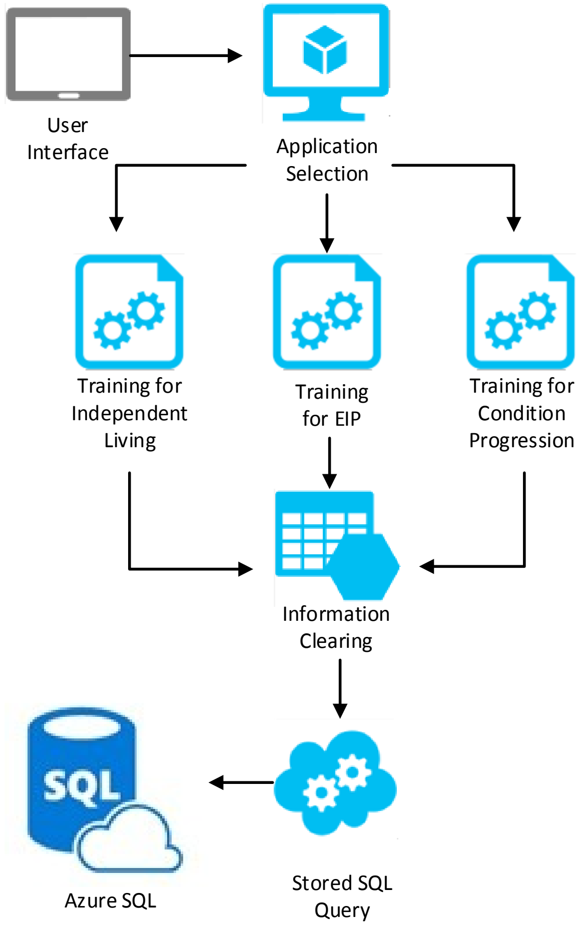

Figure 5. Information Clearing Data Collection Process.

E. Mode Two

Using the trained classifiers and generated models, the system automatically detects both normal and abnormal patient behaviour in real-time using web services. Where appropriate the system alerts the patient's support network if potential problem if detected. In the first instance, the system alerts the patient to check in, by performing specific device interaction. This reduces any possible false alarms and verifies that the patient requires no further assistance.

The system identifies if interaction has taken place; if this is not the case an alert is communicated to a third-party health care practitioner. Enabling patients to check in helps to reduce the number of false positives while allowing the system to retrain. Figure 6 shows the workflow for the prediction mode. Regular medical review is required to assess the condition or revaluate the patient's condition were appropriate. This could alter the type of health data included in the classification process, as different observations from the data might be required.

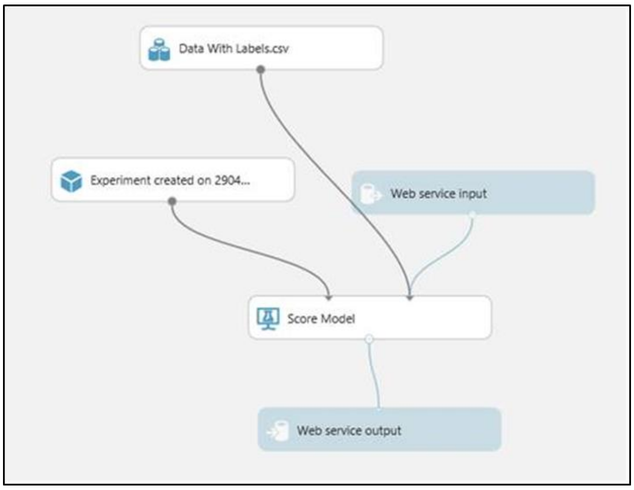

Figure 6. Azure Data Flow for Prediction Mode.

IV. CASE STUDY

In this section, a case study is presented utilising the data set generated from the energy monitor outlined above. Each 24-hour period has 86400 individual readings, as the data is recorded at 10 second intervals. Figure 7 shows an example morning highlighting usage of 2 individual devices. Firstly, a kettle, which is represented by the black dot, secondly the toaster, which is represented by the orange dots. Understanding the energy consumption and duration of usage enables the identification of an individual device. This is important to ascertain the amount of ADL's the patient is performing.

In addition to appliance monitoring, profiling the lighting within a home enables the detection of a patient's location. Lights, light fittings and bulbs create specific profiles based on the type of light and the amount of bulbs fitted. This type of monitoring is extremely beneficial in assessing a patient's wellbeing. Being able to determine how many times a patient visits the bathroom during the night can provide useful insights into their current health. For example, frequent visits may indicate a urinary tract infarction.

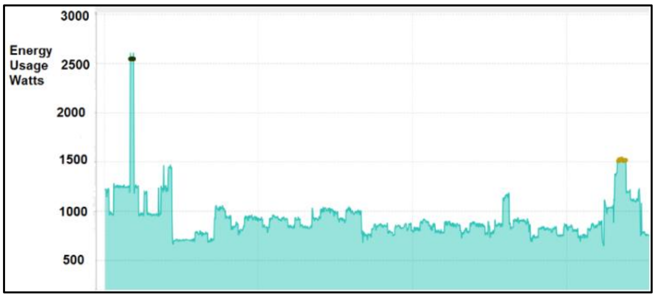

Figure 7. Morning Energy Usage.

In order to detect reduced ADL's, which is a key indicator in assessing the wellbeing of a patient, a balanced data set is created. The data set contains a total of 20 days' energy usage readings taken at 1 minute intervals equating to 1440 readings per 24-hour period. This reading frequency is selected, as it is granular enough for the detection of significant energy usage reductions. 10 days have combined daily energy usage exceeding 720000 watts while the remaining 10 days have usage readings below 620000 watts representing significant reduction in device interaction.

A. *Classification*

The system employs classification methods to identify both normal and abnormal energy usage patterns. The specific classifier used for this experiment is a Bayes Point Machine binary classifier. The classifier was selected for its ability to reduce the chance of over fitting during the training process, as it deploys a Bayesian classification model [13]. In addition, Bayes point machines often outperform Support Vector Machines (SVM) on both surrogate data and real-world benchmark data sets. Figure 8 shows a diagram of the training process. The classifier is conducted 50 times against randomly sampled training and testing sets for each iteration [14]. The hold out cross validation technique was deployed using 80% of the data for training while the remaining 20% is used for testing.

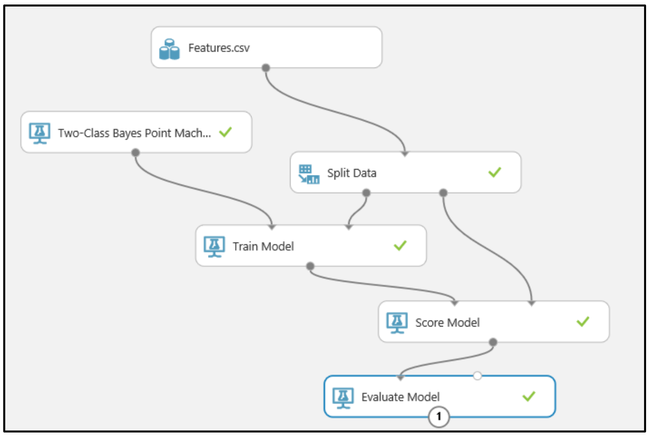

Figure 8. Training Process.

B. *Results*

In this section, the results from the training process are presented. The classifiers performance is calculated using a confusion matrix. This allows the Accuracy (AUC or Area Under Curve), Sensitivity, Specificity and error to be considered. The results from the classifier are shown in Table 2.

TABLE 2. CLASSIFICATION RESULTS 50 REPETITIONS.

Classifier	AUC (%)	Sensitivity	Specificity	Error
Bayes Point	75.00	1	0	0.25

The Bates Point classifier was able to classify 75.00% of the data accurately, with an overall error rate of 0.25. The results of the classification can largely be attributed to the use of a linear classifier. This is due to the fact that most observations are separable due to their large split in values. It is clear from the results that the classifier was able to identify the different behaviours with a reasonable degree of accuracy.

V. Conclusion

This paper discussed the challenges in providing a safe and secure independent living environment. Especially for an ever increasing proportion of the population living with self-limiting conditions. It highlighted significant gaps that exist in remote patient monitoring that is not intrusive, cost effective and facilitates EIP. There is an ever-growing focus on these disorders; both from public awareness, health, charitable and social organisation. It is widely accepted that patients should be able to live for as long as possible in their own homes. In order to address this problem, the paper introduces the concept of using smart meters for actively monitoring a patients wellbeing.

Every household in the UK will have a smart meter installed by 2020. The cost of the roll out and ongoing maintenance is being funded by energy suppliers and the UK government. The paper highlighted, that by utilising this infrastructure, energy usage reading can be obtained in real-time to identify any deviation in a patient's habit or routine. Therefore, a system framework that utilises the Azure Cloud platform to train our classification models was presented. This process demonstrates the ability to detect reduced patient activity, which would arguably be cause for concern. The paper demonstrated that the use of the Bayes Point Machine binary classifier to detect a reduction in a patient activity is possible. Using a classification approach enables alterations in routine and reduced ADLs to be detected.

Any reduction in activity would often go undetected with traditional monitoring systems. Using the techniques described in this paper monitoring both the physical and mental wellbeing of a patient becomes possible. This is important for providing a true representation of their welfare. In order to improve the classification performance, future work includes incorporating significantly larger feature sets to create a system, which is scalable. In addition, experimenting with, dimensionally reduction techniques will be undertaken. Deploying these techniques enables a reduction in the noise and the identification of the most valuable features in the dataset. This will involve the use of Principle Component Analysis (PCA) to improve the overall classification.

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