ICIC Express Letters
Part B: Applications
Volume **17**, Number **1**, January **2026**

ICIC International ©2026 ISSN 2185-2766
pp. 105–112

IMPLEMENTATION OF DEEP LEARNING CONVOLUTIONAL NEURAL NETWORK IN IDENTIFYING FOOD INGREDIENTS FOR COMPLEMENTARY FEEDING RECOMMENDATION

Reynardthan Handoko[1], Friska Natalia[1,*], Sud Sudirman[2] and Chang Seong Ko[3]

[1]Faculty of Engineering and Informatics
Universitas Multimedia Nusantara
Jl. Scientia Boulevard, Gading Serpong, Tangerang, Banten 15227, Indonesia
reynardthan.handoko@student.umn.ac.id; *Corresponding author: friska.natalia@umn.ac.id

[2]School of Computer Science and Mathematics
Liverpool John Moores University
Liverpool, L3 3AF, United Kingdom
s.sudirman@ljmu.ac.uk

[3]Department of Industrial and Management Engineering
Kyungsung University
309, Suyeong-ro, Nam-gu, Busan 48434, Korea
csko@ks.ac.kr

Received February 2025; accepted May 2025

Abstract. *Indonesia is facing a serious issue of malnutrition, resulting in stunting among infants and toddlers. Stunting can impede physical growth, health, and cognitive development in children. The government highlights the importance of education on exclusive breastfeeding and complementary feeding rich in protein as effective preventive measures. Limited understanding of complementary feeding hinders the selection of appropriate menus and cooking techniques to provide adequate nutrition to children. This research is based on the implementation of one of the deep learning algorithms, Convolutional Neural Network (CNN), to recognize and classify images by comparing the performance of two transfer learning models, VGG16 and MobileNetV2. The models are trained on images of high-protein food ingredients suitable for children aged 6 to 23 months, as recommended by the Ministry of Health. The best model is implemented in an Android application to provide Complementary Foods for Breast Milk (CFBM) recommendations. The application is developed using the Android Studio IDE with the Kotlin programming language. The model will be implemented using TensorFlow Lite. This application will provide recommendations for CFBM menu recipes based on submitted food ingredients, and users can save their favorite menus using the favorite feature.*
Keywords: Convolutional neural network, MobileNetV2, Stunting, Transfer learning, VGG16

1. **Introduction.** Indonesia faces serious challenges regarding nutrition, marked by a high prevalence of malnutrition among infants and toddlers [1]. This nutritional deficiency leads to conditions such as stunting and wasting in early childhood [2]. According to the 2023 Global Hunger Index (GHI), Indonesia ranks 77th out of 125 countries, categorized as moderate with indicators of wasting and stunting prevalence among children under five. This highlights a significant social issue requiring serious attention from the government, especially given Indonesia's GHI score of 17.6, well above the threshold for good ranking [3]. Stunting remains a major unresolved nutrition issue among toddlers in Indonesia [4]. The prevalence of stunting in Indonesia was recorded at 21.6% in 2022, according to the Indonesian Nutrition Status Survey [5,6]. This falls short of the global target set by the

DOI: 10.24507/icicelb.17.01.105

World Health Organization at 20%, crucial for achieving Sustainable Development Goals, particularly SDG 2 concerning hunger, food security, and improved nutrition [7]. The Indonesian government has committed to addressing stunting with a target prevalence of 14% by 2024, implementing initiatives such as nutritional education campaigns aimed at promoting proper infant feeding practices [8].

Stunting, a condition resulting from inadequate nutrition, has significant impacts on children's development, including physical growth retardation and heightened susceptibility to health issues [4]. Additionally, it can affect cognitive and mental development, leading to long-term intellectual impairments and decreased productivity. Moreover, stunting increases the risk of degenerative diseases later in life, such as diabetes and hypertension [4,9].

Infants under six months rely exclusively on breastfeeding to prevent stunting. However, as they reach over six months, breast milk alone does not meet their energy needs. Therefore, introducing Complementary Foods for Breast Milk (CFBM) becomes crucial [10]. CFBM aids in meeting children's nutritional needs by providing suitable and nutrient-rich foods [2]. This practice usually starts at the 6th month and continues to the 23rd month, categorized into phases based on the child's age [11]. The government recommends providing complementary foods that are high in protein [12]; however, public understanding regarding infant and toddler feeding, especially concerning breast milk adequacy and animal protein in CFBM remains low. To address these challenges, information technology can be used to facilitate access to nutritional information and recommend suitable CFBM menus. In this study, we propose using a mobile application that provides complementary feeding menu recommendations and nutritional information based on food image recognition and classification [13,14]. The application automatically classifies food ingredients from image data using a deep learning technique similar to other previous studies [15,16]. Two deep learning models are used, namely MobileNetV2 and VGG16 [17,18]. Our approach also applies the Cross Industry Standard for Data Mining (CRISP-DM) approach [19], the adaptive moment estimation for model optimization and fine-tuning [17,18,20] and the cross-validation method [15,21] for model evaluation.

The paper is organized as follows. In Section 2, we describe the data used and the methodology that was adopted. In Section 3, we present the experiment result and provide our analysis and discussion before concluding our findings in Section 4.

2. Material and Method.

2.1. Material.

We use 3,174 images manually sourced from Kaggle [22,23] containing various photographs of chicken meat, beef, eggs, fish, tofu, and tempeh. This is the main image dataset that we will use for developing the deep learning image classification models, and we refer to this dataset as the Main Dataset. The distribution of the number of images per category in the Main Dataset is summarized in Table 1.

TABLE 1. The distribution of the number of images per category in the Main Dataset

Category	**Category name**	**Size**
1	Chicken meat	543
2	Fish	501
3	Beef	519
4	Tofu	574
5	Chicken egg	544
6	Tempeh	493
	Total	3,174

We also created a smaller image dataset containing 30 photographs of the same food categories (five of each category) directly by taking pictures using our mobile phones. This dataset will serve as a field test dataset to provide some indications of the performance of the models in real-life settings. We refer to this dataset as the Small Dataset. In addition, we also collated information on complimentary foods in the form of menus, processing methods, and nutritional values. The information was obtained from several recipe books published by the Indonesian Health Ministry [11] totaling 15 food menus. The recipe data was obtained from the Indonesian Health Ministry in tabular format, with all the data stored on the Firebase platform as shown in Table 2.

Table 2. Description of the tabular datain the CFBM database

Variable	Description
menu_name	Name of each CFBM in the menu
image	Picture of each CFBM in the menu
category	Grouping of food menus into three categories based on age. Category '1' for children aged 6-8 months; Category '2' for children aged 9-11 months; Category '3' for children aged 12-23 months.
ingredients	All the main ingredients needed to prepare the CFBM.
seasonings	All the main optional seasonings that are needed to prepare the CF-BM.
fruit	Recommended fruits to accompany the CFBM.
recipes	Detailed recipe to prepare the CFBM.
servings	The number of servings of CFBM produced after following the recipe.
energy	Total calories in each serving of the CFBM.
fat	Total fat content in each serving of the CFBM.
protein	Total protein content in each serving of the CFBM.
additional_info	Additional information related to the CFBM.

2.2. **Method.** An overview of the methodology is elucidated in Figures 1 and 2. Figure 1 shows the development and evaluation of the image classification model using the Main Dataset, whereas Figure 2 shows how the best-developed model is tested using the Small Dataset and used in mobile app development. The methodology follows the CRISP-DM methodology [24,25] because it is suitable for developing an image classification model and its implementation as an Android-based mobile app. The data preparation stage starts by resizing all the images to 224 × 224 pixels dimension. The data is then divided into 80% for training and 20% for testing as part of a 5-fold cross-validation process. Data

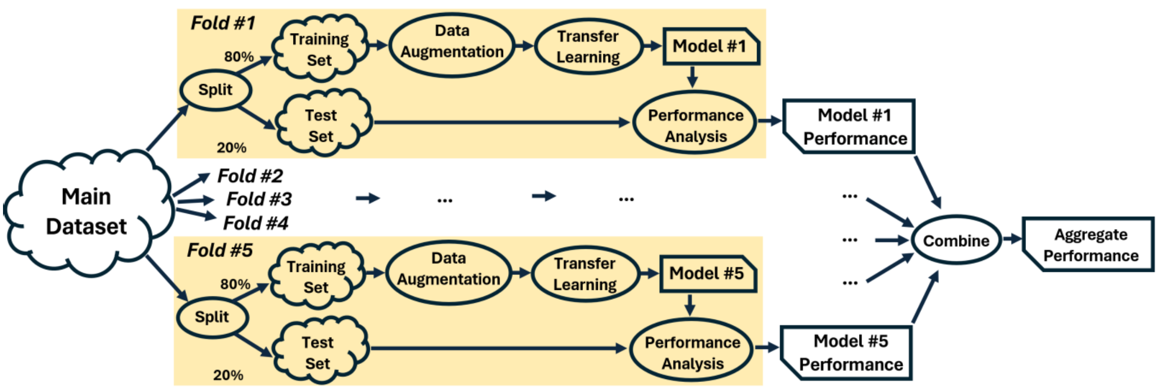


Figure 1. The development of the image classification model using cross-validation and transfer learning approach and using the Main Dataset

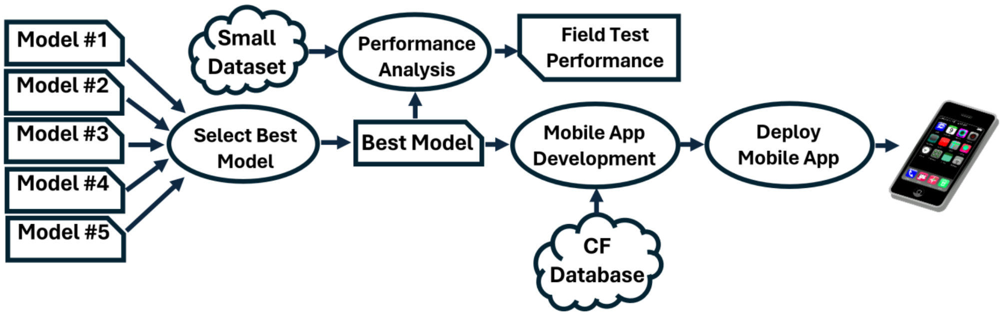


Figure 2. The process of how the best-developed model is tested in a real-life setting using the Small Dataset and used in a mobile app development

augmentation is then applied to the training set by randomly rotating the images up to 20 degrees to the right or left, applying random horizontal and vertical displacement up to 10% of the image dimensions, applying image shearing by shifting image points in a random direction up to 20% of the image width, applying image zoom in or out up to 20%, and applying random horizontal and vertical image flips.

We leveraged the use of pre-trained VGG16 and MobileNetV2 image classification models by using transfer learning. This enables us to use the deep learning architectures without having to train the models from scratch but only through fine-tuning the weights of the feature extraction layers and training the feature classification layer. We control the training process by setting the initial learning rate, the optimizer technique, and the number of epochs. In our experiment, we set the initial learning rate to 0.001, used the Adaptive Moment Estimation (ADAM) optimizer, and set the number of epochs to 25. These values were chosen as the best values from a range of typical values of training parameters that we have used in the past. For model training with cross-validation enabled, we set k equal to 5 folds utilizing the stratified k-fold function to ensure an even distribution of data across categories.

To evaluate the image classification performance of the model, we use accuracy, precision, recall, and F1-Score performance metrics. The formulas for calculating these metrics are given in [26] and provided below for convenience (TP, TN, FP, and FN are the number of True Positive, True Negative, False Positive, and False Negative, respectively).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 = \frac{Precision \times Recall}{Precision + Recall}$$

Additionally, we also examine the confusion matrix of the models, which will offer a detailed breakdown of the classification results, including true positives, false positives, true negatives, and false negatives. These metrics will provide insights into the effectiveness of the models in correctly classifying food ingredients into their respective categories. By employing these evaluation methods, the research aims to identify the best-performing model for the task of food ingredient classification. The top-performing model will be converted to TensorFlow Lite (TFLite) format for implementation in mobile applications.

The deployment process will involve creating an Android mobile application that integrates the best-performing model obtained. This application will feature support for recommending recipes based on the food ingredients submitted by users. Images captured by users will be processed to match the input format required by the model, resized to 224×224 pixels. The Android application was developed in Kotlin programming language with XML. The study applies thresholding mechanisms to helping avoid recommendation errors due to inaccuracies in detection and classification caused by too low confidence levels, with a minimum threshold set at 85% [27].

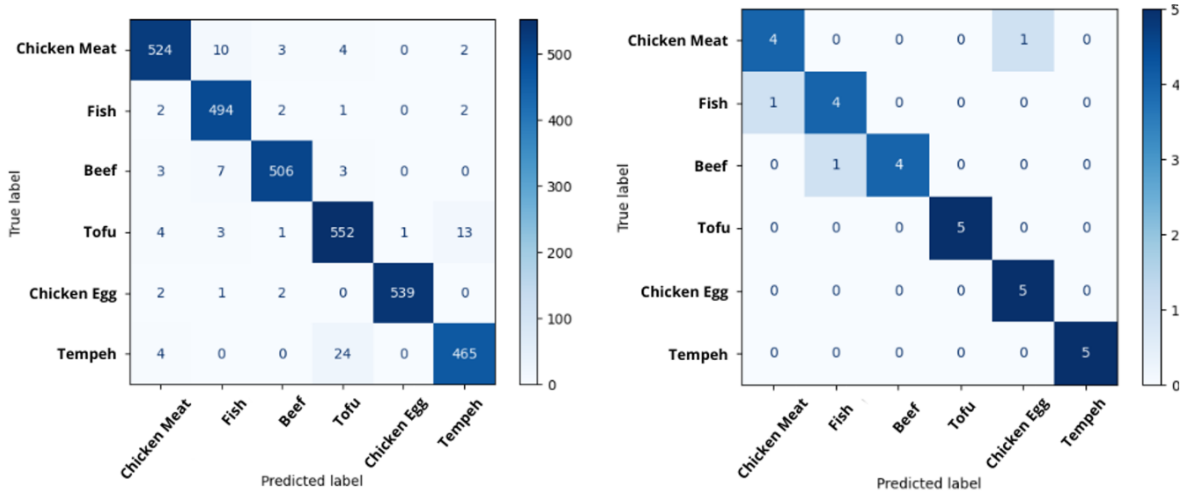
3. **Experiment Result, Analysis, and Discussion.** Several additional layers were appended to both models during training, which included a GlobalAveragePooling2D layer, a fully connected layer with ReLU activation consisting of 256 layers, and a dropout layer with a 30% rate. As the final output layer, a SoftMax activation layer comprising 6 category classes, was appended. In our experiment, we set the initial learning rate to 0.001, used the Adaptive Moment Estimation (ADAM) optimizer, and set the number of maximum epochs to 25 and batch size to 25. To obtain a better-generalized picture of the model performance, we experimented with cross-validation. For this, we implemented stratified cross-validation with 5 folds using the set of data as previously. All evaluation metrics of the model performed with cross-validation show a significant improvement, as seen in the overall evaluation values per fold from the application of stratified cross-validation in Table 3.

Table 3. The overall evaluation of each fold of the models

Fold	Model	Accuracy	Precision	Recall	F1-Score
1	MobileNetV2	0.9748	0.9760	0.9742	0.9747
	VGG16	0.8960	0.8985	0.8954	0.8964
2	MobileNetV2	0.9669	0.9673	0.9670	0.9670
	VGG16	0.8803	0.8809	0.8802	0.8803
3	MobileNetV2	0.9748	0.9748	0.9748	0.9748
	VGG16	0.8850	0.8875	0.8849	0.8851
4	MobileNetV2	0.9669	0.9667	0.9666	0.9666
	VGG16	0.8693	0.8693	0.8599	0.8601
5	MobileNetV2	0.9684	0.9688	0.9686	0.9686
	VGG16	0.8817	0.8886	0.8794	0.8815

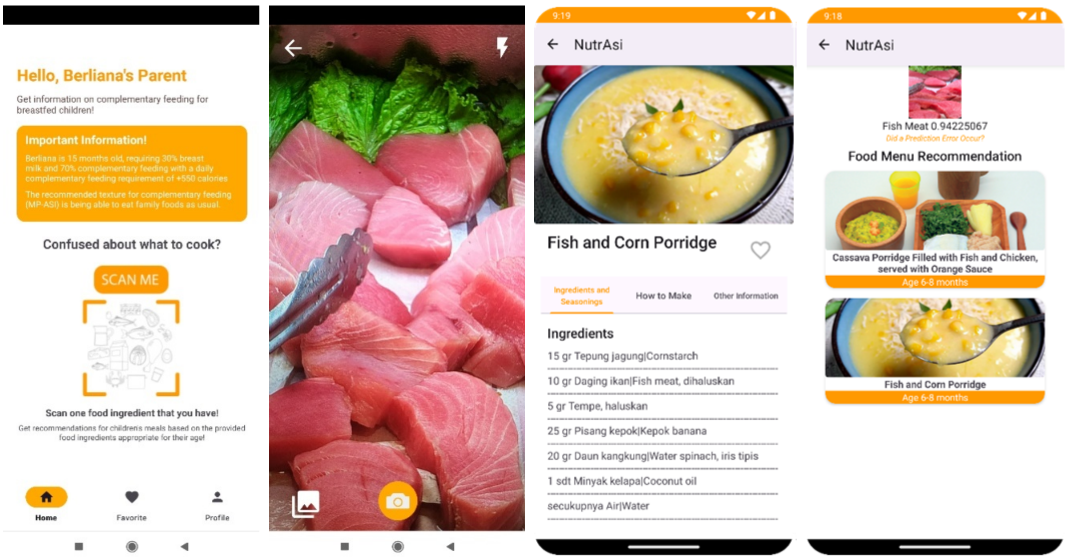
The models' performance using cross-validation has stable values across all folds, indicating that the models learn well from unseen data indicating good performance generalization. Based on the results shown in Table 3, it is found that the MobileNetV2 model still has better evaluation metrics compared to VGG16; hence the former is considered as the best model to use for the next stage of the experiment. First, we measure the aggregate performance of the model for each class across the entire dataset. We do this by combining the classification results across all five folds. We show this as a Confusion Matrix in Figure 3(a). From this Confusion Matrix, we calculate the Precision, Recall, and F1-Score for each class which range from 95% to 100%. This proves that the model has achieved a very good and stable image classification performance. The model is also tested on the Small Dataset, and its classification performance is shown as a Confusion Matrix in Figure 3(b). The result also shows a very good and stable image classification performance on these completely unseen images.

For the deployment of the image classification model in an Android app, the trained MobileNetV2 model is saved in the .h5 format and converted into a Tensor Flow Lite (TF Lite) file. The mobile app was developed using the Android Studio IDE, utilizing the Kotlin programming language and various supporting libraries for application development. The application was fully designed to support the recommendation of the CFBM menu based on the food materials provided by the user. The model operates by providing



(a) (b)

FIGURE 3. The aggregate Confusion Matrix of the MobileNetV2 model: (a) When tested on the Main Dataset across all five folds and (b) when tested on the Small Dataset



(a) (b) (c) (d)

FIGURE 4. Screenshots of the mobile application showing (a) the Home page, (b) the camera interface, (c) the CFBM recommendation page, and (d) the CFBM recipe page

labels to the backend to retrieve information related to CFBM menus and recipes. The application consists of several menus, such as Authentication, Home, Favorite, and Profile Menu, with the main feature implementing the model and recommendations on the Home menu. We impose a threshold of 85% classification score for any images submitted by the user to meet before the application proceeds to recommend any CFBM. This threshold value was determined through repeated testing and was found to be the most suitable threshold for detecting food material objects. Figure 4 shows screenshots of the mobile application showing (a) the Home page, (b) the camera interface, (c) the CFBM recommendation page, and (d) the CFBM recipe page. The recipe page displays the detailed page of the CFBM menu, featuring several tabs that can change according to the selected tab such as “Ingredients”, “Seasonings”, “How to Make”, and “Other information”. Each recipe can be saved to allow easy recall in the future.

4. **Conclusions.** This research presents a method for recognizing and classifying high-protein food ingredients to create Complementary Foods for Breast Milk (CFBM) menus aimed at preventing stunting in children aged 6 to 23 months. The detection and classification method for food ingredients uses a deep learning convolutional neural network approach, comparing two pre-trained models: VGG16 and MobileNetV2. The study uses 3,174 images for model development and 30 images for field testing. Each dataset is comprised of 6 types of food ingredients categories: chicken meat, fish, beef, tofu, chicken egg, and tempeh. The best model was determined to be MobileNetV2 with the class classification performance of at least 95% measured using Precision, Recall, and F1-Score metrics. The model was then incorporated into an Android application using TensorFlow Lite. By using this application, users, particularly parents of children aged 6 to 23 months, will receive recommendations for suitable CFBM menus that can meet their child's nutritional needs, thus preventing stunting. In the future, this system can be enhanced by adding more food material and CFBM menu data to provide users with even more varied recommendations.

REFERENCES

[1] Cable News Network, *21 Juta Warga RI Kekurangan Gizi Dan 21.6 Persen Anak Stunting (21 Million Indonesian Citizens are Malnourished and 21.6 Percent of Children are Stunted)*, 2023.

[2] Rokom, Waspada, *4 Masalah Gizi Ini Berisiko Anak Jadi Stunting (Be Alert, These 4 Nutritional Problems Risk Children Becoming Stunted)*, Sehat Negriku, 2023.

[3] K. von Grebmer, J. Bernstein, M. Wiemers, L. Reiner, M. Bachmeier, A. Hanano, N. R. Chéilleachair, C. Foley, T. Sheehan, S. Gitter, G. Larocque and H. Fritschel, *The Power of Youth in Shaping Food Systems*, Global Hunger Index, 2023.

[4] Ministry of Health of the Republic of Indonesia, *Decree of the Ministry of Health of the Republic of Indonesia*, Indonesia, 2022.

[5] Rokom, *Prevalensi Stunting Di Indonesia Turun Ke 21,6% Dari 24,4% (Stunting Prevalence in Indonesia Drops to 21.6% from 24.4%)*, Sehat Negriku, 2023.

[6] Ministry of Health of the Republic of Indonesia, *Hasil Survei Status Gizi Indonesia (SSGI) 2022 (Results of the 2022 Indonesian Nutrition Status Survey (SSGI))*, 2022.

[7] WHO, *SDG Target 2.2 Malnutrition*, The Global Health Observatory, 2024.

[8] Coordinating Ministry for Human Development and Cultural Affairs of the Republic of Indonesia, *Dengan RAN PASTI, Pasti Turunkan Stunting Jadi 14% Pada Tahun 2024 (With RAN PASTI, Stunting will Definitely be Reduced to 14% by 2024)*, 2023.

[9] E. Nuryuliyani, *Mengenal Lebih Jauh Tentang Stunting (Getting to Know More about Stunting)*, Directorate General for Health Service, 2023.

[10] N. E. Pujiastuti, *Cegah Stunting Dengan Makanan Bergizi Seimbang Pada 1000 Hari Kehidupan Pertama Anak (Prevent Stunting with Balanced Nutritious Food in the First 1000 Days of a Child's Life)*, Directorate General for Health Service, 2022.

[11] I. Ekayanti, H. Nurlita, D. O. Anggiruling, D. Rosa, D. Astuti, E. Prihastono, E. Katherini, M. Fauzi, Mursalim, N. Septiani, S. Masruroh, T. Yumeida, Z. Sholuhiyah and A. Nadiya, *Buku Resep Makanan Lokal Bayi, Balita, Dan Ibu Hamil (Local Food Recipe Book for Babies, Toddlers and Pregnant Women)*, Directorate General for Health Service, 2023.

[12] Rokom, *Cegah Stunting Pada Anak Dengan Protein Hewani (Prevent Stunting in Children with Animal Protein)*, Sehat Negriku, 2023.

[13] M. J. Akbar, M. W. Sardjono, M. Cahyanti and E. R. Swedia, Perancangan aplikasi mobile untuk klasifikasi sayuran menggunakan deep learning convolutional neural network (Designing a mobile application for vegetable classification using deep learning convolutional neural network), *Sebatik*, vol.24, no.2, pp.300-306, 2020.

[14] S. Suleman, H. Faqih, H. Lesmana and B. C. P. Utami, SI KALORI: Sistem pakar penghitung jumlah ideal kalori harian berbasis mobile (SI KALORI: Mobile based expert system for the ideal number of daily calories), *Indones. J. Softw. Eng.*, vol.9, no.1, pp.46-54, 2023.

[15] N. B. Setiawan, F. Natalia, F. V. Ferdinand, S. Sudirman and C. S. Ko, Classification of skin diseases and disorders using convolutional neural network on a mobile application, *ICIC Express Letters, Part B: Applications*, vol.12, no.8, pp.715-721, 2021.

[16] M. S. Rodrigues, F. Fidalgo and A. Oliveira, RecipeIS – Recipe recommendation system based on recognition of food ingredients, *Appl. Sci.*, vol.13, no.13, 7880, 2023.

[17] Y. Gulzar, Fruit image classification model based on MobileNetV2 with deep transfer learning technique, *Sustainability*, vol.15, no.3, 1906, 2023.

[18] N. Rachburee and W. Punlumjeak, Lotus species classification using transfer learning based on VGG16, ResNet152V2, and MobileNetV2, *IAES Int. J. Artif. Intell.*, vol.11, no.4, 1344, 2022.

[19] G. L. Elena Maquen-Niño, A. A. Sandoval-Juarez, V.-L. Rosa, R. Andres, G. Carrión-Barco, I. Adrianzén-Olano, H. Vega-Huerta and P. De-La-Cruz-VdV, Brain tumor classification deep learning model using neural networks, *Int. J. Online & Biomed. Eng.*, vol.19, no.9, 2023.

[20] R. Thangaraj, S. Anandamurugan and V. K. Kaliappan, Automated tomato leaf disease classification using transfer learning-based deep convolution neural network, *J. Plant Dis. Prot.*, vol.128, no.1, pp.73-86, 2021.

[21] S. Prusty, S. Patnaik and S. K. Dash, SKCV: Stratified K-fold cross-validation on ML classifiers for predicting cervical cancer, *Front. Nanotechnol.*, vol.4, 972421, 2022.

[22] J. Sambhuwara, Food dataset, *Kaggle*, https://www.kaggle.com/datasets/jiwasambhuwara/food-ingredients, 2024.

[23] Aliff07, Bahan Makanan (Food Ingredients), *Kaggle*, https://www.kaggle.com/datasets/aliff07/bahan-makanan, 2024.

[24] C. Wulandari, Y. Anshori and K. F. H. Holle, CRISP-DM method on Indonesian micro industries (UMKM) using K-means clustering algorithm, *Matics J. Ilmu Komput. dan Teknol. Inf.*, vol.14, no.2, pp.35-40, 2022.

[25] E. Chandra and F. Natalia, Comparative analysis of decision tree and random forest algorithms in predicting potential buyers and sellers in the healthcare sector, *2024 7th International Seminar on Research of Information Technology and Intelligent Systems (ISRITI)*, pp.617-622, 2024.

[26] O. Rainio, J. Teuho and R. Klén, Evaluation metrics and statistical tests for machine learning, *Sci. Rep.*, vol.14, no.1, pp.1-14, 2024.

[27] A. Archilles and A. Wicaksana, Vision: A web service for face recognition using convolutional network, *TELKOMNIKA (Telecommunication Comput. Electron. Control)*, vol.18, no.3, pp.1389-1396, 2020.