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FoodSnap: Mobile Application Instant Pricing with Image Recognition

Muhammad Haziq Azizan[1], Romiza Md Nor [2*]

[1,2]*College of Computing, Informatics and Mathematics,*
Universiti Teknologi MARA (UiTM) Perlis Branch, Arau Campus, 02600 Arau, Perlis, Malaysia

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ABSTRACT

This project enhances traditional food pricing methods by employing image recognition and machine learning. Unlike physical price tags which can lead to inconsistencies, this app enables users, particularly financially constrained students, to capture food images and receive accurate pricing information instantly. The mobile application is built on a robust dataset to ensure the model's accuracy across various cuisines. The development process follows the waterfall model, consisting of five phases: Requirement Analysis, Design, Development, Evaluation, and Documentation. Key technologies used include TensorFlow for machine learning model training, MySQL for secure data storage, and Flutter for cross-platform mobile application development. This combination allows users to seamlessly capture images and receive real-time pricing details. The applications accuracy and usability were tested through user acceptance tests (UAT). During testing, all modules worked flawlessly, and the application was praised for its simplicity and effectiveness. The findings highlight that this mobile application significantly improves food pricing accessibility and accuracy. With ongoing updates, it holds the potential to transform consumer interaction with food pricing, increasing transparency and enhancing overall user satisfaction.

1. INTRODUCTION

Food holds paramount significance for everyone, and our dining experiences often revolve around restaurants. As we know, price of the food is increasing over time. This will affect everyone especially student (Zin, 2022). It can be challenging for students to decide what to eat because food prices have been rising recently, and costs can vary depending on the type of dish, portion size, meal quantity, and even the cashier has difficulty in determining the correct price. These individuals must ensure they are getting the best value for their money, which is particularly crucial when working with a limited budget. The decision-making process becomes even more challenging when relying on traditional methods, like listing prices on a menu board or paper menu, as these can be laborious and time-consuming to navigate. Currently, the price tag usually places below the food tray or behind it which make it hard to be seen by customer. The usage of signage is where the menu price was written on chalkboards or whiteboard to display their special

[2*] Corresponding author. *E-mail address*: romiza@uitm.edu.my
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menu and price. The problem is it does not display price for all menu but only one or two. This makes the customer having hard time to know the price for another menu. Price stickers are another common method sellers use to label their products. However, since prices are not fixed and may Currently, the price tag usually places below the food tray or behind it which make it hard to be seen by customer. The usage of signage is where the menu price was written on chalkboards or whiteboard to display their special menu and price. The problem is it does not display price for all menu but only one or two. This makes the customer having hard time to know the price for another menu. Price stickers are another common method sellers use to label their products. However, since prices are not fixed and may change, it can be difficult for customers to know the latest price (Nordin et al., 2019). Additionally, the sticker might display an outdated, higher price, causing customers to avoid purchasing the item, even if the price has since been reduced. A more modern approach to displaying food prices involves using quick response (QR) codes. The customer needs to scan the code get access for the prices. The problem is sometimes the code could not be read by QR scanner and make the customer clueless about the price. Another most significant challenges faced by consumers while shopping for food is the ability to accurately estimate the cost of their purchases. Pricing varies based on different factors such as location, seasonality, quality, and quantity, which makes it difficult for consumers to have an accurate estimate of the total cost of their food. There are some students that need to fast as they need to save money to survive in university (Zakaria, 2022). Therefore, technologies like image recognition and machine learning can be used to improve this system. By recognizing the dish and give the student correct pricing information by taking a picture of the item. Time is saved, and the decision-making process is made simpler and more open as a result (Nordin et al., 2019). Traditionally, a computer is needed to run image recognition. However, with the rapid development of technology, image recognition can now be run using a mobile phone, which almost every student has. This means that the system can be easily accessed and used by anyone with a smartphone. This makes it a cost-effective solution that is accessible to everyone. This motivate me to solve this problem so that the student would not be starving to save money anymore. There is a few Images Recognition technique. For example, like Artificial Neural Networks, Convolutional Neural Network, and Recurrent Neural Networks. For Artificial Neural Network, it is interconnected layers of artificial neurons with each neuron connected to every neuron in the adjacent layers (Schmidgall, 2023). It also processes data independently without any temporal relationships. Widely used in various field such as pattern recognition and data mining. For Convolutional Neural Networks, it consists of connected layers. It is also designed for processing grid-like data such as images Convolutional Neural Network is also good for image related task such as image detection (Patil, 2021). Food plays an integral role in our daily lives (Lee et al., 2019)., and dining experiences are often influenced by various factors, including the price of the food items. The pricing mechanisms in restaurants and eateries can be diverse, ranging from portion-based pricing to variations based on culinary preparation methods. This diversity sometimes leads to a lack of transparency in pricing, creating challenges for consumers seeking consistent and reliable information.As the pricing can vary depending on the type of dish, the quantity, the size of the meal, and even the cashier, it will lead to problems. One of it is unsatisfaction. This happen when the customer sees the other customer paid for the same item but with different price. So, they will start questioning why there is more expensive from others. This inconsistent pricing will also damage customer trust in business which will lead to negative review and will hurt business reputation (Quinn, 2023).

2. LITERATURE

2.1 Food Image Recognition

Food image recognition refers to the field of computer vision and artificial intelligence that focuses on the automatic recognition and classification of food products or dishes in digital images or photos. It involves analysing the visual patterns, features and characteristics contained in food photos to classify them into specific food groups or to identify specific dishes (Nordin et al., 2019). The goal of food image recognition is to develop algorithms and models that can accurately and efficiently recognize and classify

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foods based on their appearance. Food image recognition is based on advanced techniques from computer vision and machine learning. Initially, a dataset of tagged food images is collected, with each image being associated with a specific food or dish (Reddy et al., 2022). These images are then used to train machine learning models, such as convolutional neural networks (CNNs), which can automatically learn and extract relevant visual features from the images. During training, models learn to recognize and distinguish different attributes of food, such as colour, texture, shape, and arrangement (Salim et al., 2021). They also learn to identify specific ingredients, dishes or even cooking styles based on visual clues in pictures. Overall, food image recognition is a specialized field that combines computer vision and machine learning to automatically recognize and classify food products or dishes in images. Its applications range from diet tracking to improving food-related services, and continued advancements in this field offer promising prospects for food-related industries (Salim et al., 2021). and different nutrition.

2.2 Convolutional Neural Networks

Convolutional Neural Networks (CNNs) are a specialized type of neural network designed specifically for image analysis. They excel at capturing spatial relationships and local patterns within images. By utilizing convolutional layers, CNNs automatically learn and extract relevant features at different scales and orientations, making them highly effective for tasks such as image classification, object detection, and image segmentation (Yamashita et al., 2018). Convolutional Neural Networks (CNNs), are specifically designed for image analysis tasks, making them highly suitable for recognizing and categorizing food items based on their visual characteristics. With convolutional layers, CNNs can automatically extract relevant features at various scales and orientations, enabling them to capture important details such as shape, colour, and texture. This makes them highly effective in distinguishing between different types of food. Additionally, CNNs are capable of robust feature extraction, learning hierarchical representations from raw pixel values. This allows them to discern both low-level details and high-level semantic information, making them adept at identifying complex food patterns and structures. Another advantage of CNNs is their translation invariance property, enabling them to recognize food items regardless of their position or orientation within the image. The availability of pretrained models trained on large-scale image datasets, such as ImageNet, provides a head start for the application. By fine-tuning these models on the specific food image dataset, leverage transfer learning is possible to enhance accuracy and efficiency (Reddy et al., 2022). Moreover, CNNs offer efficient image analysis, robust feature extraction, translation invariance, and the convenience of pretrained models, making them an excellent choice for the food image recognition application. Using food image recognition has many advantages, including reducing the workload for workers in the food sector. By automating the process of identifying food items, workers can focus on other tasks, such as preparing and serving food. This can lead to increased efficiency and productivity in the workplace. Additionally, food image recognition can enhance the user experience by providing instant information about the food price and nutritional content. This makes it more convenient for users to make informed decisions about their food choices. Overall, food image recognition has the potential to revolutionize the food industry by improving efficiency and enhancing the user experience.

3. METHODOLOGY

The waterfall methodology is a project management strategy that employs phases such as requirements analysis, system design, development, testing, and documentation in a sequential order. Collect and document the project's unique requirements and goals in requirement analysis phase. Understanding the objectives and features anticipated from the system is the focus of this phase. The system design phase, where the design team develops a complete blueprint of the system, including database design, modules, and user interface, starts once the requirements are established. Based on the design specifications, the system is coded and implemented during the development phase. The system is tested after development to guarantee functionality and conformity to specifications. Testers run a variety of test scenarios and

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document any problems from the desired behaviour. Throughout the entire waterfall process, a comprehensive documentation for the project results and findings are created.

The experimental layout of the mobile application for food image recognition is shown in Fig. 1. The user is given two alternatives when they first interact with the process: either they may use the device's camera to take a picture of the food, or they can select to upload an image from their gallery. The application uses TensorFlow, a potent machine learning framework, when the user submits 0an image to determine the image's contents. TensorFlow applies deep learning algorithms to identify the image based on recognised patterns after analysing the visual data. By doing this, we make sure that the application can recognise the precise food item that is shown in the photograph. The application then loads the results after analysing and classifying the image. To do this, the pertinent data about the specified food item must be fetched, including the name, attributes, and cost. This information is retrieved by the programme from either an external source or a predetermined database. The user is then shown the price of the food. The application concludes the image identification process by displaying the item's pricing. Users can easily check the pricing of the food item they have photographed or uploaded using this information.

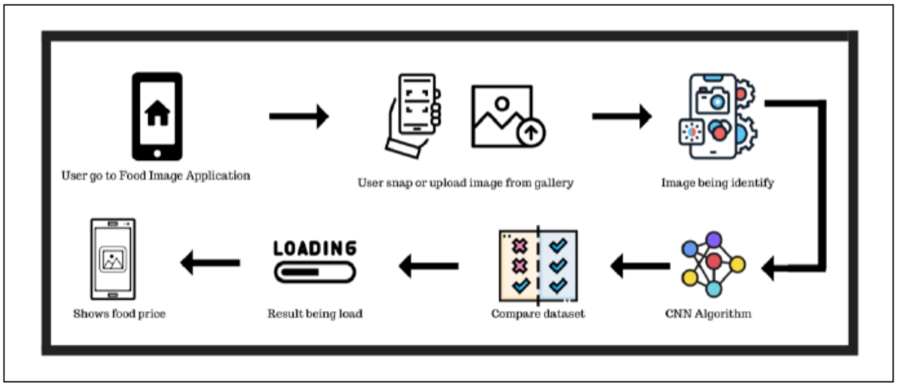

Fig. 1. Experimental design of FoodSnap

3.1 Dataset Design

The dataset design phase is crucial for setting up and training the machine learning model. It involves collecting, curating, and pre-processing a diverse and representative set of food images. Data augmentation techniques are applied to enhance variability and improve model robustness. The dataset is then divided into training, validation, and test sets. Feature engineering extracts important patterns from the images, while labels are assigned to support supervised learning. Special attention is given to avoid biases and ensure the dataset accurately reflects real-world conditions. This phase ultimately produces a cleaned and optimized dataset, forming the foundation for a high-performing food image recognition model in the mobile application.

3.2 Web Scraping

Web scraping is an automated method used to collect information or images from websites, and in this case, it focuses on food-related images. These images are crucial for training a food recognition model. Web scraping helps gather a diverse and comprehensive dataset, which is key to building a robust model capable of identifying various food items. In this context, manual selection plays a role alongside web scraping. A human operator carefully selects and removes images to ensure that the dataset is diverse and of high quality, representing a wide range of food categories. This curation process improves the effectiveness of the model by ensuring that the dataset is representative of the types of images the model

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will encounter in real-world scenarios. Overall, combining web scraping with human oversight ensures a relevant, well-structured dataset, optimizing the model's performance in food identification applications.

3.3 Development

The Flutter framework, a flexible UI toolkit from Google, is used in the development of Foodsnap to produce a single codebase across desktop, online, and mobile applications. This part presents the development effort’s climax, displaying the final User Interface (UI) design that complies with aesthetic hierarchy and minimalism principles. Included are illustrative code samples that highlight important features and Flutter-implemented algorithms, providing insights into the application’s core logic. The database component is also examined, emphasizing FoodSnap’s effective information management and retrieval, which is essential for precise pricing computations. This extensive presentation highlights FoodSnap’s effective integration of Flutter for a smooth and user-focused mobile experience while encapsulating the technical and aesthetics components of the platform.

3.4 Model Training

FoodSnap development start with model training. The first step in training the model with Google's Teachable Machine is to create unique classes that are necessary for the recognition assignment. Various food categories were represented in this instance by classes like 'Nasi,' 'Ayam Masak Merah,' 'Nasi dan Ayam Masak Merah,' 'Ayam Goreng,' 'Nasi dan Ayam Goreng', ‘Daging Masak Hitam’, and ‘Nasi dan Daging Masak Hitam’. Each class is created by gathering a picture collection that corresponds to that class, guaranteeing representation and diversity of different cases within that class. The model can correlate visual patterns with each class name thanks to this procedure, which allows supervised learning. Next is to start the training process when the food recognition model classes have been created in Teachable Machine. Default number of Epochs is 50 Epochs.

One epoch means that each sample in the training dataset has been fed through the training model at least once. Next batch size is set, which is the default value, 16. A batch is a set of samples used in one iteration of training. The training process is started by Teachable Machine by clicking the "Train Model" button. In this phase, the model uses the supplied image dataset to learn how to differentiate between the defined classes. The training makes use of machine learning methods, such as transfer learning, to modify previously acquired knowledge for the classes that are made. During the training phase, the parameters of the model are modified to maximise its capacity for precise image recognition and classification within the designated categories. With the help of Teachable Machine's feedback, users may keep an eye on the training process and evaluate its effectiveness. After training, the model learns to predict fresh, unseen photos, which allows the mobile application to recognise food in an efficient manner. Fig. 2 shows the machine learning being train. Testing the performance of the trained and quantized model is an essential next step. To test the model's accuracy in identifying and categorising various food groups, fresh and un-viewed photos are fed into it. After training, the model is tested using unseen images to evaluate its accuracy in classifying various food groups. This testing process ensures the model generalizes well to real-world scenarios, allowing for adjustments if necessary. The final step is downloading the trained model, with quantization applied to reduce its size for mobile deployment. This is crucial for efficient performance when integrated with MobileNetV2, ensuring the food recognition feature works seamlessly on mobile devices.

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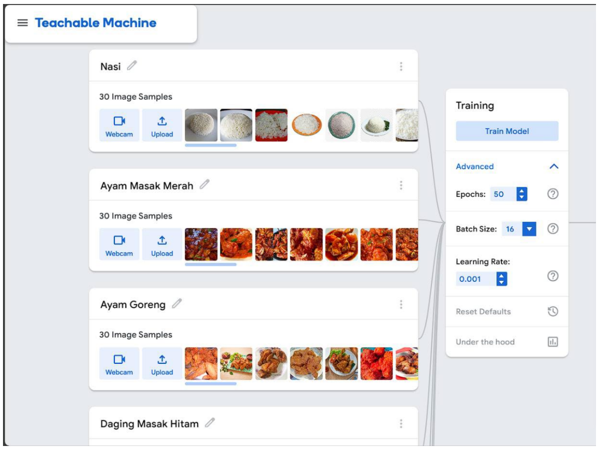

Fig. 2. Model training of FoodSnap

3.5 Accuracy Per Class

The accuracy of each class is visualized to assess the model's performance during testing with sample photos. This visualization shows how well the model recognizes and classifies food items within specific categories like "Nasi," "Ayam Masak Merah," "Nasi dan Ayam Masak Merah," "Ayam Goreng," "Nasi dan Ayam Goreng," "Daging Masak Hitam," and "Nasi dan Daging Masak Hitam." Higher accuracy percentages indicate that the model effectively identifies and differentiates between photos in each class.

The accuracy results reveal that some classes, such as "Nasi," "Ayam Goreng," "Daging Masak Hitam," "Nasi dan Ayam Masak Merah," and "Nasi dan Daging Masak Hitam," achieved a perfect accuracy of 100%. Classes like "Ayam Masak Merah" and "Nasi dan Ayam Goreng" had an 80% accuracy rate. Each class was tested with five samples, and the image dataset was divided into a Training Dataset (85% of images) and a Samples Dataset (15%). This division allowed the model to be trained on most of the data and evaluated on a smaller subset to test its generalization capabilities.

Overall, these results suggest that the model performs well in recognizing and classifying various food categories, with some areas showing particularly strong accuracy (Fig. 3).

Accuracy per class

CLASS	ACCURACY	# SAMPLES
Nasi	1.00	5
Ayam Masak Merah	0.80	5
Ayam Goreng	1.00	5
Daging Masak Hitam	1.00	5
Nasi dan Ayam Masa...	1.00	5
Nasi dan Ayam Gore...	0.80	5
Nasi dan Daging Ma...	1.00	5

Fig. 3. Accuracy per class of FoodSnap

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3.6 Conversion Matrix

Fig. 4 shows the conversion matrix for this machine learning. A confusion matrix summarizes how accurate the model's predictions are. This matrix can be to figure out which classes the model gets confused about. The y axis (Class) represents the class of the samples. The x axis (Prediction) represents the class that the model, after learning, guesses those samples belong to. So, if a sample's Class is "Ayam Masak Merah" but its Prediction is "Ayam Goreng", that means that after learning from the dataset, the model misclassified that "Ayam Masak Merah" sample as "Ayam Goreng". This usually means that those two classes share characteristics that the model picks up on, and that particular "Ayam Goreng" sample was more like the "Ayam Masak Merah" samples. In this conversion matrix, "Nasi dan Ayam Masak Merah" class and "Nasi dan Ayam Goreng" class got one confusion just like "Ayam Masak Merah" class and "Ayam Goreng" class.

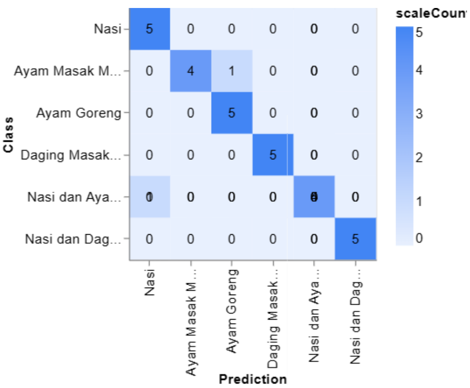

Fig. 4. Conversion matrix of FoodSnap

3.7 Accuracy per epoch

Accuracy per epoch measures a machine learning model's accuracy at each epoch during training, where an epoch represents one full pass through the training dataset. Accuracy is calculated as the percentage of correct classifications by the model. For instance, if the model correctly classifies 70 out of 100 samples, the accuracy is 70%. Fig. 5 illustrates accuracy per epoch, with epochs on the x-axis and accuracy on the y-axis. Initially, the accuracy for the test dataset is 94% during the first 10 epochs, indicating the model is learning and making accurate predictions. From the 12th to the 34th epoch, accuracy significantly improves, reaching a peak of 97%, suggesting effective pattern recognition and learning. However, on the 35th epoch, there is a slight drop in accuracy to 94%, which persists through the final epoch. Such fluctuations may indicate potential issues such as dataset complexity, overfitting, or a need for adjustments in the model's architecture or training parameters. Analysing accuracy per epoch is essential for assessing how well the model generalizes to new data and identifying areas for potential improvement (Fig. 5).

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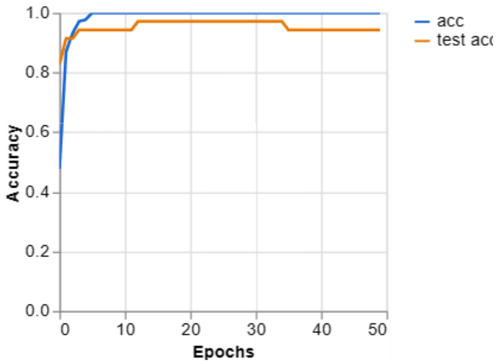

Fig. 5. Accuracy per epoch of FoodSnap

3.8 Loss per epoch

Loss is a key metric in machine learning that quantifies the difference between a model's predictions and the actual values in the training dataset. The objective during training is to minimize this loss, with zero loss indicating perfect predictions. Fig. 6 illustrates the loss evolution over epochs, with the y-axis representing the loss value. Initially, at epoch zero, the loss is relatively high at 90%. As training progresses, the loss decreases, showing improvement in the model's accuracy. By epoch 10, the loss has reduced significantly to 20%, indicating better prediction accuracy. Between epochs 40 and 49, the loss stabilizes around 15%, suggesting that the model has achieved a competent level of performance. This downward trend in loss reflects the model's effective learning from the training data and its progression toward more accurate predictions. Monitoring both training and test loss is crucial to ensure that the model not only performs well on the training data but also generalizes effectively to new, unseen data.

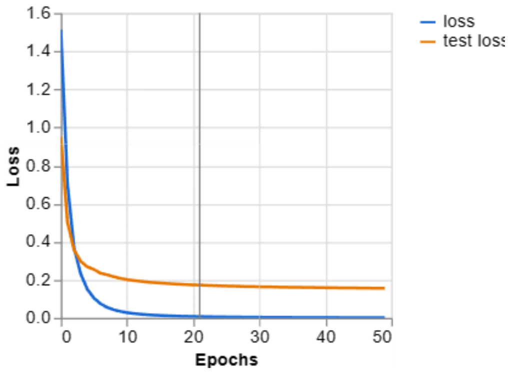

Fig. 6: Loss per epoch of FoodSnap

4. RESULTS AND DISCUSSIONS

Fig. 7 shows a sample of FoodSnap user interface. After a user captures a photo using FoodSnap's "take a photo" function, the image is placed in a central placeholder. The application's machine learning model then identifies the food, displaying the price fetched via an API. For example, if the food is recognized as "Ayam Masak Merah," its price of RM6 is shown. Additionally, the application displays the confidence level of the machine learning model, indicating how certain it is that the captured image is correctly identified as "Ayam Masak Merah". The usability acceptance test was carried out in person, enabling the

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participants to engage in direct conversation and seek clarification on any inquiries that may have been present. The test dissemination was expedited through the utilization of Google Forms, which offered a readily available interface for participants to offer their evaluations. By employing both in-person and digital distribution methods, a thorough and intuitive strategy was established to gather significant data regarding user acceptance.

Demographic information, perceived ease of use (PEU), perceived usefulness (PU), attitude of using (ATT), and behavioural intention (BI) are the topics covered in the five sections of this questionnaire. After giving them a quick rundown of the system, respondents answered the questionnaire. This survey also considers the respondents' behavioural intentions to determine how much customers plan to use the application to find the price of food. The purpose of this survey is to help developer better understand how users perceive the price calculating process while utilising image recognition. The findings of this survey serve as the foundation for enhancing the system's benefits and shortcomings to satisfy users who utilise the programme in their day-to-day operations. Total respondent is 33 people. Six of the respondents are expert users include business owners and others are students in Universiti Teknologi MARA, Perlis.

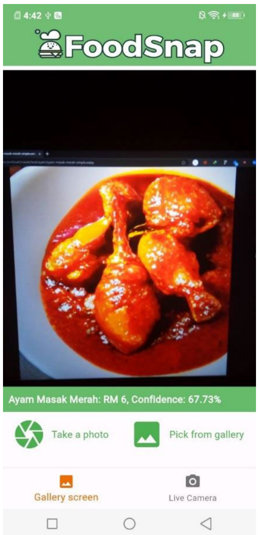

Fig. 7: FoodSnap user interface

4.1 Perceived Ease of Use (PEU)

Student feedback on the application reveals a largely positive response regarding the ease and speed with which users can understand its basic features. Most users find the application intuitive and easy to navigate, aligning with the goal of creating a user-friendly interface. Clear and helpful instructions also received praise, with students giving an average rating of 4.3 out of 5, underscoring the positive outcome. Additionally, the tips and hints provided in the application were deemed sufficient and useful, further contributing to the application's overall user-friendliness. This positive feedback suggests that the guidance features effectively help users navigate and utilize the application's functionalities, enhancing their overall experience with *FoodSnap*.

4.2 Perceived Usefulness (PU)

Most users agree that *FoodSnap* allows them to quickly locate food items and their prices via the mobile application. However, some users reported slower experiences due to internet connection issues

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during testing. With a mean score of 4.2, most users found *FoodSnap* helpful in providing quick food and price information. The mention of internet-related problems highlights the importance of addressing connectivity issues to improve the user experience. Regarding the process flow, most users felt that *FoodSnap* did not involve unnecessary steps, though one user noted some perceived inefficiencies. With a mean score of 4.2 for simplicity and effectiveness, developers may want to investigate potential improvements in the user flow based on this outlier feedback. In summary, while users generally view *FoodSnap* as useful, there are opportunities to enhance the application by addressing connectivity challenges and refining the process flow to ensure an even smoother experience.

4.3 Attitude of Using (ATT)

The results gathered shows students' *Attitude of Using (ATT)* assessments, indicate a generally positive attitude towards *FoodSnap's* use of picture recognition for price calculation. The overall mean score of 4.3 reflects a substantial level of acceptance, despite some students being ambivalent. This suggests that most users see picture recognition for price calculation as a smart and innovative solution that aligns with their expectations. Regarding recommending the feature, most students agreed, with a high mean score of 4.6. This indicates that students not only appreciate the feature but are likely to recommend it to others. Only a small portion of users remained indifferent. In terms of belief in the concept, most students held a positive view, with an average score of 4.5. Overall, the data shows that students generally support the use of picture recognition for pricing, viewing it as a valuable and functional feature. The consistently high mean scores and positive feedback suggest that students believe *FoodSnap's* picture recognition for price calculation is a beneficial and recommendable feature, contributing to its potential success and broader adoption.

4.4 Behavioural Intention (BI)

Most users find the navigation of the application's features and sections simple, indicating a user-friendly design that enhances the overall experience. When asked about the simplicity and minimalism of the interface, most students agreed, with an average score of 4.4. This suggests that users generally appreciate the clean, clutter-free interface. Simplified and intuitive designs are often associated with improved user experiences. In terms of user-friendliness and ease of use, the application received a mean score of 4.5, showing a positive assessment of its simplified features and straightforward functionality, despite some ambivalence. This suggests that the application has effectively made its operations clear and accessible to typical users. Overall, positive feedback from users indicates a strong intention to continue using the application. It is clear, concise features and simple interface contribute to a favourable impression, which enhances both usability and the likelihood of ongoing use.

5. CONCLUSION AND RECOMMENDATIONS

Users of the FoodSnap application have made recommendations to enhance its functionality. Firstly, expand food options, which they suggest broadening the variety of food items in the application to better reflect the diversity of food available in the market. This update would cater to various dietary preferences and cultural choices, improving the user experience. Secondly, add offline functionality, this to address potential connectivity issues, especially for users with slow internet, experts recommend enabling offline use. This feature would allow the application to function smoothly without internet access, ensuring inclusivity for users in different regions and network conditions. It is also recommended to implement an admin dashboard; there is a need for an admin dashboard, allowing business owners to easily update prices and manage products. This feature would streamline backend operations and offer a user-friendly interface for businesses to stay up to date with market changes. Lastly, there are many ways to improve the results, such as feature image extraction. For example, to differentiate 'ayam masak merah' and 'ayam goreng', one

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could simply use the color 'red' to distinguish between these two menu items. Perhaps it will be used in future enhancement of this research.

For future works, the mobile application can be improved by focusing on a few important areas that will increase both its usability and functionality. Enhancement of the dataset need to be employed for machine learning. Future iterations will give priority to broadening the image dataset and adding more variety to the food classifications. The purpose of this augmentation is to improve the picture recognition model's accuracy to provide more thorough and accurate identification of a wider variety of food items.

6. ACKNOWLEDGEMENTS/FUNDING

A special appreciation also goes to all participants who involve in this study at the entire phases.

7. CONFLICT OF INTEREST STATEMENT

The authors agree that this research was conducted in the absence of any self-benefits, commercial or financial conflicts and declare the absence of conflicting interests with the funders.

8. AUTHORS' CONTRIBUTIONS

Muhammad Haziq Azizan: System design, development and conduct testing; **Romiza Md Nor**: Analysis of testing, supervision, paper review and editing.

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