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Deep Learning-based Algorithms for Malaysian Food Image Recognition and Calories Estimation

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Abstract — **Diabetes is a prevalent health concern among Malaysian adults, with dietary intake monitoring playing a crucial role in managing the disease. Existing dietary tracking approaches often overlook the diversity of Malaysian cuisine and therefore suffer from low accuracy in recognizing and estimating portion sizes for local dishes. To address these limitations, this study employs deep learning techniques for food recognition to develop an effective calorie estimation system tailored to Malaysian food culture. The study focuses on the investigation of three distinct models which are MobileNetV2, VGG19, and ResNet-50 in accurately identifying and classifying Malaysian food items from images. At present, there is lack of food dataset images for Malaysian cuisine, which presents a significant challenge to calorie counter or food logging app developers. Thus, 20 classes of Malaysian cuisine were generated with a total of 2,076 images used in the models. We then compared the performance of the three models using accuracy, precision, recall and F1-score metrics. The MobileNetV2 model shows a promising result with an accuracy of 97.83% compared to VGG19 with 71.05% accuracy. Meanwhile ResNet-50 achieved the lowest accuracy of 18.11%. Additionally, we evaluated the performance of MobileNetV2 on larger and more diverse cuisines to measure its scalability.**

Keywords — Image Recognition, Calorie Estimation, Malaysian Cuisine, MobileNetV2, VGG19, ResNet-50, Scalability.

I. INTRODUCTION

As of 2019, 18.3% of adults in Malaysia suffer from diabetes [1]. The escalating prevalence of diabetes in Malaysia underscores the pressing need for proactive and innovative approaches to address this public health concern. Inadequate control of diabetes mellitus can lead to complications affecting multiple bodily systems, particularly the eyes, kidneys, nerves, and cardiovascular system.

There are three main types of diabetes mellitus, type 1 diabetes (T1D), type 2 diabetes (T2D) and gestational diabetes (diabetes while pregnant) [2]. It is known that appropriate and consistent self-management is key to long-term health maintenance and complication reduction in diabetes mellitus regardless of the type of diabetes [3]. Nonetheless, existing self-monitoring methods necessitate individuals to document all their food intake, a task that can prove burdensome and unsustainable, potentially hindering the adoption of dietary behavior changes [4].

Malaysian cuisine reflects the country's rich multicultural heritage. The culinary landscape is diverse and complex, representing the various ethnic groups that make up the Malaysian population, including Malay, Indian, Chinese, Nyonya (Peranakan), and Eurasian communities [5]. Each of these groups has its own distinct culinary traditions, ingredients, and cooking methods.

Despite the rich culinary heritage, there is currently lack of publicly available comprehensive database of Malaysian food images and nutritional information. This presents significant challenges for Malaysian users and visitors who wish to track their food intake using modern technological solutions. The lack of a dedicated food database limits the effectiveness of existing food recognition and calorie estimation applications, which are often tailored to Western cuisines or general Asian foods.

Most existing food image datasets focus on specific regional cuisines. For instance, Vireo-Food 172 [6] and ChineseFoodNet [7] include images of Chinese dishes, whereas Food-50 [8], UECFOOD-100 [9], and UECFOOD-256 [10] mainly showcase Japanese foods [11]. Similarly, other datasets like TurkishFoods-15 [12], the Pakistani Food Dataset [13], and THFOOD-50 [14] are restricted to their respective national cuisines. However, there is no dataset with sufficient size of labelled food images of Malaysian cuisine publicly available. This gap underscores the need for a specialized dataset to support the development of effective food recognition and calorie estimation tools for Malaysian foods.

In this paper, we propose a method for Malaysian food image recognition and calorie estimation using deep learning and evaluate the performance of our method on our own dataset to enable Malaysian citizens and visitors to accurately record their daily food intake.

This research has contributed to the:

- Generation of a dataset of 2,076 images of twenty different Malaysian food cuisines.
- Development of deep learning model that can recognize and classify Malaysian food items from images.
- Calorie estimation based on the recognized images.

This paper is organized as follows: Section II provides the literature review on the deep learning techniques of food image recognition and calorie estimation. The methodology used to build and verify the deep learning models is described in Section III. Section IV explains the results and detailed discussion of the deep learning models. Finally, Section V concludes the paper.

II. Related Studies

Research papers have demonstrated the significant attention of deep learning in the field of food recognition. Techniques such as Convolutional Neural Networks (CNNs), Deep Convolutional Neural Networks (DCNNs), and pre-trained models which utilize the concept of transfer learning are among the prominent methods applied for food image recognition tasks [15]. The common pre-trained models used in these tasks are MobileNet, VGG, Residual Neural Network (ResNet), Inception V3 and AlexNet [11, 15, 16]. Pre-trained models are neural network models that have been previously trained on large benchmark datasets, such as ImageNet, which contains millions of labeled images across thousands of categories.

The study in [17] used improved convolutional neural network to classify food images. ChineseFoodNet [7] was used as the dataset which consists of 180,000 food images with 22 categories of Chinese cuisine. Four different neural networks, including VGG19, MobileNetV2, DenseNet, and a traditional CNN architecture, were compared. The results showed that MobileNetV2 with data augmentation performed the best, achieving an accuracy of 93.90%.

Based on the work in [18], a method combining transfer learning and ensemble learning was proposed for food image recognition. Initially, generic image features were extracted using four pre-trained CNN models mainly VGG19, ResNet50, MobileNet V2, and AlexNet. These models were fine-tuned on the Food-11 dataset [19] to optimize their performance for food image classification. The study reported that VGG19 achieved 92.58% accuracy, ResNet50 achieved 91.06% accuacy, MobileNetV2 achieved 86.51% accuracy, and AlexNet achieved 83.25% accuracy.

The authors of [20] explored the application of CNN and ResNet for food image recognition on six distinct food classes: Apple, Orange, Avocado, Milo, Vico, and Koko, based primarily on colour features. The datasets used in the experiments consisted of 400 images for each food class, sourced from various sources to ensure diversity and robustness in the classification systems. The results indicated that the CNN method achieved a classification accuracy of 98.67%, outperforming ResNet, which achieved an accuracy of 96.67%.

III. Proposed Work

This study proposes a solution to classify Malaysian food items, evaluate model performance, estimate calorie intake from recognized images, and assess the scalability of the trained models across various cuisines.

A. Dataset Acquisition and Processing

To build a comprehensive dataset for Malaysian food image recognition and calorie estimation, web crawling techniques were employed. The dataset comprises twenty (20) distinct food categories which was selected based upon the existing literature on most commonly consumed food by individual with diabetes in Malaysia [21, 22].

The selected classes for the dataset include *apple, banana, beef rendang, cucur udang, curry puff, fish and chips, fried chicken, fried noodles, fried rice, guava, kaya toast, kuih lapis, burger, milk, pisang goreng, teh tarik, tomato, laksa, roti canai, nasi lemak*, covering a diverse range of commonly consumed Malaysian dishes.

The dataset comprises approximately 100 images for each class, totalling 2076 images, with each image stored in respective folders labelled with the food name. All images in the dataset were standardized to a resolution of 224x224 pixels to ensure consistency and facilitate uniform processing across all samples. The food images for each class are shown in Fig. 1.

Fig. 1. Ten Distinct Cuisine Food Images.

B. Building and Verification of Deep Learning Model

MobileNetV2, VGG19 and ResNet-50 which are pretrained models were considered due to their efficiency and versatility.

The dataset used for this study is stored in a directory, and an Image Data Generator is employed for data augmentation. This generator rescales pixel values by 1/255 and applies a variety of transformations, including rotation, width and height shifts, shearing, zooming, and horizontal flipping. These augmentations enhance the robustness of the model by simulating different viewing conditions.

The data is then split into training (70%), validation (15%), and test (15%) sets. Separate data generators are created for each subset, with the training generator performing augmentation and shuffling, while the validation and test generators do not shuffle the data.

The core of the proposed method is the transfer learning models, pre-trained on the ImageNet dataset. The model is loaded without its final classification layer, and its layers are frozen to retain the learned weights and features. The pre-trained layers are frozen to preserve the learned weights and features. Atop this pre-trained base, a new classifier is constructed. This classifier includes a global average pooling layer followed by a dense layer with 256 neurons and ReLU activation. To mitigate overfitting, a dropout layer with a 50% dropout rate is incorporated. Finally, a dense layer with softmax activation is added to produce output probabilities across the 20 classes of interest.

Furthermore, to evaluate the performance of the deep learning models, confusion matrix is plotted to serve as a valuable tool for analysing the model's ability to recognize and distinguish different food categories accurately. Fig. 2 shows the confusion matrix.

	Actually Positive (1)	Actually Negative (0)
Predicted Positive (1)	True Positives (TPs)	False Positives (FPs)
Predicted Negative (0)	False Negatives (FNs)	True Negatives (TNs)

Fig. 2. Confusion Matrix [23].

In addition to the confusion matrix, several key evaluation metrics were employed to verify the performance of the models such as accuracy, precision, recall, and F1 score. These metrics provide a comprehensive assessment of the models' classification capabilities.

C. Calorie Estimation

For calorie estimation, the Nutritionix API [24] is used and integrated into the implemented deep learning models. The approaches involve leveraging the predicted class from the food image recognition model (deep learning model). Subsequently, the identified food name is passed as input to the Nutritionix API, which retrieves and displays the corresponding nutrition facts. As shown in Fig 3., when the food name “nasi lemak” was queried, the respective nutrition facts was displayed by the Nutritionix API.

```
query = {"query" : "nasi lemak"}
HEADERS = {'content-type': 'application/json',
           'x-app-id': app_id,
           'x-app-key': api_key
          }
r = requests.post(end_pt_url, headers=HEADERS, json=query)
data = json.loads(r.text)
new_string = json.dumps(data, indent = 2)
print(new_string)
```

✓ 0.9s


```
{
  "foods": [
    {
      "food_name": "nasi lemak",
      "brand_name": null,
      "serving_qty": 1.5,
      "serving_unit": "cups",
      "serving_weight_grams": 297,
      "nf_calories": 572.01,
      "nf_total_fat": 32.27,
      "nf_saturated_fat": 13.77,
      "nf_cholesterol": 125.06,
      "nf_sodium": 1227.66,
      "nf_total_carbohydrate": 52.34,
      "nf_dietary_fiber": 2.18,
      "nf_sugars": 7.07,
      "nf_protein": 20.56,
      "nf_potassium": 543.67,
      "nf_p": 302.08,
```


Fig. 3. Example of Nutritionix API.

Since publicly available data on Malaysian food nutrition facts is limited, the Nutritionix API was utilized, which maintains the world's largest verified nutrition database comprising over 600,000 foods. Fig. 4 shows the system flow.

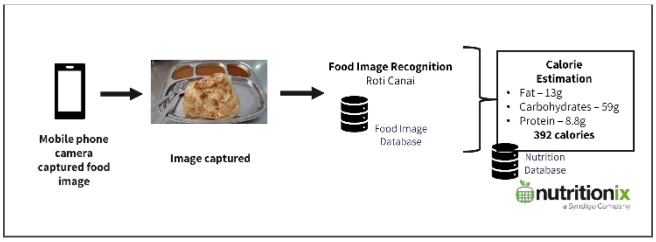


Fig. 4. Food recognition and calories estimation system flow.

D. Building and Verification of Scalability Across Diverse Cuisine

To evaluate the scalability of the trained MobileNetV2 model with different cuisines, the dataset was expanded to encompass 10 distinct classes representing a diverse range of international cuisines. This augmentation included American (caesar salad, nachos, grilled salmon, omelette), Korean (bibimbap), Japanese (ramen, miso soup), Vietnamese (pho), and Chinese (dumplings, Peking duck), sourced from the publicly available Food 101 dataset [25]. Each class contain 100 images, result in a total of 1000 images. Fig. 5 shows the 10 distinct cuisine classes used.

Fig. 5. Ten Distinct Cuisine Food Images.

To achieve scalability across diverse cuisines, the existing trained models were loaded, and their output layers were modified for the new classes. Subsequently, the models were compiled and trained. Training accuracy, testing accuracy, and validation accuracy will serve as key performance evaluation metrics for assessing the scalability of our models across diverse cuisines.

IV. Results and Discussion

This section presents the results and discussion of the three pre-trained models for food image recognition, by evaluating the performance of three models, and calorie estimation.

A. Performance Evaluation

Three models were built using different pre-trained architectures which are MobileNetV2, VGG19, and ResNet-50.

Fig. 6 displays the confusion matrix for MobileNetV2. The confusion matrix for MobileNetV2 demonstrates a high classification accuracy across most food categories. Specifically, the model shows perfect or near-perfect classification for several food items such as "apple," "banana," and "tomato," with 100% correct predictions. There were some misclassifications observed, such as "currypuff" being confused with "fish and chips" and "beef rendang" being confused with “fried chicken.” The misclassifications between “currypuff” and “fish and chips” are due to visual similarities.

Both dishes often have a golden-brown, crispy exterior. The battered coating of fish and chips might resemble the flaky pastry of a "currypuff." This confusion could arise from visual similarities in and colour. Both dishes often have a brown exterior.

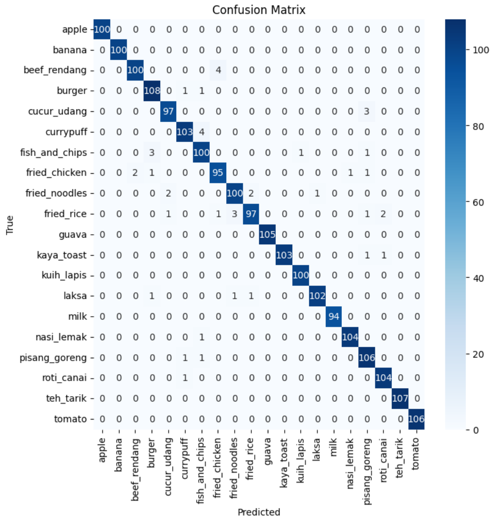


Fig. 6. Confusion Matrix of MobileNetV2.

On the other hand, Fig. 7 demonstrates the confusion matrix of VGG19. The VGG19 model performs well in certain classes like fruits (guava, apple, banana, tomato). This suggests the model has effectively learned to identify distinctive features of these fruits. However, the model shows significant confusion in several categories. Notably, burger (49/110) and "fish and chips" (43/100) have lower accuracy rates, with frequent misclassifications between each other and with other dishes like "beef rendang" and "cucur udang". This suggests difficulty in distinguishing between certain meat-based or fried dishes. "Pisang goreng" presents a particular challenge, with only 27/108 correct classifications and frequent confusion with "currypuff" and "fish and chips." This indicates a struggle in recognizing the specific characteristics of this local fried snack.

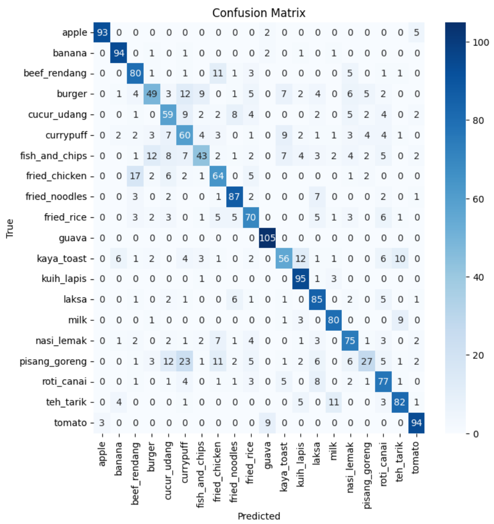


Fig. 7. Confusion Matrix of VGG19.

Fig. 8 illustrates the confusion matrix of ResNet-50. ResNet-50 model shows the weakest performance among the three. Despite its depth, it struggles with many categories, including some that are typically easy to classify like apples and bananas. It exhibits significant confusion between various dishes, even those with distinct characteristics. Local Malaysian dishes like "nasi lemak", "roti canai", and "pisang goreng" show moderate performance but are often misclassified among each other or with visually similar dishes. The possible reason causing the misclassifications includes the model's ability to capture fine-grained distinctions.

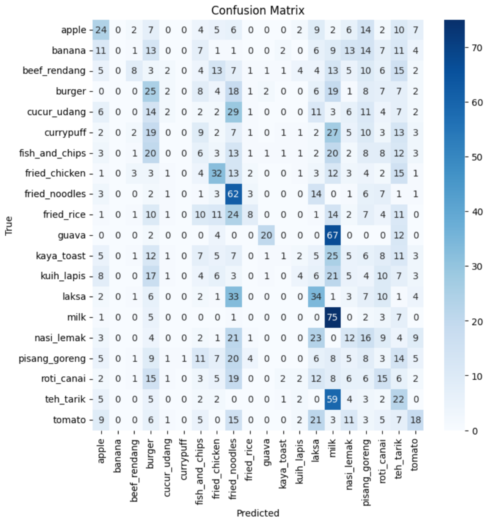


Fig. 8. Confusion Mtarix of ResNet-50.

B. *Accuracy, Precision, Recall and F1 Score*

By using confusion matrix from Fig. 6, Fig. 7 and Fig. 8, the accuracy, precision, recall and F1 score are calculated and tabulated in Table I for all three models.

TABLE I. ACCURACY, PRECISION, RECALL AND F1 SCORE OF DEEP LEARNING MODELS

Model	Accuracy	Precision	Recall	F1 Score
MobileNetV2	97.83%	97.85 %	97.83%	97.83%
VGG19	71.05%	70.65%	71.05%	70.02%
ResNet-50	18.11%	19.76%	18.11%	14.90%

Based on the accuracy, precision, recall and F1 score reported, MobileNetV2 achieved the highest accuracy of 97.83%, followed closely by VGG19 with 71.05% and ResNet-50 with 18.11%. This metric indicates the overall correctness of the models in predicting the correct food classes.

MobileNetV2 also demonstrated the highest precision at 97.85% indicating its superior ability to correctly identify positive samples with minimal false positives. In contrast, VGG19 had a precision of 70.65%, which, while decent, reflects its relatively higher rate of false positives compared to MobileNetV2. ResNet-50 lagged significantly with a precision of 19.76%.

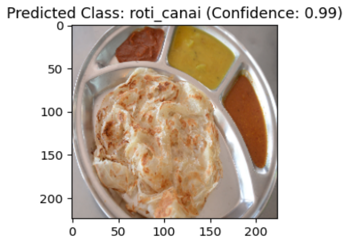
In terms of recall, which measures the model's ability to capture all relevant instances, MobileNetV2 again performed best at 97.83%. VGG19 followed with a recall of 71.05%, showing its moderate effectiveness in identifying true positive cases. ResNet-50's recall was only 18.11%, highlighting its struggles in identifying true positives.

Finally, the F1 score, which balances precision and recall, further underscores MobileNetV2's superiority with a score of 97.83%. VGG19 achieved an F1 score of 70.02%, indicating a balance between its precision and recall despite not excelling in either. ResNet-50 had the lowest F1 score at 14.90%, reinforcing its overall poor performance in this task.

Overall, these results indicate that MobileNetV2 is the most effective model for Malaysian food image classification, with VGG19 performing moderately well and ResNet-50 showing significant deficiencies. Therefore, MobileNetV2 is chosen to be used in our work.

C. Calorie Estimation

A testing was conducted on calorie estimation using the example of "roti canai". An image of "roti canai" was inputted into the system, and the food image recognition model successfully classified it as "roti canai". Following this, the name "roti canai" was sent to the Nutritionix API. The API returned detailed nutritional information, including calorie content, which was then displayed to the user. Fig. 9 shows the result.




```
{
  "foods": [
    {
      "food_name": "roti canai",
      "brand_name": null,
      "serving_qty": 1,
      "serving_unit": "Piece",
      "serving_weight_grams": 135.42,
      "nf_calories": 391.8,
      "nf_total_fat": 12.92,
      "nf_saturated_fat": 7.65,
      "nf_cholesterol": 54.09,
      "nf_sodium": 395.75,
      "nf_total_carbohydrate": 59.05,
      "nf_dietary_fiber": 2.03,
      "nf_sugars": 1.8,
      "nf_protein": 8.79,
      "nf_potassium": 98.66,
      "nf_p": 100.67,
```


Fig. 9. Nutrition Fact of Roti Canai.

The Nutritionix API displayed a calorie content of 391.8 calories for "roti canai", based on a serving size of 135g. This value was compared against the calorie content obtained from the Malaysian Food Composition Database (MyFCD) [26], which reported a lower value of 301 calories for a 95g serving size. To standardize the comparison, the calorie content from Nutritionix was recalculated for a 95g serving size, resulting in an adjusted value of approximately 275.71 calories. This recalculation shows a difference of approximately 41.15 calories less than the MyFCD value. The correctness of the calorie information provided by the Nutritionix API was benchmarked against local databases like MyFCD. Although Nutritionix is a reputable source, slight variations in calorie content, as observed with "roti canai", underscore the importance of database localization.

D. Scalability Across Diverse Cuisines

The performance of the new MobileNetV2 model is further evaluated on a dataset with variety cuisines to investigate its scalability ability 10 different cuisine classes. The new MobileNetV2 model was then evaluated based on training accuracy, testing accuracy, and validation accuracy. The accuracy scores achieved are tabulated in Table II.

TABLE II. ACCURACY SCORES

Training Accuracy	Validation Accuracy	Test Accuracy
57.51%	49.02 %	65.34%

These results demonstrate the model's ability to generalize beyond the initial Malaysian cuisine dataset, though with varying degrees of success. The training accuracy of 57.51% indicates that the model was able to learn the new classes to some extent during the training phase. However, the lower validation accuracy of 49.02% suggests that the model struggled with overfitting, indicating a need for further fine-tuning and potential augmentation of the training data to better capture the variability in the new classes.

The test accuracy of 65.34% is encouraging as it reflects the model's capability to perform reasonably well on unseen data from diverse cuisines. This performance indicates that the MobileNetV2 model, with its modified output layer, retains a level of robustness when exposed to different culinary categories not present in the initial training set.

V. CONCLUSION AND FUTURE WORK

In conclusion, this paper has focused on developing and evaluating three distinct deep learning models which are MobileNetV2, VGG19 and ResNet-50 for the accurate identification and classification of Malaysian food items from images. The study involved curating a dataset comprising 20 classes of popular Malaysian dishes, totaling 2076 images. The achievement of 97.83% accuracy by the MobileNetV2 model underscores its robust performance in recognizing and classifying Malaysian food items from images. Furthermore, the scalability assessment of the MobileNetV2 model across diverse cuisines further validates its potential applicability beyond Malaysian dishes, offering promising implications for enhancing dietary monitoring tools and health management applications. In future, we aim to enhance the dataset by expanding the number of classes and increasing the diversity of images to further improve the models' robustness and accuracy in recognizing a wider range of Malaysian dishes.

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