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Comparison of CNN-based Algorithms for Halal Logo Recognition

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Abstract. The market for halal products has been continuously growing from day to day. Along with this, the demand for halal product verification has grown. As a certification symbol, a unique halal logo can be presented on the products, and the logos are uniquely designed by each halal certification body. However, there are instances where an irresponsible party creates a fake halal logo and displays it on their product, deceiving Muslim consumers. In Malaysia, the Department of Islamic Development (JAKIM) has introduced a standard halal logo for locally manufactured products. It currently recognizes other halal logos from foreign certification bodies around the world for products imported into Malaysia. Our work proposes the use of deep learning methods to identify the various halal logos from different countries. Existing methods and algorithms are used to identify and recognize halal logos. Three deep learning methods, notably YOLOv5, Back Propagation Neural Network and MobileNetV2-SSD are compared, and it is shown that the Back Propagation Neural Network outperforms the other two methods with F1-score of 0.949. This method is then implemented on a mobile application that can be used to capture a halal logo from a product followed by recognizing the logo and its country of origin.

Keywords: logo recognition, Halal logo, backpropagation neural network, yolov5, SSD, deep learning

1. Introduction

The escalating growth of the global halal industries in these past and upcoming years, specifically in Malaysia, has raised the awareness of the authenticity of the halal products in the market. Muslim consumers are very concerned about the halal status of a product as there are many cases of fraudulent halal products fabricating the halal logos. In the latest case on the smuggling of frozen meat from abroad repackaged with fake halal logos (*Fake Halal Logo: Authorities to Meet on Monday*, n.d.) and one of the 15 most prominent cases in 2014, there were syndicates involved in selling fake halal logos to small and medium enterprises (SMEs) without approval from JAKIM (*Fake Halal Cert Syndicate Found | The Star*, n.d.). This manipulation issue affects the reliability of the halal logo itself, especially of the food products. According to (Maison et al., 2018), purchasing decision for the Muslim consumer is heavily affected by the halal logo or label. It will lead to the loss of confidence in the halal certified logo itself. Overcoming the issue, there have been several technologies developed and have been summarized by (Razak et al., 2019). There have been only a few studies relating to the detection and recognition of halal logos in recent years. Many of the studies in halal status verification focus more on the RFID and QR code implementation rather than verifying the halal logo itself in mobile applications. However, in terms of practicality for both local and foreign halal products, the halal logo is still the best way to identify the product's halal status.

Besides, the studies on the halal logo are also focusing more on the local Malaysia halal logo and not much on the imported halal products. These imported halal products would have various halal logos printed on them, depending on the issuer. It will be difficult for most consumers to keep track of all the different halal logos acknowledged by JAKIM. In addition to that, the limitation on collecting the database of halal logo images on actual products in the market is one of the challenges to be addressed in this paper.

For this paper, we plan to discover the proof-of-concept on the halal logo detection and recognition for both local and imported products available in the Malaysian market, helping the consumers to distinguish the approved products from JAKIM by detecting the unique JAKIM approved halal logos from each country attached to the products.

2. Literature Review

In multiple attempts to assist the consumer in recognizing Halal products specifically in Malaysia, there had been several technologies introduced.

2.1. Past technologies

The technologies have been summarized by (Razak et al., 2019), having several mobile-based technologies and web-based technologies. For web-based technology, all of them will ask the user for input of keyword, asking the details of the product such as the product name and the ingredients. MYeHalal (*Sistem Pensijilan Halal Malaysia (MYeHALAL)*, n.d.) is one of the web-based applications that is still active until now. Meanwhile, mobile-based technologies have employed several different technologies, from SMS to Multimedia Messaging Service (MMS), keyword searching as the web-based application, bar code scanning, QR code scanning and RFID. However, to our knowledge, currently, there are no active mobile applications for recognizing halal products based on the halal logo on the packaging.

2.2. Logo detection

Various methods have been applied to identify real logos to help consumers recognize authentic logos. The most common methods include image acquisition, image pre-processing and detection followed by logo recognition.

2.2.1. Image acquisition

Before performing any other stages in the object identification system, image acquisition is the first crucial step to be done. Image data is collected in various ways in this phase. For halal logos, most of the papers acquire the images from the internet (Mohd et al., 2008)(Saipullah et al., 2012)(Razali et al., 2015), only (Kassim et al., 2020) using digital cameras in capturing the halal logo images and (Razak et al., 2019) use mobile phone in capturing the images from food packages (Figure 1). Different angles and light conditions are taken into consideration in (Razak et al., 2019) paper to vary the visual appearance of the logos and train the model better, which results in higher recognition accuracy. The images are then organized into folders based on the logo origin.

2.2.2. Image pre-processing

Collected pictures are then pre-processed as all the images have distinct sizes and conditions. This step is crucial as it helps to improve the performance of the processes later. Contrast enhancement, noise reduction, image restoration, and image compression are some of the ways of improving image quality (Razak et al., 2019). Resizing the pictures is also a necessary step to go through to get a better consistency. Then, images need to be converted into grayscale (Kassim et al., 2020).

Fig. 1: Logos collected by (Razak et al., 2019).

2.3. Deep learning methods

There are only a handful of papers about detecting halal logos and most of them are modelled based on the neural network (Kassim et al., 2020). Only one of them used Fractionalized Principle Magnitude (FPM) (Saipullah et al., 2012). Accordingly, the use of deep learning to recognize or identify the halal logo on product packaging has not been thoroughly investigated yet.

Nevertheless, the scope can be broadened to logo detection and object detection, where more works involving deep learning can be found. We intend to focus on these three deep learning methods; Back Propagation Neural Network (Kassim et al., 2020), YOLOv5 (Kim et al., 2020)(Benjumea et al., 2021) and Single Shot MultiBox Detector (Bombonato et al., 2017).

2.3.1 Back propagation neural network

The back propagation algorithm is the most frequent algorithm to be used in detecting and recognizing halal logos. Out of four papers mentioned in 2.3, three of them used the method. Its popularity is due to its efficiency in computing one layer at a time and ease of implementation compared YOLOv5 and SSD.

This network computes the gradient but does not define how the gradient is used. It generalizes computation in delta rule and fine tuning of the weight and biases of network will be done during the training to get the best results (*How to Build Your Own Neural Network from Scratch in Python | by James Loy | Towards Data Science*, n.d.). (Kassim et al., 2020) used the network in classifying and recognizing the halal logos. These works implement the neural network in MATLAB using the neural network tool. In [4], the default setting was used and produced the best result.

2.3.2 You only look once (YOLOv5)

YOLO has been dominating the object detection field for a long time and in May 2020, there has been significant breakthrough with two updated versions of YOLOv4 and YOLOv5. YOLOv4 was developed by the conventional authors Joseph Redmon and Alexey Bochkovskiy (Bochkovskiy et al., 2020), the other being the freshly released YOLOv5 by Glenn Jocher (Jocher et al., 2022). The v5 model has shown a substantial performance increase from its predecessors.

The YOLOv5 network consists of three main parts; Backbone with CNN layer aggregate image features at different scales; Neck with set of layers to combine image features and pass them forward to prediction; and Head that takes features from the neck and performs localization and classification.

2.3.3 Single shot multibox detector

SSD is a method based on a feed-forward CNN that uses a set of fixed-size of bounding boxes to generate scores for the presence of object class instances. The final detections are produced through a non-maximum suppression step. It is essentially detecting multiple objects in an image in a single shot. However, being implemented in application it is equally heavily dependent on both speed and accuracy. SSD is designed in such a way it could be integrated with various networks and MobileNet architecture is one of them.

Improving the speed of SSD, MobileNet was integrated with SSD. It is a model that can cater to a decent speed. As of today, there have been two versions of MobileNet, with the first version lowered the model size and complexity cost of the network to a decent level by having a depthwise separable convolution. The upgraded version, MobileNetV2 has an inverted residual structure that provides much better modularity that can help in the removal of non-linearities in narrow layers (Kim et al., 2020).

Integration of MobileNetV2 and SSD provided superior performances in improving the accuracy while maintaining the model’s speed (Bombonato et al., 2017). It was termed MobileNet-SSD and MobileNetV2-SSD has been used in the paper to analyse the performance. The integrated architecture can be seen in Figure 2.

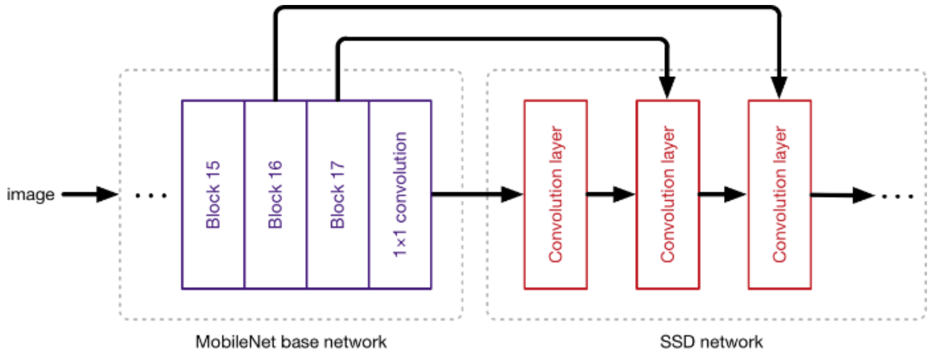

Fig. 2: Mobile default structure from (Benjumea et al., 2021).

2.4. Proposed work

There are two significant gaps identified after doing the literature review; the lack of presence of halal logo recognizer in application and problems with recognizing images acquired in real time from digital camera and mobile phone. This is important as the halal logo is the easiest and conducive way for the consumer identify whether the product is halal or not. Other than that, based on the past papers there were not much work in recognizing the halal logo and most of the works acquire the image from online resources and not directly via digital camera and mobile phone.

On top of that, based on (Kassim et al., 2020), they failed to detect logos that were acquired via digital camera and can only detect images via online resources. Only (Razak et al., 2019) managed to detect the images that were acquired beforehand via mobile phone, and not in real-time processing. However, there is no mobile application built from the work.

Hence, this paper intends to fill these two big gaps by comparing three different deep learning algorithm, Back Propagation Neural Network, YOLOv5 and MobileNetV2-SSD to detect the halal logo. Accordingly, we develop a mobile application that is capable of capturing and recognizing the halal logo in real time. Ultimately, we intend to make our dataset public in the end, given there is now no publicly available dataset of halal logos.

3. Methodology

3.1. Dataset

The dataset used is built from 600 images of halal logos on the product packaging in the Malaysian's market. The images were acquired via mobile phone from two different angles, 45 and 90 degrees and in two different light conditions under normal lighting and better luminance condition under ring light. The method of capturing the images is improved from (Razak et al., 2019) where the dataset used in the paper were taken from different angles and light conditions but without consideration of specific angles and luminance as seen in Figure 3.

Fig. 3: Logos captured via mobile phone under different luminance and angle conditions.

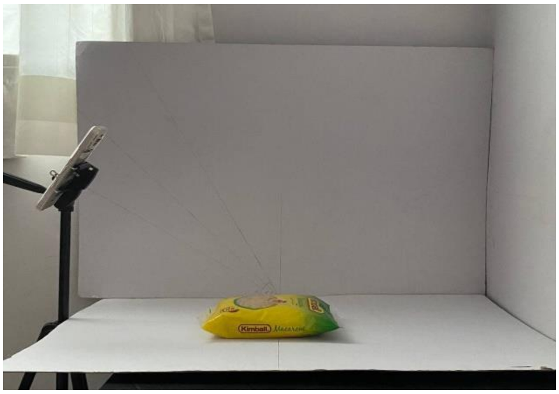

Fig. 4: One of the experimental setups of taking the images from a 45 ° angle setup under normal lighting conditions without a ring light.

After the acquisition, as all the models that will be used are deep learning-based algorithms, a bigger data set needed to be produced especially for the training. Then the images were renamed and put in folders based on the origin countries. Augmentation is then done with different zoom range, width and height shift range, and the brightness. The number of images increases from 600 to 1292 images, with 50 different classes of 31 different countries that differ from (Razak et al., 2019) with only 10 classes. This dataset is available to download at halal logo dataset[1].

[1] https://github.com/IzzatiZulkeefli/halal-logo-detection-recognition

Table 1: Classes dataset according to countries.

Country	Type of Logo
Austria	1
Australia	2
Bosnia	1
Bangladesh	1
Belgium	1
Brazil	1
Canada	1
China	5
Germany	1
Spain	1
France	1
Indonesia	1
India	3
Iran	1
Italy	2
Japan	4
Korea	1
Sri Lanka	1
Morocco	1
Malaysia	1
Netherlands	3
New Zealand	1
Philippines	1
Pakistan	1
Singapore	1
Thailand	1
Turkey	2
Taiwan	1
United Kingdom	2
United States	2
Vietnam	2
South Africa	2
Total	50

Annotation of images for the dataset is then done as part of YOLOv5 and SSD requirement for training using labelImg (*LabelImg Graphical Image Annotation Tool and Label Object Bounding Boxes in Images*, n.d.) with PASCAL VOC format. Roboflow is then used to convert the annotation format according to YOLOv5 with COCO, and SSD with tfRecord format. These annotations contain the locations of the bounding boxes. The images are then split into training, validation, and test sets.

3.2. Training

The models were trained using a Google Cloud platform instance on Nvidia Tesla T4 GPU having 12GB of RAM. The Back Propagation Neural Network used three convolutional layers followed by max-pooling layers, with a dropout layer added after that to avoid overfitting. Adam optimizer and SparseCategoricalCross entropy were used as the optimizer and the loss function with learning rate of 0.000001 for smoother curve. Softmax action function used in the last dense layer. The settings for Back Propagation Neural Network were based on (Razak et al., 2019) and further improvised with few more experiments. Both YOLOv5 and SSD were trained with batch size of 12 and 930 images set to train, 337 for validation, and 25 for testing. The YOLOv5 model was trained with 50 epochs with pretrained weight of yolo5l. Meanwhile, the SSD was trained for 30,000 steps. Thorough experiments on these settings have been done on YOLOv5 model and SSD to get the performance.

4. Results

All three models were then compared after the completion of training process. The performance of the models was evaluated with precision, recall and F1-score. When working with class-imbalanced data sets, it is believed that the F1-score is the best evaluation to be used. The fittest model was then implemented in the mobile application.

Table 2: Performance analysis of three models.

Model	Back Propagation Neural Network	YOLOv5	MobileNetV2 -SSD
Precision	0.960	0.927	0.830
Recall	0.940	0.963	0.870
F1-Score	0.949	0.945	0.850
Processing time (hours)	1.5	3.5	5.3

Comparing the best experiment from each model based on Table 2, Back Propagation Neural Network performed the best with F1 score of 0.949 compared to the other two models YOLOv5.3 and SSD.6 with F1 score of 0.945 and 0.85, which reflects the balance average of recall and precision values, implying that it delivers great value for both. There is only slight difference between YOLOv5 and Back Propagation Neural Network, and the performance is believed to be better if a YOLOv5 model is trained with bigger epoch and batch size.

For recall, it illustrates the model sensitivity, which is used to quantify the number of positive class predictions made from all the positive classes in the dataset. Meanwhile, precision shows the model's capacity to quantify the number of positive class predictions that are genuinely positive class predictions. We can see, YOLOv5 has highest recall, 0.963 compared to the other two but only with slight difference of 0.023. However, Back Propagation Neural Network scores the highest precision with the difference of 0.031 compared to YOLOv5. Back Propagation Neural Network also has the shortest processing time of 1.5 hours comparing to the other models that can take up to 3.5 and 5.3 hours.

From these evaluations, we can see the best model to be implement in the mobile application is the Back Propagation Neural Network as it has the highest F1-score, precision and just slight difference in recall with the shortest processing time. ease acknowledge collaborators or anyone who has helped with the paper at the end of the text.

4.1. Mobile application

The main page of the application can be seen as Figure 4.1. The camera page will be the place where user snaps a picture of the logo and the origin country and confidence of the halal logo will be shown (Figure 4.2). The Back Propagation Neural Network algorithm is implemented in this page. Meanwhile, in the Halal Logo Information page, all the halal logos certified by JAKIM are listed there with the details.

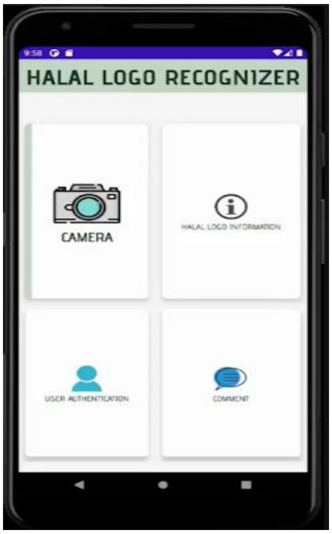

Fig. 5: Main page consists of four features, camera, information, comment and user authentication.

Fig. 6: Camera page.

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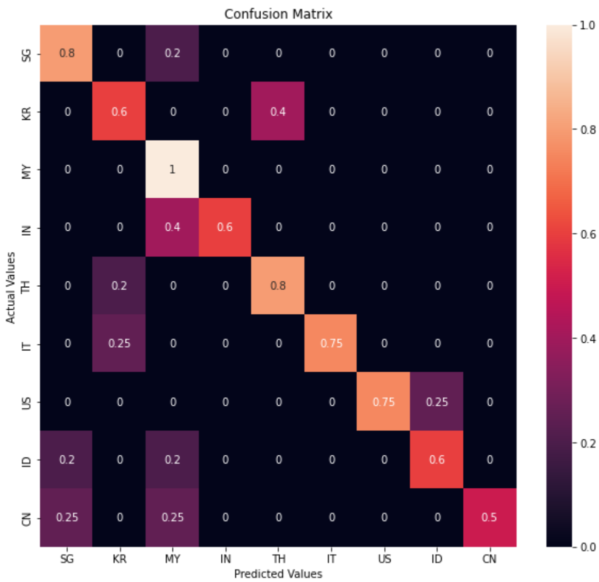

Fig. 7: Confusion matrix for testing on real-time capturing and recognizing halal logos on mobile phone.

42 halal product's logos from 9 different countries were captured and recognized real-time with the developed mobile application. These images are made sure that they are not the same as the training images used for training. The results were then plotted into confusion matrix, which analyze the accuracy and the error rate of the network. From the confusion matrix, we can see there's a few classes that had more

accuracy compared to the others, like Malaysia (MY), Singapore (SG) and Thailand (TH). The precision, recall and F1-score for testing are lower compared to the training with precision of 80%, recall of 71% and F1-score of 72%. The results were lower compared to training as there are many factors to be considered when it is used in real-time mobile application, such as the luminance, reflectiveness and the angles of the product taken.

5. Conclusion

There are a numbers of halal technologies available to facilitate consumers in Malaysia to authenticate the halal products. Nevertheless, previous works were more focused on the JAKIM's Halal Logo and only one work give attention to the JAKIM's certified foreign international bodies' logo, which only explore 10 different classes with only one model, which is neural network (Razak et al., 2019). Thus, we intend to fill the gap. The paper explored into more deep learning methods to detect and recognize the different halal logos, with YOLOv5 and SSD on top of the Back Propagation Neural Network. We also proposed a new dataset, with more number of countries available in the dataset and more systematic image acquisition, fixed angle and lighting conditions.

A mobile application has also been developed to allow a real-time recognition process, which has not been done previously, with Back Propagation Neural Network algorithm implemented in it. Results and the application can enable the consumers to get prompt results and increase their confidence in purchases including imported products. In future, the work can be extended to include all 84 Islamic bodies authorized by JAKIM, explore more into the YOLOv5 as the result is just a slight difference and improve the accuracy and detection of the mobile application.

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