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Vision Based System for Banknote Recognition Using Different Machine Learning and Deep Learning Approach

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***Abstract*—Visually impaired people faced a problem in identifying and recognizing the different types of banknote due to some reasons. This problem draws researchers' attention to introduce an automated banknote recognition system that can be divided into a vision-based system and sensor-based system. The main aim of this study is to have deeper analysis on the effect of region and orientation on the performance of Machine Learning and Deep Learning respectively using Malaysian Ringgit banknotes (RM 1, RM 5, RM 10, RM 20, RM 50 and RM 100). In this project, two experiments conducted on two types of banknote image: different region and orientation captured by using handphone camera in a controlled environment. Feature extraction of the RGB values called RB, RG, and GB from banknote image with different region were used to the machine learning classification algorithms such as k-Nearest Neighbors (kNN) and Decision Tree Classifier (DTC), Support Vector Machine (SVM) and Bayesian Classifier (BC) for recognizing each class of banknote. Banknote image with different orientation was directly feed to AlexNet, a pre-trained model of Convolutional Neural Network (CNN), the most popular image processing structure of Deep Learning Neural Network. Ten-fold cross-validation was used to select the optimized kNN, DTC, SVM, and BC which was based on the smallest cross-validation loss. After that, the performance of kNN, DTC, SVM, BC and AlexNet model was presented in a confusion matrix. Both kNN and DTC achieved 99.7% accuracy but both SVM and BC perform better by succeeded to achieve 100% accuracy. It also can be concluded that AlexNet can only perform great in testing new data if only the data had previously been trained with similar orientation. Orientation does give effect to the performance of AlexNet model.**

***Keywords*—Banknote Recognition, Region, Orientation, Machine Learning, AlexNet**

I. INTRODUCTION

Banknote identification is a relatively easy job for the human with normal eyes as the brain is capable of absorbing different information and recognizing them with less effort. But for visually impaired people, banknote identification has become one of the difficult things to be face mostly because of the characteristic of the banknote itself. Until now, the very little different in size of banknote and an easily fade away tactile mark on the surface of banknote continuously give suffer to visual impaired people to detect and classify banknote properly [1].

In general, detection of banknotes images can be either using sensor (sensor based) or camera (vision based). Although approach using sensor-based is interesting, it suffers from less accuracy than vision-based. The main shortfall of sensor-based system is the involvement of several electrical components and limitation of the sensor. The aim of this study is to evaluate the feasibility of machine learning and deep learning approaches in recognizing the Malaysian banknote. In more technical view, this study is divided into two stages which are: 1) the analysis on the effect of different region of Malaysian Ringgit banknote on conventional machine learning approaches and 2) the effect of different banknote orientation on deep learning approaches.

In broader view, this finding gives big contribution to the new development of assistive technologies for visually impaired people especially in Malaysia to completing their daily tasks and routine including groceries activities.

II. RELATED WORKS

Recent years, different works have been done on producing an automated banknotes recognition device which itself is a painstaking and complicated work involving a variety of methods for data collection, feature selection and classification model. In general, there are two main approaches for banknote data collection: one is by using sensor and some electrical component (sensor-based system) and the other is using camera (vision-based system).

The work in [2] developed on a method for banknote image collection system using TMS320C6416DSK as DSP, a processing platform of banknote image collection. The DSP platform include image sensor SV253A4, analog electronic switch MAX4624, sensor processor XRD98L23, cache driver SN74HC244. In [3], the researchers use a color sensor to detect colors of Malaysian banknote then being processed by a microcontroller to identify and send a programmed sound pattern to a buzzer as indication. The banknote collection method in [4] capture banknote images using one dimensional visible light sensor.

Several scholars have proposed numerous vision-based banknote recognition system. The work in [5] implement a computer vision system capable of reliably recognize banknotes using a camera. The work in [1] captured the Hungarian notes by using a cell phone camera. The existing studies based on sensor-based system suffers from less accuracy because involvement of many electrical components and the limitation with the sensor [11]. Therefore, vision-based system was chosen because it is one of the most practical and more accurate medium to take images.

The work in [6] proposed an Indian currency recognition system which by selecting the most prominent features such as central numeral representing denomination, the national emblem, identification mark and the color band. The work in [7] selected the four corners and edges of Yuan RMB banknote as the best features in the banknote recognition. The work in [8] also find edge distribution as most effective feature to be select for USD, Euro, Bangladeshi Taka and Indian Rupee banknote.

A recent review of the literature on this area found that there are few attempts to implement Deep Learning especially Convolutional Neural Network (CNN) into vision-based system. Recently, CNN have been emerging into various kind of research field for example in medical field like detection of breast cancer [9] and security and surveillance like license plate recognition [10]. However, there still little previous research conduct on banknote using deep learning. Therefore, the aim of this study is to analysis the feasibility of conventional machine learning and deep learning in recognizing the banknote.

III. METHOD

As mentioned earlier, the study was divided into two stages which are: 1) the analysis on the effect of different region on conventional machine learning approaches and 2) the effect of different banknote orientation on deep learning approaches. The databases were constructed using 6 values of Malaysian Ringgit banknotes (RM 1, RM 5, RM 10, RM 20, RM 50 and RM 100) taken by handphone camera under a controlled environment with fixed scale (focal length).

Figure 1 shows the block diagram for both stages. For the first stage experiment, the total images are 168 images consist of 48 sample images of new and old RM1 and 24 sample images of each other values. There are 3 databases: Database 1 and 2 consists of 168 sample images in informative region (see Figure 2) and whole region (see Figure 3) respectively and Database 3 consist of 336 sample images in combination of both regions. For second stage experiment, the total images 84 images consist of 24 sample images of new and old RM 1 and 12 sample images of each other values. There are 4 different databases for experiment in second stage. Data were divided into training and testing with ratio of 80:20. Database 4 and 5 consist of 84 sample images in horizontal (H) orientation (see Figure 4a) and vertical (V) orientation (see Figure 4b) respectively. Database 6 consist of 363 sample images in diagonal (D) orientation (see Figure 4c) and database 7 consist of 672 images in combination (C) of vertical, horizontal and diagonal orientation.

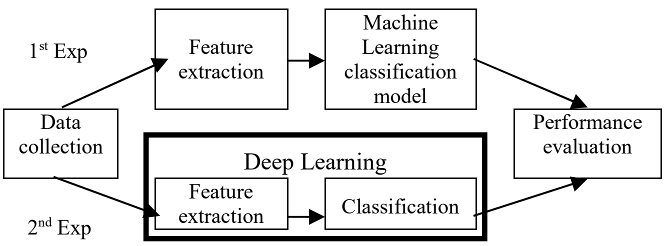

Fig.1. Block diagram.

After data collection, both experiment proceeds to the processing part that consist of feature extraction and classification process. In the first stage experiment, each of banknote being manually cropped in different region by using TrainingImageLabeler (MATLAB tool) in MATLAB version 2016a. After that, each of databases were used in extraction of colour features: red, green and blue intensity average values called as RB, RG and GB using equations (1) to (3):

$$RB = \bar{r} - \bar{b} \quad (1)$$

$$RG = \bar{r} - \bar{g} \quad (2)$$

$$GB = \bar{g} - \bar{b} \quad (3)$$

whereby $\bar{r}$ is the average intensity value for red channel, $\bar{b}$ is the average intensity values for blue channel, and $\bar{g}$ is the average intensity values for green channel of the pixels inside the cropped region. Finally, Machine Learning Classification model such as k-Nearest Neighbor (kNN), Decision Tree Classifier (DTC), Support Vector Machine (SVM) and Bayesian Classifier (BC) were used to recognize and classify the different values Malaysian Ringgit Banknote based on the RB, RG, and GB values. Cross validation was used to formulate the confusion matrix that represent the performance of each classifiers model in term of percentage of accuracy.

For the second stage experiment, each database being tested with different database using Alex.Net model. In machine learning, features were crafted by human, and a classifier will sort the images. With deep learning, the automated feature extraction and modelling steps are performed directly without human intervention. This automated feature extraction makes deep learning highly accurate for computer vision tasks especially image classification. Confusion matrix was also used to evaluate the performance of AlexNet model using the 4 type of databases.

Fig.2. Informative region

Fig.3. Whole region

(a) (b) (c)

Fig.4. Sample of RM 1 banknote in (a) Horizontal (b) Vertical and (c) Diagonal orientation.

IV. RESULTS AND DISCUSSION

For first stage experiment, both kNN and DTC achieved the same rate of 99.7% accuracy (see Figure 5). The performance of kNN was increased after the combination for both region due to the adequate data to find the optimum centroid point of each classes. For the performance of DTC, the accuracy become decreased after the combination of two region could be because the white region in whole region was considered as a noise, DTC suffered with data overlapping and causing the precise border cannot be created. Both SVM and BC succeeded to achieve the same rate of 100% accuracy (see Figure 6) for all three regions. So, SVM and BC perform better than kNN and DTC. Table I shows the summarization performance of machine learning classification model.

TABLE I. THE PERFORMANCE (ACCURACY) OF MACHINE LEARNING CLASSIFICATION MODEL

Machine Learning classification model	**Accuracy (%)**		
	Informative region	Whole region	Combination region
k Nearest Neighbor (k-NN)	99.4	99.4	99.7
Decision Tree Classifier (DTC)	100	100	99.7
Support Vector Machine (SVM)	100	100	100
Bayesian Classifier (BC)	100	100	100

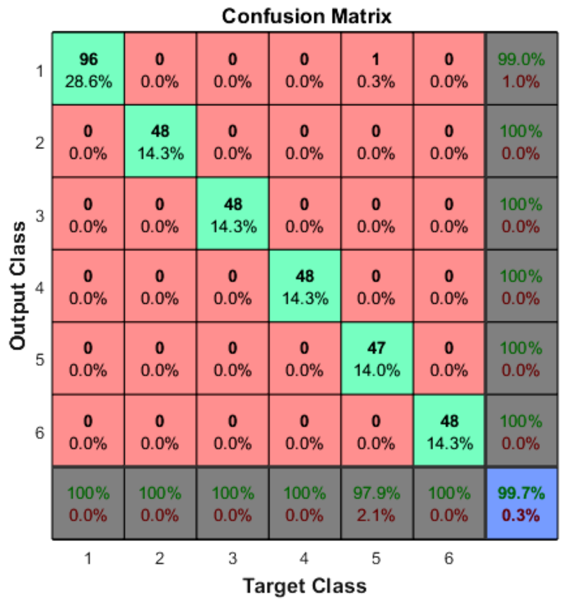

Fig.5. The confusion matrix for k-NN and DTC using the combination region

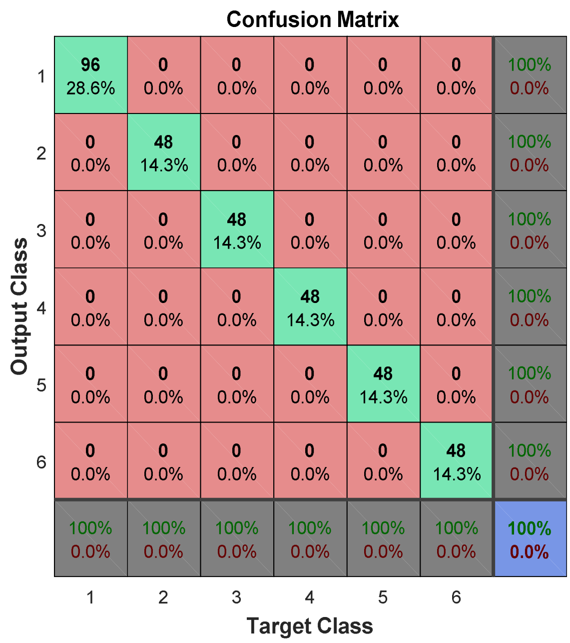

Fig.6. The confusion matrix for SVM and BC using the combination region.

For second stage experiment, it can be interpreted that the performance of horizontal and vertical database was drastically decreased after being tested with others dataset with different orientation as referred to Table II. The performance of diagonal database was slightly decreased after being tested with other database but have much better performance than horizontal and vertical database. Combination database was excellently great for all types of dataset. It can be concluded that AlexNet can only perform great in testing new data if only the data had previously been trained with similar orientation. From this experiment, orientation does give effect to the performance of pre-trained model (AlexNet) of Convolutional Neural Network (CNN).

TABLE II. THE SUMMARIZATION OF ALEXNET PERFORMANCE

Databases	**Testing Dataset**	**Accuracy (%)**
H	H	100
	V	75.0
	D	84.5
	C	86.3
V	V	100
	H	52.4
	D	64.3
	C	69.3
D	D	96.4
	H	91.7
	V	90.5
	C	94.0
C	C	100
	H	100
	V	100
	D	100

For overall, the performance of both machine learning and deep learning model in recognizing and classifying Malaysian Ringgit banknote was excellently great. It is recommended on using deep learning because deep learning no need human grafted features extraction technique. In machine learning, features were chosen manually by human, and a classifier will sort images but with deep learning, it eliminates the manual feature extraction-feature are learned directly along with the classification tasks.

V. CONCLUSION

As conclusion, a vision based automated algorithm that can recognize and classify Malaysian Ringgit banknote using machine learning and deep learning model were well developed. Both SVM and BC give better and static performance in sorting database with 3 different regions than kNN and DTC. Alex.Net unable to perform well in testing the new database with different orientation but give great 100% accuracy with database of similar orientation. From this algorithm, the visually impaired people able to improve their quality of life by reduce the dependency to other especially during groceries activities.

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