

# Image Based Ringgit Banknote Recognition for Visually Impaired

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**Abstract**—Visually impaired people face a number of difficulties in order to interact with the environment because most of the information encoded is visual. Visual impaired people faced a problem in identifying and recognizing the different currency. There are many devices available in the market but not acceptable to detect Malaysian ringgit banknote and very pricey. Many studies and investigation have been done in introducing automated bank note recognition system and can be separated into vision based system or sensor based system. The objective of this project was to develop an automated system or algorithm that can recognize and classify different Ringgit Banknote for visually impaired person based on banknote image. In this project, the features extraction of the RGB values in six different classes of banknotes (RM1, RM5, RM10, RM20, RM 50, and RM100) was done by using Matlab software. Three features called RB, RG and GB extracted from the RGB values were used for the classification algorithms such as k-Nearest Neighbors (k-NN) and Decision Tree Classifier (DTC) for recognizing each classes of banknote. Ten-fold cross validation was used to select the optimized k-NN and DTC, which was based on the smallest cross validation loss. After that, the performance of optimize k-NN and DTC model was presented in confusion matrix. Result shows that the proposed k-NN and DTC model managed to achieve 99.7% accuracy with the RM50 class causing major reduction in performance. In conclusion, an image based automated system that can recognize the Malaysian banknote using k-NN and DTC classifier has been successfully developed.

**Index Terms**—Banknotes Recognition; Cross-validation; Decision Tree Classifier, k-Nearest Neighbors.

## I. INTRODUCTION

According to World Health Organization, 285 million people worldwide are estimated to be visually impaired with 39 million people totally blind and 246 million people have low vision. Visual impairment is defined as severe minimizing in vision that cannot be corrected with the contact lenses or even standard glasses and reduces a person's ability to perform certain or all tasks [1].

Visual impairment may cause people to have difficulties and limit their activities of daily living such as doing housework, cooking, shopping, watching television, reading, walking, socializing with other and so on. Therefore assistive technology is needed to help them to overcome these challenges. Assistive technology requires two major areas which are information transmission and mobility assistance. Most of the existing technologies for information transmission designed for recognizing the household object

which will help the visual impaired person perform their activities of daily living [1-4]. However, only few technologies are designed to assist visual impaired people in recognizing banknote, which will help them with grocery purchase.

Automated bank note recognition can be separated into vision based system [5-13] and sensor based system [14, 15]. The sensor based systems suffered from inaccuracy because the systems involved many electrical components and there are limitations in providing adequate data, hence, hampering the recognition process. However, most of the studies on vision based system claimed to have a higher percentage in term of accuracy since the image which consists of high volume of data is preferred in developing the system.

Therefore, an automated algorithm that can recognize different Ringgit Banknote for visually impaired person which is based on banknote images has been proposed in this study. Three features called RG, RG and GB were extracted from the images before feeding the features into Decision Tree Classifier (DTC) and k-Nearest Neighbors. The proposed project will potentially help the visual impairment person in Malaysia perform their grocery shopping.

## II. LITERATURE REVIEW AND RELATED WORKS

### A. Assistive Technology Available in the Market for Visual Impaired People

Visual impairment has a serious influence on individual quality of life [16]. Almost 85% of totally blind people lose their capability to perform activities of daily living [17]. For the blind, the loss of sight is a main barrier in daily living such as information access, mobility, way finding, interaction with the environment and other people. Those are challenging issues for them [2]. Almost half of the visually impaired feel moderately and completely cut off from the people and things around them. Their problems go unnoticed from the sight of normal people. Visually impaired people face many challenges and assistive technology helps them to overcome these challenges. According to the International Organization for Standardization (ISO), assistive technology is an umbrella term for equipment, product system, hardware, software or service that increase accessibility for an individual. It is used for people with disabilities to support body function and prevent any activity limitation or participation

restriction.[18]. Assistive technology enables people with disabilities independently perform their daily living activities and improved their quality of life.

For the blind, this supportive system (assistive technology) is focusing on two major areas which are information transmission and mobility assistance [2]. The definition of information transmission is changing a form of data that is hard to understand into another form that can be easily understood [1]. Information transmission for the blind are mainly concerned on reading, recognition of characters and transmitting 2D and 3D graphical information. Transmission information for the blind is mostly via tactile and auditory sensation.

There are some examples for information transmission. One of the examples is Finger Reader [14]. Finger Reader is a forefinger wearable gadget that helps the visually impaired in reading printed message by filtering and output the words as synthesized speech. This work features hardware and software that includes video processing algorithms and multiple output modalities, including tactile and auditory channel. Work in [4] proposed an E-book reading that used two tactile refreshable Braille cells consisting of six solenoid pins each, for conversion of alphanumeric character into Braille character. Secure Disk (SD) Card is used for file storage. Text is printed with each word alternatively printed on display unit. The user reads words by placing both hands, one on each of the two tactile units.

Mobility assistance involves spatial information of the immediate environment, orientation and obstacle avoidance. Mobility assistance is more challenging than information transmission. There are several examples of mobility assistance. One of the examples is "Smart Guide" (SG) [19] device that helps the blind find way around obstacle by using mobile phone. The main function of SG is to convert signal of sensing objects to an audio output to help visually impaired people move without colliding with surrounding or people. Study in [20] developed a modified walking stick which can be used by the blind in accessing a public transport such as buses. The walking stick features object detection, bus stand identifier and bus route identifier. Since RGB-D Camera was introduced, there are also a few attempts in implementing this technology for visual impaired person. For example, work in [21] embedded this camera in wearable navigation system. The navigation system consists of mobile phone user interface, head mounter RGB-D camera, navigation software and haptic feedback vest.

Most of the existing technologies for information transmission focused on assisting the visually impaired person in recognizing household object as well as text for activities of daily living (ADLs). Limited technologies are available to help the visually impaired community in performing the grocery shopping, especially in recognizing the bank note.

### *B. Bank Notes Recognition Devices for Visual Impaired People*

Studies and investigations have been done in introducing automated bank note recognition system for different countries. These investigations can be separated into two main categories: 1) vision based system; and 2) sensor based system.

For vision-based system, mostly camera was used to assist the impaired person. Camera would take the image of

sample (banknote) and underwent various images processing approaches and ended up with classification mechanism such Neural Network in recognizing the banknote. For instance the work in [5] speeded up robust features (SURF) to detect the interest point from the banknote image before extracting the descriptor that can be used in matching process between the descriptor and the banknote image references. The study in [8] also used the interest point concept in recognizing the banknote. However, this study proposed the interest point which in under the denomination region before applying the geometrical pattern in reducing the error rate of the system. Besides that, color based features was introduced in [6] for classifying the Indian currency. Another example was work by [12] that suggested the template matching process in recognizing the Egyptian banknote while work in [13] preferred the dimension reduction technique such as Principle component analysis (PCA) in extraction the meaningful information that can represent different type of banknote.

As for sensor based system, most of the study proposed different types of sensing modalities. Work in [14] used the color sensor (TCS230) in classifying the Malaysian banknote while work in [15] established the RGB information from banknote using the Light Dependent Resistor (LDR) and Light Emitting Diode (LED).

The existing studies based on sensor-based system are involving many electrical components and the expected result was not accurate because of the limitation with the sensor. Therefore most of the studies on vision-based system claimed having a higher percentage in term of accuracy.

## III. MATERIAL AND METHOD

### *A. Methodology*

Figure 1 shows the main process in producing the image based Malaysian Ringgit banknote recognition algorithm. For data collection, images of Malaysian Ringgit Banknotes (RM1, RM5, RM 10, RM20, RM 50 and RM 100) were taken by using hand phone camera under a controlled environment. Six banknote samples per class were used in this project with total of 168 banknote images taken in horizontal and vertical positions for both sides of each banknote sample (see Figure 2).

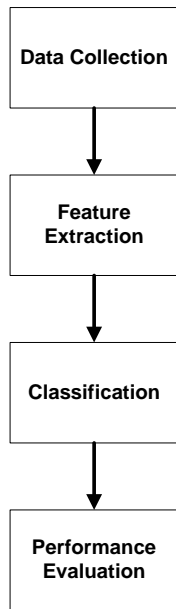


Figure 1: Block diagram for methodology



Figure 3: The informative region for RM1 [new and old], RM5 and RM10 banknote



Figure 2: The samples (images) collections of Malaysian Ringgit banknotes



Figure 4: The informative region for RM20, RM50 and RM100 banknote



Each of the banknote images were cropped in two different regions, which were informative region (see Figure 3 and 4) and whole region (see Figure 5 and 6) by using a Matlab tool called TrainingImageLabeler in order to have wider and bigger set of data.

Figure 5: The whole region for RM1 [new and old], RM5 and RM10 banknote



Figure 6: The whole region for RM20, RM50 and RM100 banknote

After that, the cropped regions (both informative region and whole region) from the collected images were used in extraction the color features called RB, RG and GB. These features were formulated using Equations (1) to (3):

$$RB = \bar{r} - \bar{b} \tag{1}$$

$$RG = \bar{r} - \bar{g} \tag{2}$$

$$GB = \bar{g} - \bar{b} \tag{3}$$

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.

Next, the three features (RB, RG, and GB) were used as the main features in modelling the DTC using MATLAB. Cross validation with ten-fold was used in this process to utilize as much data as possible for training proses. In this project, cross validation was used in selecting the optimum DTC by varying the minimum leaf size. After producing the optimum DTC, the performance of this model was compared with other classifier model which are Naïve Bayesian and k-Nearest Neighbor.

Finally, Classification algorithm such as k Nearest Neighbor (k-NN) and Decision Tree Classifier (DTC) were used to recognize and classify the Malaysian Ringgit banknote based on the RB, RG and GB features calculated from the previous section. In selecting the optimum Decision Tree Classifier (DTC) and evaluating the performance of both k Nearest Neighbor (k-NN) and Decision Tree Classifier (DTC), cross validation with ten-folde r was used to formulate the confusion matrix that represent the performance of each proposed classification model. The data were segmented into 10 equal sized partitions by the 10-folder cross validation process. During each run, one of the partitions was chosen for testing, while the rest of them were used for training. This procedure is repeated 10 times so that each partition is used for testing exactly once. Cross validation was used in selecting the optimum Decision Tree Classifier (DTC) by varying the minimum leaf size. Overall, the work for this project can be categorized into internal and external parts. The internal part

consisted of the processor and programming part which modelled the optimum DTC in Arduino Lilypad. For this part, the rule-based algorithm generated from optimum DTC was implemented in Lilypad Arduino. The rule-based algorithm as well as other functions will operate according to the flowchart as illustrated in Figure 3. The external part was related to the design of the device. Solidworks software was used to develop the 3D design of the banknote recognition device.

#### IV. RESULT AND DISCUSSION

##### A. Result from Feature Extraction

For feature extraction, the red, green and blue intensity average values from each of the banknotes were taken from the both cropped region and then, RB, RG and GB features were calculated by using Equations (1) to (3) before recorded the features obtained using Microsoft Excel (see Figure 7 and 8). As mentioned earlier in previous chapter, the RB, RG and GB were extracted from the informative region and whole region of each sample. These two regions need to be considered in simulating the uncertainty that occurs in the input image that might be influence the performance of the proposed algorithm.

RB	GB	RG	OUTPUT
-7.69976	-4.79824	-2.90152	1
-10.2365	-6.23158	-4.00493	1
-13.386	-4.54131	-8.84472	1
-10.1195	-3.58057	-6.5389	1
-9.88322	-7.75511	-2.12811	1
-11.1484	-8.32476	-2.82367	1
-11.1007	-5.85252	-5.24816	1
-15.2759	-8.92846	-6.34742	1
-9.06501	-7.13641	-1.9286	1
-8.57336	-6.74911	-1.82425	1
-14.2754	-7.79011	-6.48526	1
-14.3294	-7.81187	-6.5175	1
-5.46951	-3.7848	-1.68472	1
-6.14594	-4.24597	-1.89997	1
-8.41838	-3.00676	-5.41162	1
-9.98821	-4.29263	-5.69558	1
-8.84995	-6.98168	-1.86828	1
-7.76159	-7.03807	-0.72352	1
-11.3488	-5.00169	-6.34712	1
-12.786	-6.33806	-6.44795	1
-7.93047	-4.77869	-3.15178	1
-7.52563	-4.74503	-2.7806	1
-10.0868	-3.28605	-6.80072	1
-10.5607	-4.44476	-6.11594	1
5.01841	9.294595	-4.27619	1

Figure 7: The sample of RM1 features that obtained from the informative region

RB	GB	RG	OUTPUT
-0.32891	1.137583	-1.46649	1
-2.76407	-0.43682	-2.32725	1
-3.92903	1.139094	-5.06812	1
-0.95973	2.033702	-2.99344	1
-1.17988	-0.77236	-0.40752	1
-2.25585	-1.58622	-0.66964	1
-0.79089	0.420503	-1.2114	1
-6.13369	-3.02857	-3.10512	1
-1.31311	-0.88991	-0.42319	1
-1.15952	-1.0839	-0.07561	1
-3.55476	-1.41727	-2.1375	1
-5.21081	-2.14012	-3.0707	1
2.12863	2.328179	-0.19955	1
1.221203	1.438239	-0.21704	1
1.352953	2.890917	-1.53796	1
-0.52229	1.748973	-2.27126	1
-0.82951	-0.34487	-0.48463	1
0.033079	-0.82962	0.862702	1
-0.48	1.158399	-1.6384	1
-3.3052	-0.50399	-2.8012	1
-0.71962	1.233022	-1.95264	1
0.189976	1.329852	-1.13988	1
0.239341	2.545217	-2.30588	1
-1.70016	0.901639	-2.60179	1
5.225615	9.387166	-4.16155	1

Figure 8: The sample of RM1 features that obtained from the whole region

**B. Finding the Optimum Decision Tree Classifier (DTC)**

Optimum Decision Tree was chosen based on varying the number of minimum leaf size. In order to obtain the optimum DTC, cross validation losses from several different DTC with different minimum leaf size were obtained using the 10-folder cross validation approach. Minimum leaf size will determine the complexity of the produced DTC model. The larger the number of minimum leaf size, the less branches the tree will have and the lower the complexity. The cross validation loss versus the minimum number of leaf size using different cropped regions (informative region only, whole region only and combination between informative and whole region) are presented in Figure 9 to 11.

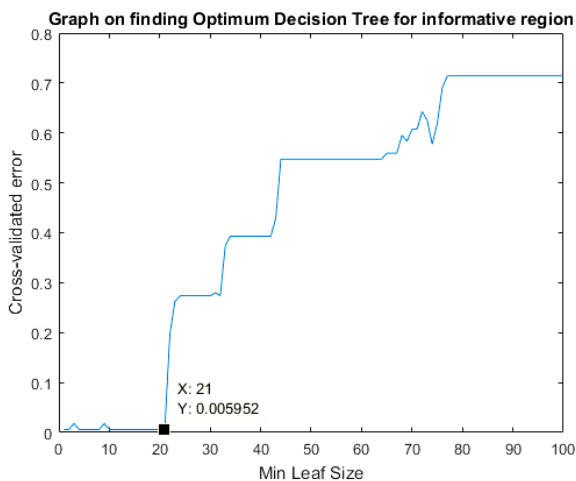


Figure 9: The cross validated error for informative region is the lowest when the minimum leaf size is 21.

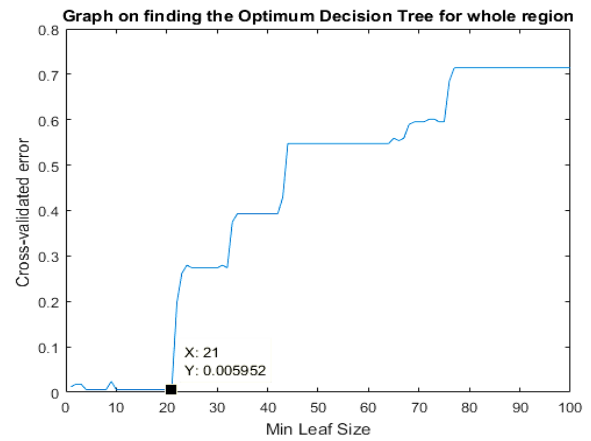


Figure 10: The cross validated error for whole region is the lowest when the minimum leaf size is 21.

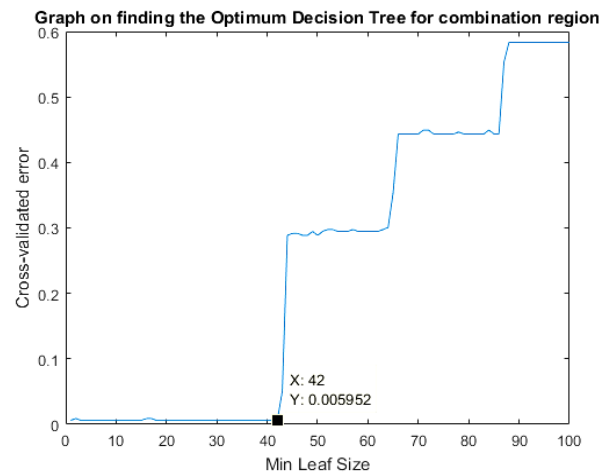


Figure 11: The cross validated error for combination region is the lowest when the minimum leaf size is 42.

It can be concluded that minimum number of leaf size is from 1 until 21 (for the informative and whole region) and 1 until 42 (for combination region) produce the smallest cross validation loss. In case of information and whole region, 21 was selected as the best minimum leaf size because it produces less complex Decision Tree Classifier (DTC) while resulting in the smallest cross validation loss. However, 42 were selected for the whole region case. If the minimum leaf size is more than 21 and 42, the Decision Tree Classifier (DTC) will result in bigger cross validation loss. Figure 12-14 present the optimum DTC model of each case.

**C. Confusion Matrix for K-Nearest Neighbor (k-NN) and Decision Tree Classifier (DTC)**

Confusion matrix was used to evaluate the performance of both k-Nearest Neighbor (k-NN) and Decision Tree Classifier (DTC). Confusion matrix contains all possible classes in both horizontal and vertical directions. The columns represent the result for predicted class and the rows represent the actual class of the variables. Anything on the leading diagonal (the diagonal that starts at the top left of the matrix and runs down to the bottom right) is a correct answer for each different ringgit banknote values (RM1, RM5, RM10, RM20, RM50, and RM100). At this stage, the

optimum DTC was selected to represent the DTC which is compared with the k-NN.

Figure 15 to 17 indicate the performance of the k-NN for three different cases. It can be interpreted that the performance of k-NN was increased after the combination of two regions. This might be because during the training session, the data fed into the k-NN for the first two cases are not adequate in finding the optimum centroid points each classes. As stated earlier, k-NN needs to compute the distance (or similarity) of all training samples for each test sample in the process of selecting k-nearest neighbors (the centroid points). So after the combination, the centroid points are better and tackle the uncertainty since the huge training data is feed into the classification model during the training process. Figure 18 to 20 illustrate the performance of DTC for three different cases. It can be concluded that the

performance of DTC was decreased after the combinations of two regions. This could be due to the white region in the whole region case which can be considered as the noise interferes with the training process. Thus, the generated DTC model in combination region case is suffered with data overlap between one class to another and the precise border cannot be created. But by overall, both k-NN and DTC managed to achieve 99.7% accuracy with RM50 class provides the major contribution in reducing the performance of both classifiers. This is due to one of the RM50 samples was predicted as RM1.

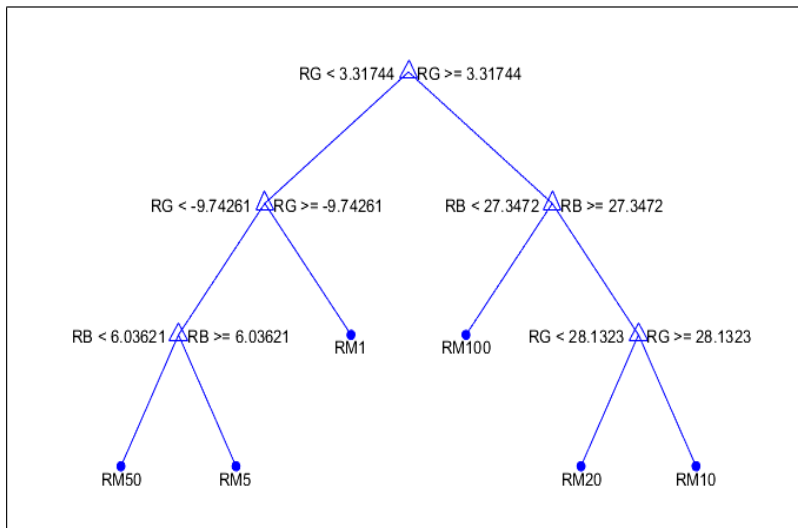


Figure 12: The optimized DTC with only 3 levels after applied minimum leaf size = 21 for informative region

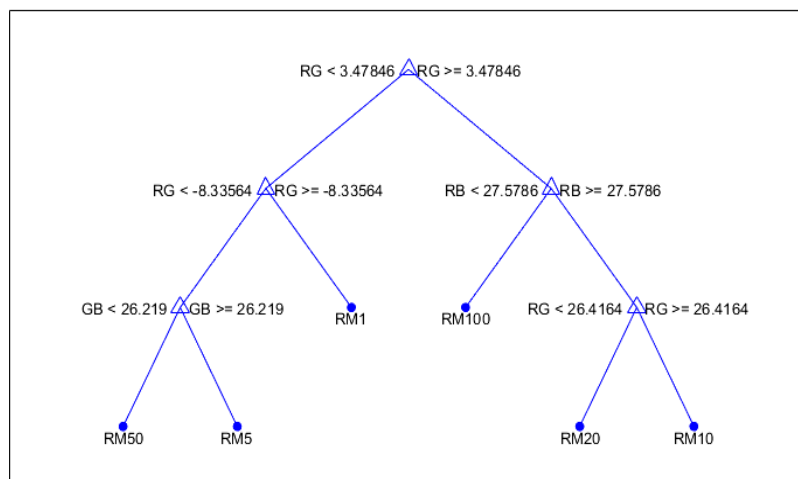


Figure 13: The optimized DTC with only 3 levels after applied minimum leaf size = 21 for whole region

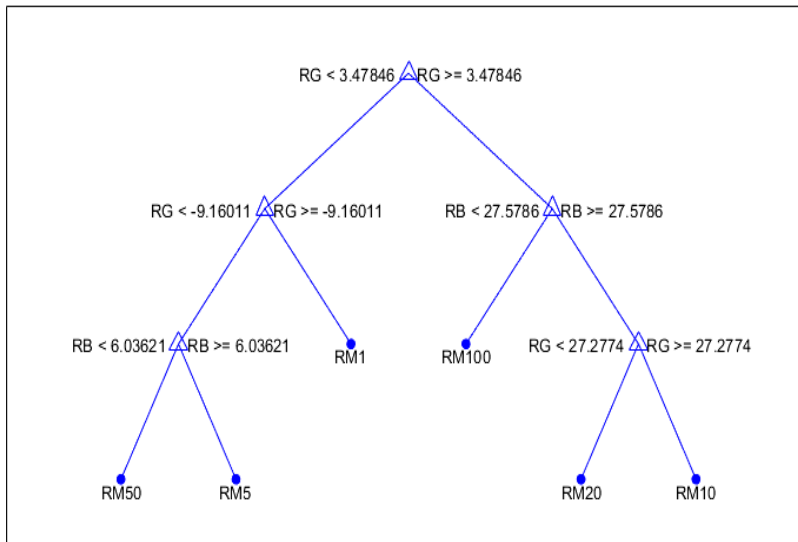


Figure 14: The optimized DTC with only 3 levels after applied minimum leaf size = 21 for combination region

**Confusion Matrix**

Output Class	1	2	3	4	5	6	
1	48 28.6%	0 0.0%	0 0.0%	0 0.0%	1 0.6%	0 0.0%	98.0% 2.0%
2	0 0.0%	24 14.3%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
3	0 0.0%	0 0.0%	24 14.3%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
4	0 0.0%	0 0.0%	0 0.0%	24 14.3%	0 0.0%	0 0.0%	100% 0.0%
5	0 0.0%	0 0.0%	0 0.0%	0 0.0%	23 13.7%	0 0.0%	100% 0.0%
6	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	24 14.3%	100% 0.0%
	100% 0.0%	100% 0.0%	100% 0.0%	100% 0.0%	95.8% 4.2%	100% 0.0%	99.4% 0.6%
	1	2	3	4	5	6	

Figure 15: The confusion matrix for k-Nearest Neighbor (k-NN) using the informative region.

**Confusion Matrix**

Output Class	1	2	3	4	5	6	
1	96 28.6%	0 0.0%	0 0.0%	0 0.0%	1 0.3%	0 0.0%	99.0% 1.0%
2	0 0.0%	48 14.3%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
3	0 0.0%	0 0.0%	48 14.3%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
4	0 0.0%	0 0.0%	0 0.0%	48 14.3%	0 0.0%	0 0.0%	100% 0.0%
5	0 0.0%	0 0.0%	0 0.0%	0 0.0%	47 14.0%	0 0.0%	100% 0.0%
6	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	48 14.3%	100% 0.0%
	100% 0.0%	100% 0.0%	100% 0.0%	100% 0.0%	97.9% 2.1%	100% 0.0%	99.7% 0.3%
	1	2	3	4	5	6	

Figure 17: The confusion matrix for k-Nearest Neighbor (k-NN) using the combination region.

**Confusion Matrix**

Output Class	1	2	3	4	5	6	
1	48 28.6%	0 0.0%	0 0.0%	0 0.0%	1 0.6%	0 0.0%	98.0% 2.0%
2	0 0.0%	24 14.3%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
3	0 0.0%	0 0.0%	24 14.3%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
4	0 0.0%	0 0.0%	0 0.0%	24 14.3%	0 0.0%	0 0.0%	100% 0.0%
5	0 0.0%	0 0.0%	0 0.0%	0 0.0%	23 13.7%	0 0.0%	100% 0.0%
6	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	24 14.3%	100% 0.0%
	100% 0.0%	100% 0.0%	100% 0.0%	100% 0.0%	95.8% 4.2%	100% 0.0%	99.4% 0.6%
	1	2	3	4	5	6	

Figure 16: The confusion matrix for k-Nearest Neighbor (k-NN) using the whole region.

**Confusion Matrix**

Output Class	1	2	3	4	5	6	
1	48 28.6%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
2	0 0.0%	24 14.3%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
3	0 0.0%	0 0.0%	24 14.3%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
4	0 0.0%	0 0.0%	0 0.0%	24 14.3%	0 0.0%	0 0.0%	100% 0.0%
5	0 0.0%	0 0.0%	0 0.0%	0 0.0%	24 14.3%	0 0.0%	100% 0.0%
6	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	24 14.3%	100% 0.0%
	100% 0.0%	100% 0.0%	100% 0.0%	100% 0.0%	100% 0.0%	100% 0.0%	100% 0.0%
	1	2	3	4	5	6	

Figure 18: The confusion matrix for Decision Tree Classifier (DTC) using informative region.

**Confusion Matrix**

Output Class	1	48 28.6%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
	2	0 0.0%	24 14.3%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
	3	0 0.0%	0 0.0%	24 14.3%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
	4	0 0.0%	0 0.0%	0 0.0%	24 14.3%	0 0.0%	0 0.0%	100% 0.0%
	5	0 0.0%	0 0.0%	0 0.0%	0 0.0%	24 14.3%	0 0.0%	100% 0.0%
	6	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	24 14.3%	100% 0.0%
			100% 0.0%	100% 0.0%	100% 0.0%	100% 0.0%	100% 0.0%	100% 0.0%
		1	2	3	4	5	6	
		Target Class						

Figure 19: The confusion matrix for Decision Tree Classifier (DTC) using the whole region.

**Confusion Matrix**

Output Class	1	96 28.6%	0 0.0%	0 0.0%	0 0.0%	1 0.3%	0 0.0%	99.0% 1.0%
	2	0 0.0%	48 14.3%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
	3	0 0.0%	0 0.0%	48 14.3%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
	4	0 0.0%	0 0.0%	0 0.0%	48 14.3%	0 0.0%	0 0.0%	100% 0.0%
	5	0 0.0%	0 0.0%	0 0.0%	0 0.0%	47 14.0%	0 0.0%	100% 0.0%
	6	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	48 14.3%	100% 0.0%
			100% 0.0%	100% 0.0%	100% 0.0%	100% 0.0%	97.9% 2.1%	100% 0.0%
		1	2	3	4	5	6	
		Target Class						

Figure 20: The confusion matrix for Decision Tree Classifier (DTC) using the whole region.

V. CONCLUSION AND FUTURE WORK

In conclusion, a vision based automated algorithm that can recognize and classify Malaysian Ringgit Banknote using k Nearest Neighbor (k-NN) and Decision Tree Classifier (DTC) has been developed. This algorithm can potentially be used in embedded system such as raspberry pi and FPGA or can be extended as a mobile device application for the usage of visual impaired people in Malaysia to perform grocery shopping.

With this algorithm, the visually impaired people can improve their quality of life by reducing the dependency on other people in completing their daily tasks and routine especially in the grocery activities. This vision based automated algorithm having a higher percentage of accuracy in recognizing and classifying banknotes.

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