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Counterfeit Malaysian Banknotes Detection Using Discrete Wavelet Transform

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Abstract

The number of counterfeit banknotes has increased year by year, due to the enhanced developments in printing technology. Due to technological advancement, counterfeit banknotes can pass the physical feature and chemical property-based counterfeit banknotes detection system undetected. The end-user least accepts the fake detection tools because of poor accuracy, unavailability and expensive. As a result, counterfeit banknotes have become a major issue for most countries in the world, including Malaysia. This paper proposes a method for the Malaysian counterfeit banknote detection machine to use the Haar wavelet transform as the featured extraction technique. The features were then classified by using the K-Nearest Neighbour (KNN) and Support Vector Machine (SVM) classifiers. The proposed models would produce 85% and 50% accuracies respectively for KNN and SVM. In the future, this system can be enhanced into real-time banknotes detection

Keywords: Malaysian banknotes detection, DWT, Haar Wavelet Transform, KNN, SVM

I. INTRODUCTION

Banknote or currency refers to the money used as a medium for exchange. Counterfeit banknotes were created to imitate government-produced banknotes. People can easily copy the currency with the use of digital graphics, since the computer and photocopy industries have been evolving at a fast rate in terms of technology. Counterfeiters planned to produce more realistic reproductions of the genuine banknotes by mastering any security features available. Newspapers and online articles had reported a vast cache of counterfeit banknotes being seized regularly. In the U.S, 70 percent of $78 million fake currency has been circulated around the country and was a product of digital printing (Murakami, 2021; Bartkiewicz et al., 2017). Most of the widely used currencies such as the U.S dollar, Euro and British pound sterling have higher counterfeiting rates than others (Letts, 2019). The number of counterfeit banknotes found in Malaysia is one out of every million (Carvalho et al., 2020) The number of detected counterfeit notes for every banknote in circulation is in pieces per million (PPM). In Malaysia, the number of PPM has reduced to 1.4 PPM in 2016, 1.2 PPM in 2019 and 1.0 PPM in 2020. According to Quercioli et al. (2015), the counterfeiting rate among countries around the world are affected by several factors, such as the escalation of crime rate, the utilisation of money, the insurance of a banknote, and the cost of equipment used to make counterfeit banknotes. An awareness of banknote security features can help many people identify counterfeit notes. Unfortunately, illiterate people could not recognise the difference between genuine and counterfeit banknotes. When the banknotes are damaged, aged and filthy, the human eye and touch have a hard time to identify the features of these banknotes. In addition, manual counterfeit banknotes detection is a time-consuming process (Velling et al., 2019).

In general, the security features have some categories that the human senses can detect and features that could not be detected by human senses, and it requires some essential tools to find it. Chambers et al. (2014) has mentioned that the security features are classified into three classes: One of the security features can easily be recognized via human senses. The second class is a detection using a magnifying glass or UV light. The third class is through the intrinsic features that were produced from the manufacturing process. According to Bank Negara Malaysia, people can apply the feel, look, tilt and check principles to differentiate between counterfeit Malaysian banknotes and legitimate Malaysian banknotes. The reason is that the production of counterfeit banknotes usually used low-quality materials. Nevertheless, it appears to look genuine to the public. Several tools in the market can be used to detect these counterfeit banknotes, for example, the Munshii Jet70 banknote discriminator (n.d), Safescan (n.d), Counterfeit Money Detector Pen (n.d), and Money Detector (n.d).

Upadhyaya et al. (2016) reviewed eleven different currencies, that are: Indian rupee, Australian dollar, Canadian dollar, European Euro, Hong Kong SAR, Japanese Yen, Singapore Dollar, Swedish Krona, Swiss Franc, UK Pound and US Dollar. They compared seventeen features used in each currency. The banknote features are intaglio printing or raised printing, see-through, watermark, microprinting, micro lettering, hologram, thread, security inks, ultraviolet test feature, denomination value mark, latent image, anti-photocopying feature, different size and colours for a different denomination, serial number, spot for blind and unique features. Indian rupees have all these features except holograms. According to (BankingInfo, n.d.) the main security features of a Malaysian banknote are:-

A. Watermark

In the clear panel on the left-hand side of the banknote, the shaded watermark portrait of the First Yang di-Pertuan Agong can be seen when the banknote is held up against the light. The watermark has a 3D look with shady without sharp outlines, appearing soft and different dark and light tones. It is a visible number, i.e., 50 for RM50 denominations at the base of the watermark.

B. Intaglio Print

The denomination figures, a portrait of the First Yang di-Pertuan Agong and “BANK NEGARA MALAYSIA’ words are printed with intaglio ink to give a raised feel and good overall tactility.

C. Portrait of Yang di-Pertuan Agong

The anti-counterfeiting feature that is difficult to be replicated is the First Yang di-Pertuan Agong portrait that is located at the right-hand side of the banknote.

D. Micro-lense security thread

On the left-hand side of the banknote, there is a holographic strip for denominations of RM50 and RM100.

E. Paper

The manufacturing of Malaysian banknotes is made from cotton, which is a high-quality paper. It has a uniquely crisp sound when crunched and a slightly rough surface.

Furthermore, each Malaysian banknotes have different dominant colours and sizes (Mohamed et al,. 2012). Nevertheless, counterfeited money could avoid the physical feature and chemical property-based counterfeit banknotes detection system due to technological advancements. The end-user least accepts the fake detection tools because of the poor accuracy, unavailability, high cost and lack of user-friendliness (Sowmyashree et al., 2015). In the literature, researchers have proposed many solutions, such as using computer vision and image processing in a banknote verification system that extracts banknotes’ characteristics (Thakur et al., 2014; Prasanthi et al., 2015; Kang et al. 2016). Feature extraction is the process used to obtain the relevant features that characterise a class and make it easy to distinguish (Kumar et al., 2014; Halim et al., 2021].

Velling et al. (2016) introduced integrated approaches used to recognise counterfeit Indian banknotes. The integration is between the hyperspectral imaging and image processing technique. In hyperspectral imaging, there are five different colour lights ranging from 360 nm used. The colours are Ultraviolet (UV) light, Normal LED Bulb, Red LED light, Green LED light, and Blue LED. While in image processing, entropy and means are used as the feature extraction technique. It is observed that the results were nearly accurate. Another work to detect counterfeit Indian banknotes is by using the pixel's colour statistical features, such as mean, standard deviation, skewness together with the Canny edge detection method (Landge et al., 2018). Hardani et al. (2019) used a combination of Gray Level Co-occurrence Matrix (GLCM) and K-Nearest Neighbour (KNN) to identify the authenticity of the Rupiah banknote. A different number of k has produced different results. 100% accuracy is achieved when k is assigned to 1 for the KNN classifier. Alshayeji et al. (2015) used the bit plane slicing method to extract the essential features from the image of the counterfeit notes. This technique breaks down images with a level of 256 gray-scale into corresponding eight images. In addition, the Canny edge detection algorithm gives a significant result and less error when applied on higher bit planes. However, the weakness of using this algorithm is that it is expensive. Abburu et al. (2017) used the template matching technique to identify the currency's origin and size ratio, colour and text features in order to identify the currency's denomination. Deep learning is an algorithm that could extract sophisticated features marvelously to differentiate the original and counterfeit banknotes to overcome the limitations of previous algorithms (Kamble et al., 2019; Lee et al., 2019; Ibrahim et al., 2018).

Recently, Wong et al. (2021) presented a Malaysian banknote identification system based on image processing and a fuzzy logic algorithm. This system is built using discrete cosine transform as the feature extractor and fuzzy logic. The findings were promising, indicating that the proposed technique could be useful for recognizing Malaysian banknotes. Sufri et al. [50] used Malaysian Ringgit banknotes (RM 1, RM 5, RM 10, RM 20, RM 50, and RM 100) to investigate the effects of region and orientation on machine learning and deep learning performance. Feature extraction of RGB values named RB, RG and GB from banknote images with distinct regions are used in this study. As a result, KNN and decision tree both achieved 99.7% accuracy, SVM and Bayesian classifiers outperform KNN and SVM classifiers by achieving 100% accuracy. They also discovered that deep learning could only perform well when similar image orientation is used during training.

Wavelet transform is another method to get features from images. Because of its capacity to localize time-frequency information of a signal, multi-resolution analysis, and flexibility of choice, wavelet transforms surpass all other time-domain and frequency-domain approaches for feature extraction (Saini et al. 2018; Irulappasamy et al. 2021; Kamal et al. 2018). In wavelet transformation, there are two crucial parameters to consider when determining the quality of the output, that is wavelet family and scale (Albkosh et al., 2019). Examples of wavelet families are Haar, Daubechies, Morlet, Coiflets, Biorthogonal and Meyer. Choosing the appropriate wavelet family and scale is essential because proper representation retains the important characteristics of the signal (Saini et al. 2018). For all other wavelet families, the Haar transform can be used as a model (Thakral et al., 2019). Ragavi et al. (2020) has used feature variance and skewness of wavelet transform and K-Means clustering for banknotes authentication. A combination of wavelet transforms, and an Adaptive Neuro-Fuzzy Inference System (ANFIS) is used to classify counterfeit banknotes (Iraji et al. 2016). The results of this study achieved 100% accuracy. Reference (Prabakaran et al., 2019; Rao et al., 2016) compared discrete cosine transform and discrete wavelet transform performance to detect forge image. It was found that wavelet transform works well in the noisy and compressed region. In contrast, discrete cosine transform produces less performance for any noisy image. As for the classifier, previous researchers have used many kinds of classifiers for counterfeit banknotes detection. Some of the classifiers are KNN (Neeraja, 2019; Raho et al., 2015), random forest (Jaiswal, 2019), support vector machine (Gopane et al. 2020; Uddin et al. 2016), multilayer perceptron (Ghazwani et al. 2014) and radial basis function network (Sarfraz et al. 2015). Comparison has been made on the performance of eleven classifiers on counterfeit banknotes detection (Khairy et al., 2021). MLP, KNN, Random Forest and Fuzzy Nearest Neighbor (FNN) give the best results, which is between 98% to 99% accuracy. This paper aims to determine counterfeit Malaysian banknotes based on wavelet transform features using KNN and SVM classifiers. The paper is organized as follows: Section 2 presents the methodology of describing the proposed methodology. The results of the proposed method and the accuracy comparison between the two classifiers are explained in Section 3. The concluding remark of this study is shown in Section 4.

II. METHODOLOGY

Figure 1 shows the flowchart of the research. There are four main processes in this method: image acquisition, image pre-processing, feature extraction, classification, and performance evaluation.

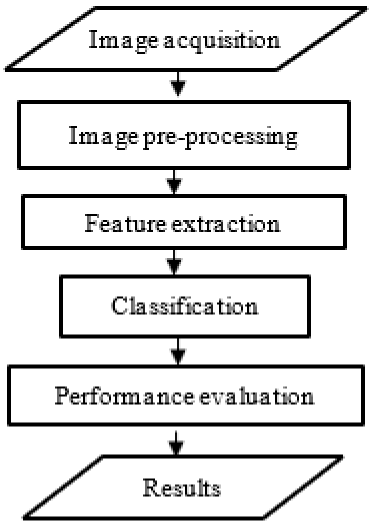

Figure 1 – Proposed Methodology

A. *Image acquisition*

In this stage, the original Malaysian banknotes are digitized and turned into images. Then, counterfeit banknotes are created by printing these authentic banknote images and scanned again to get the counterfeit banknote images. The dataset consisted of 100 images of genuine banknotes and counterfeit banknotes. The dataset is split with a ratio of 80:20 for training and testing purposes. Table 3.2 shows the test dataset used for each denominator.

Table 1 – Malaysian banknotes dataset

Ringgit Malaysia	Counterfeit	Genuine
1	10	10
5	10	10
10	10	10
20	10	10
50	10	10

B. *Image pre-processing*

Images are resized to 1250 x 500 pixels to maintain the standard size and reduce the computational cost. Next, these RGB colour images are converted to grayscale. It is easy to identify the pixels in grayscale when compared to colour images. The following process is median filtering; to remove the noise in the grayscale image. A 3x3 kernel is used to get the best noise reduction results.

C. *Feature extraction*

Figure 2 shows the overview of the feature extraction process. The Malaysian banknote image must go through the Haar wavelet transform method to obtain the feature vector.

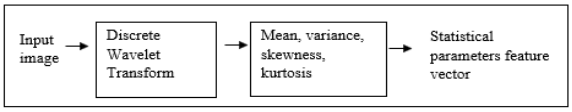

Figure 2 – Proposed Methodology

Figure 3 shows the detail of the discreted wavelet transform decomposition process. There are two wavelet transform filters: the low pass filter and the high pass filter. The equations for the low pass filter and high pass features are shown in (1) and (2).

Haar lowpass filter (H_0) $= 1/\sqrt{2}\,[1\ 1]$ (1)

Haar highpass filter (H_1)$= 1/\sqrt{2}\,[1 -1]$ (2)

Figure 3 shows the wavelet transform process of an image. To calculate the wavelet transform of an image for the first decomposition level, the image's rows have to be convoluted with a low-pass filter (H_0). The convolution process is done by sliding the low-pass filter, multiplying the image rows with the low-pass filter coefficients and summing the results. Next, the rows transformed coefficients are convoluted again with the low-pass filter. These will produce the lowpass-lowpass (LL) coefficients or approximation coefficients containing the image's low-frequency information. The next step is to calculate the lowpass-highpass rows (LH) coefficients of the image. This is done by convolving the original image with the low-pass filter, then convolving the transformed row with the high-pass filter (H_1). Similarly, to obtain the high-pass low-pass (HL) coefficients, the original image is convolved with the high-pass filter on the rows and low-pass filters on the columns of the transformed rows. To obtain the highpass-highpass coefficients (HH), the original image is convolved with the high-pass filter on the rows and high-pass filters on the columns of the transformed rows. The same process is done for the second level to obtain LL, LH, HL, and HH coefficients from the LL coefficients. The acquired coefficients are the features of the image. The decomposition level used in this study is level 1.

In the next step, the mean values, kurtosis, skewness and variance are calculated from the collected LL, LH, HL and HH wavelet coefficients. Four statistical parameters were used to form the feature vector. The mean value represents the contribution of the individual pixel intensity for the entire image. Variance is used to identify the difference between pixels that are different from the neighbouring pixels, and is used in pixel classification in different regions. Skewness is used to measure the symmetry or more precision. Kurtosis is used to measure if the data are peaked or flat in relation to a normal distribution. For the feature extraction, the libraries used were OpenCV(Bradski, 2000) and PyWavelets (Lee et al., 2019). OpenCV is an open-source library for computer vision and machine learning. PyWavelets is a Python package implementing a number of n-dimensional discrete wavelet transforms and the 1D continuous wavelet transformation.

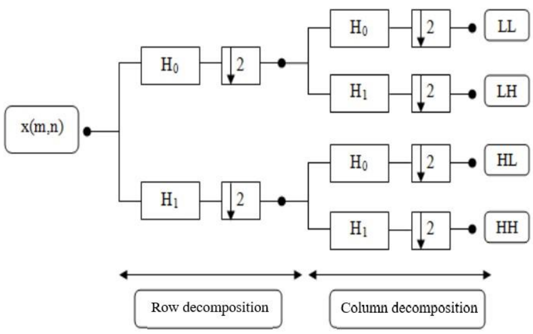

Figure 3 - Discrete wavelet transform decomposition process

D. Classification

Classification is a process of organising the features that have been extracted into several classes. This process is used to give the results' prediction. In this phase, the k-Nearest Neighbour (k-NN) and SVM are used to classify the features, and put them into counterfeit and Genuine classes

1) Support Vector Machine (SVM)

SVM was developed by Vapnik (1995) as a supervised learning machine tool for pattern identification and classification problems. Because SVM training can handle huge feature vector dimensions, it is effective in large classification applications. In the SVM classifier, the RBF kernel has been employed.

2) K-Nearest Neighbour (KNN)

The KNN algorithm will find the distance between a query and all examples in the data, and then it will select a specified number of examples, k, that is the closest to the query (Zin et al, 2020). Finally, it will vote for the most frequent label for the classification process. In this study, the selected value for k is two.

E. Performance Evaluation

To determine the system's performance, the number of the classification of each class is compared with the total number of each dataset in order to evaluate the result of the classification. True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN) are the parameters used in calculating the True Positive Rate (TPR) and False Positive Rate (FPR) to get the accuracy.

Accuracy can be calculated using (3).

$$\text{Accuracy}=\frac{TP+FN}{TP+TN+FP+FN}\frac{TP+FN}{TP+TN+FP+FN} \quad (3)$$

Precision is used to test its ability to determine the number of notes that the classifier labelled as genuine as in (4).

$$\text{Precision}=\frac{TP}{TP+FP}\frac{TP}{TP+FP} \quad (4)$$

Sensitivity is used to test its ability to determine the genuine banknote precisely as in (5),

$$\text{Sensitivity}=\frac{TP}{TP+FN}\frac{TP}{TP+FN} \quad (5)$$

F-measure or F1-score is the harmonic average of precision and sensitivity. Because both FP and FN are important, it considers precision and recall using a single score. The formula to calculate F-score is given in (6).

F-Measure=

$$2\,x\,\frac{precision\ x\ recall}{precision + recall}2\,x\,\frac{precision\ x\ recall}{precision + recall} \quad (6)$$

III. RESULTS AND DISCUSSION

The accuracy and efficiency of the proposed method are tested in this experiment. Each RM1, RM5, RM10, RM 20, and RM50 Malaysian banknote has 20 parts. For the KNN classifier, RM50 and RM1 have the highest successful recognition rate (up to 100%) among the tested Malaysian banknotes, while RM20 has the highest mistake rate (up to 50%). According to (Wong et al. 2021), the reason for this could be that RM10 and RM20 belong to the same colour group (red and orange, respectively). Because orange contains red colour components, red is frequently mistreated as orange. While for the SVM classifier, all Malaysian banknotes have a 50% successful recognition rate. KNN fulfils the goal to get high prediction performance. Figure 4 shows the performance comparison of the KNN and SVM classifier. The KNN classifier achieved 85% accuracy, 100% precision, 70% sensitivity and 85% F-score. SVM gives accuracy of 50%, 50% precision, 100% sensitivity and 50% F-score. KNN's performance outperforms SVM for accuracy, precision and F-measure except sensitivity. Therefore, SVM is able to classify counterfeit banknotes better than KNN.

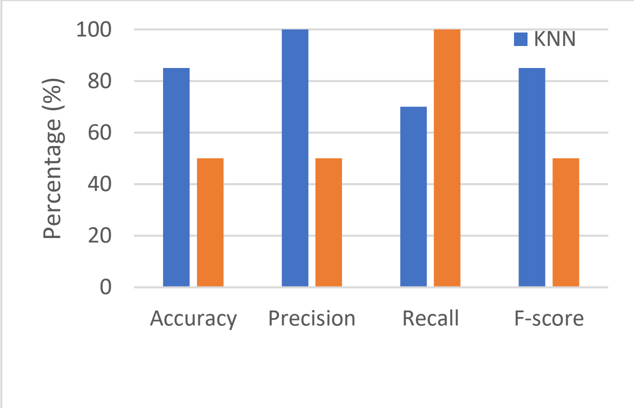

Figure 4 - Performance of KNN and SVM classifiers

Table 2 – Malaysian banknotes classification results

Ringgit Malaysia	Our approach KNN (Accuracy)	Our approach SVM (Accuracy)	Wong et al. (2021) Fuzzy Logic (Accuracy)
1	100%	50%	95%
5	100%	50%	96%
10	50%	50%	93%
20	50%	50%	92%
50	100%	50%	96%

In order to validate our results and the reliability of our work, we perform a comparison with published methods in similar research works. Among these works, we can find the Malaysian banknote recognition proposed by Wong et al. (2021). According to our experiments and the results of the published methods (see Table 7), we find that all the classifiers of Malaysian banknotes meet a problematic issue which is the fact of not being able to provide good predictive accuracy for RM10 and RM20. Nevertheless, our approach managed to get 100% accuracy for RM1, RM5 and RM50. Therefore, we can conclude that the combination of Haar wavelet transform and the KNN classifier is suitable for counterfeit Malaysian banknotes detection.

IV. CONCLUSION

This paper determines the counterfeit Malaysian banknotes based KNN classifier gives the best performance for counterfeit banknote detection. For future work, we plan to use different wavelet families to extract the banknote features. In addition, we plan to embed this method into mobile devices. It is to enable the detection of counterfeit banknotes quickly and easily. Hopefully, this proposed method will benefit the country by reducing the counterfeit banknotes issue.

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