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Malaysian Banknote Reader Featuring Counterfeit Detection Using Fuzzy Logic Weighted Specific (FLWS) Algorithm

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***Abstract* — To identify fake Malaysian banknotes, this research suggested a revolutionary fuzzy logic weighted specific (FLWS) approach in image processing techniques. The FLWS Algorithm has the benefit of a more accurate model because it is a human guidance learning algorithm that demands training to obtain the precise weights for each security feature. The trial outcomes also demonstrated that, for the purpose of detecting counterfeit Malaysian banknotes, the FLWS model outperformed the parallel fuzzy logic weighted averaging (FLWA) algorithm, MobileNet model, and VGG16 model. Its adoption of well-known watermark features, with specific weights assigned, and well-known machine learning techniques to distinguish between genuine Malaysian banknotes and counterfeit Malaysian banknotes gives it a clear advantage over earlier or current banknote counterfeit detection techniques.**

Keywords— Image Processing, Fuzzy Logic, Malaysian Banknotes, Banknote Reader, Counterfeit Detection

I. INTRODUCTION

According to Nabila Hussain's essay "More can be done for the visually impaired"[1], blindness affects about 1.2% of Malaysia's population. A person's daily indoor and outdoor activities will be more challenging if they have vision issues. Some of the difficulties they encounter while performing routine duties include being unable to work or attend school, move about, deal with their surroundings, and carry out easy indoor and outdoor activities on their own or with assistance. Object identification and recognition, using technology for communication, reading writing, travel, and reading money or banknotes are among the most challenging tasks for visually impaired people.

Banknotes are a type of negotiable promissory notes that are issued by a bank or governmental agency as notes or paper money. By letting individuals to pay for goods and services directly rather than through bartering, banknotes help people live easier lives. Vision-good people will be able to tell the difference between a real and fake banknote based on how the watermark image appears on the banknotes. However, it could be difficult for someone with visual impairment to see and identify those watermarks. Researchers in Malaysia have proposed a variety of Ringgit banknote identification systems to help those who are visually challenged identify and categorise Ringgit banknotes [2-8]. However, they can only be used to identify the value of Malaysian Banknote Ringgit. There is no implementation of counterfeit detection in these electronic banknote recognizers. To improve accessibility and recognition of Ringgit Malaysia currency notes for visually impaired users, the banknote recognition system developers are still working hard on detecting fake banknotes.

Using deep learning and the VGG16 algorithm, Indian researchers [9] have developed a vision-based system that can detect and identify Indian rupee notes. This approach is intended to help people who are visually impaired recognise cash notes, even when they are used and worn. With a high categorisation efficiency of 99.07%, the suggested approach can

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lower fraud occurrences and lessen dependency on others for the nation's visually impaired population.

Deep learning (AI) was used by Ethiopian researchers [10] to develop a banknote recognition system for Ethiopian currency. To detect fake notes, various optimisation strategies were used, and several AI models, including Inception V3, MobileNetV2, XceptionNet, and ResNet50, were tested. The MobileNetV2 model with the RMSProp optimisation technique produced the greatest results, with an accuracy of 96.4%. This system, which was created as a web-based programme for the identification of various denominations of Ethiopian banknotes, was developed using a Raspberry Pi computer with a Logitech camera.

Researchers from Malaysia developed the fuzzy logic weighted averaging (FLWA) algorithm in image processing techniques to identify fake Malaysian banknotes [11]. Since the technique is based on human guidance learning and does not require enrolling to obtain the precise weights for each security feature, it has the advantage of being simpler. As it examines the security aspects of the banknotes, the system may identify fake Malaysian banknotes. Each security measure is given the same weight. However, it is anticipated that if the weights for each security feature are further driven, the detection system's accuracy can be increased even more, since the weight assignment in the model is more specific with the various levels of emphasis under consideration.

Hence, an alternative Fuzzy Logic based Weighted Specific (FLWS) Malaysian Banknotes Counterfeit detection algorithm is introduced in this research to explore the possibility of improving the accuracy of counterfeit banknotes detection. The FLWS algorithm has been compared to THREE state-of-the-art parallel methods (VGG16 model using 2D Convolution Layer [9] at TensorFlow's Keras API, MobileNet model using RMSprop Loss Function [10] at TensorFlow's Keras API, and fuzzy logic weighted averaging (FLWA) algorithm [11]). The experimental findings shown that FLWS outperforms the three parallel approaches in terms of accuracy, processing speed, and complexity. Three primary sections are used to classify the study's remaining portions. Section II presents the suggested Fuzzy Logic Weighted Specific (FLWS) Algorithm for Malaysian banknotes readers with counterfeit detection, Section III presents the performance analysis and results, and Section IV concludes the study.

II. FUZZY LOGIC BASED WEIGHTED SPECIFIC (FLWS) MALAYSIAN BANKNOTES COUNTERFEIT DETECTION ALGORITHM

This section discussed the entire process of the Fuzzy Logic-based Weighted Specific (FLWS) Malaysian Banknote Counterfeit Detection Algorithm. Feature extraction method for the eight intended Ringgit watermarks can be viewed in [11]. The Fuzzy Logic based Weighted Specific (FLWS) for Malaysian Banknote Counterfeit Detection Algorithm can be covered in FOURTEEN (14) essential steps, as shown below:

Step 1: Banknote Confirmation: By measuring the received light intensity of the notes, a colour sensor will be utilised to identify the entered banknotes:

$$RLI = [R, G, B] \tag{1}$$

, where R = Red color saturation level, G = Green color saturation level, B = Blue color saturation level.

$$CSL = [CSL_{max}, CSL_{min}, CSL_{diff}] \tag{2}$$

, where CSL_{max} = maximum color saturation level, CSL_{min} = minimum color saturation level, CSL_{diff} = difference between maximum and minimum color saturation level.

The HSV model's foundational attribute, hue, is utilized to appropriately identify or classify colours. Hue enables the identification of colors using a single variable and is expressed as an angle on a color wheel. Next, determine the RGB color model's hue value.

$$\mathrm{H_R} = (60 \times ((\text{G-B}) \div \mathrm{CSL_{diff}})) \tag{3}$$

$$H_G = (60 \times \left((B - R) \div CSL_{diff}\right) + 120) \tag{4}$$

$$H_B = (60 \times \left((R - G) \div CSL_{diff}\right) + 240) \tag{5}$$

IF $(\mathrm{CSL_{max}} == \mathrm{B})\ \mathrm{AND}(\mathrm{H_B} > \mathrm{V_B})$,
THEN the slotted in note can be an RM1 banknote, set the color sensor output, CS=1, proceed to Step 2.
ELSE IF $(CSL_{max} == G)\ AND(H_G \leq V_G)$,
THEN the slotted in note can be an RM5 banknote, set the color sensor output, CS=5, proceed to Step 2.
ELSE IF $(CSL_{max} == R)\ AND(H_R \leq V_R)$,
THEN the slotted in note can be an RM10 banknote, set the color sensor output, CS=10, proceed to Step 2.
ELSE IF $(CSL_{max} == R)\ AND(H_R > V_R)$,
THEN the slotted in note can be an RM20 banknote, set the color sensor output, CS=20, proceed to Step 2.
ELSE IF $(CSL_{max} == G)\ AND(H_G > V_G)$,
THEN the slotted in note can be an RM50 banknote, set the color sensor output, CS=50, proceed to Step 2.
ELSE IF $(CSL_{max} == B)\ AND(H_B \leq V_B)$,

THEN the slotted in note can be an RM100 banknote, set the color sensor output, CS =100, proceed to Step 2.

ELSE Output "The entered currency is NOT Malaysian Banknote".

, where V_R is the value of red in the RGB color model.

V_G is the value of green in the RGB color model.

V_B is the value of blue in the RGB color model.

Step 2: Banknote Position Detection and Re-adjustment: Identify the position of the entered currency and prompt users to make any necessary adjustments. The camera's front light is turned on and is focused on the banknote. When the banknote is laid flat, the camera will take an image of it and save it as "Pos_B." The details of the banknote positioning steps can be found in [11].

Step 3: Capturing a Flat Currency notes Image: Currently, the image "Pos_B" is only in the UPBACK or UPFRONT positions. In addition, the "Pos_B" picture needs to be stored as either "Flat_FB_Flight" for UPFRONT Banknote positions or "Flat_BB_Flight" for UPBACK Banknote positions. Likewise, capture "Flat_FB_Blight" for positions of UPFRONT banknotes or "Flat_BB_Blight" for positions of UPBACK banknotes. The ultraviolet light is activated, the image of the banknote is taken, and it is stored as "Flat_FB_UVlight" for positions of UPFRONT banknote or "Flat_BB_UVlight" for positions of UPBACK banknote.

Step 4: Tilt Banknote and Capture an Image: On the RM10, RM20, and RM50, the tilt mechanism was employed. The tilt will be on both the UPFRONT and UPBACK positions of the RM10 and RM20, whereas the RM50 will only have the tilt on the UPBACK position. Tilt the inserted banknote to $\phi_{optimum}$ the angle that will show the color shifting on the same banknote. Turn on the front light and the camera will capture in the tilted banknote, stored it as "Tilt_FB_Flight" for UPFRONT Banknote positions or "Tilt_BB_Flight" for UPBACK Banknote positions.

Step 5: Fully Capture the Banknote: To obtain the other banknote position, ask the user to take out the banknote, turn it over the banknote and then re-insert it into the Banknote Reader as shown in Fig. 1. Repeated back those steps 1 to 4. Fully capture the banknote mean by having UPFRONT Banknote positions and UPBACK Banknote positions.

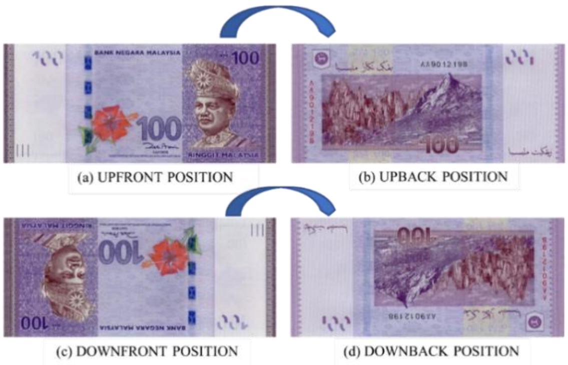

Fig. 1. Reverse the banknote RM100 (A sample).

Step 6: Shadow Image Detection: Detect Shadow Image in RM N, where N = 1 or 5. Perform Shadow Image Detection function [11] and determine the Shadow Image fuzzy membership value, SI_N using:

$$SI_N(\text{Ratio}) = \begin{cases} 0 & \text{if Ratio} \le a \\ \frac{\text{Ratio-a}}{\text{b-a}} & \text{if a} \le \text{Ratio} \le \text{b} \\ \frac{\text{c-Ratio}}{\text{c-b}} & \text{if b} \le \text{Ratio} \le \text{c} \\ 0 & \text{if Ratio} \ge \text{c} \end{cases} \quad (6)$$

, where: $Ratio = H_{SI}/W_{SI}$ is the shadow image bounding box's height (H_{SI}) to width (W_{SI}). N is the number of Ringgit value.

$$a = 2\text{Th}_{SI(min)} - \left(\frac{\text{Th}_{SI(max)} - \text{Th}_{SI(min)}}{2}\right),$$
$$b = 2\text{Th}_{SI(min)} + \left(\frac{\text{Th}_{SI(max)} - \text{Th}_{SI(min)}}{2}\right),$$
$$c = 2\text{Th}_{SI(max)} - \left(\frac{\text{Th}_{SI(max)} - \text{Th}_{SI(min)}}{2}\right).$$

$\text{Th}_{SI(min)}$ and $\text{Th}_{SI(max)}$ are the minimum and maximum threshold of "shadow image" height to width ratio.

Step 7: Watermark Portrait Detection: Detect Watermark Portrait in RM N, where N =10, 20, 50 or 100. Perform Watermark Portrait Detection function [11] and determine the Watermark Portrait fuzzy membership value, WP_N using:

$$WP_N(Ratio, x) = \mu_N(Ratio)\big(\mu_{numeral1}(x) \times \mu_{numeral0}(x) + \mu_{numeral2}(x) \times \mu_{numeral0}(x) + \mu_{numeral5}(x) \times \mu_{numeral0}(x) + \mu_{numeral1}(x) \times \mu_{numeral00}(x)\big) \quad (7)$$

, where $\mu_{numeral\,1}(x)$, $\mu_{\text{numeral }2}(x)$, $\mu_{numeral\,5}(x)$, $\mu_{\text{numeral }0}(x)$, $\mu_{\text{numeral }00}(x)$ are numeral "1" membership function, numeral "2" membership function, numeral "5" membership function, numeral "0" membership function and numeral "00" membership function defined in [11].

Step 8: Perfect See-through Register Detection: Detect Perfect See-through register in RM *N*, where *N* =1, 5, 10, 20, 50 or 100. Perform Perfect See-through Register Detection function [11] and determine the Perfect See-through register fuzzy membership value, PS_N using:

$$\begin{aligned}\mathrm{PS_N}(\mathrm{x}) = {} & \mu_{1,\mathrm{backlight}}(\mathrm{x}) \times \overline{\mu_{1,\mathrm{frontlight}}(\mathrm{x})} \\ & + \mu_{5,\mathrm{backlight}}(\mathrm{x}) \times \overline{\mu_{5,\mathrm{frontlight}}(\mathrm{x})} \\ & + \mu_{1,\mathrm{backlight}}(\mathrm{x}) \times \mu_{0,\mathrm{backlight}}(\mathrm{x}) \\ & \times \overline{\mu_{1,\mathrm{frontlight}}(\mathrm{x})} \times \overline{\mu_{0,\mathrm{frontlight}}(\mathrm{x})} \\ & + \mu_{2,\mathrm{backlight}}(\mathrm{x}) \times \mu_{0,\mathrm{backlight}}(\mathrm{x}) \\ & \times \overline{\mu_{2,\mathrm{frontlight}}(\mathrm{x})} \times \overline{\mu_{0,\mathrm{frontlight}}(\mathrm{x})} \\ & + \mu_{1,\mathrm{backlight}}(\mathrm{x}) \times \mu_{00,\mathrm{backlight}}(\mathrm{x}) \\ & \times \overline{\mu_{1,\mathrm{frontlight}}(\mathrm{x})} \times \overline{\mu_{00,\mathrm{frontlight}}(\mathrm{x})}\end{aligned} \tag{8}$$

, where $\mu_{M,backlight}(x)$ is the numeral "*M*" detected at back light image's membership function and $\mu_{M,frontlight}(x)$ is the numeral "*M*" detected at front light image's membership function defined in [11].

Step 9: Non-transparent Window Detection: Detect Non-transparent Window watermark in RM *N*, where *N* =1, 5. Perform Non-transparent Window Detection function [11] and determine the Non-transparent Window fuzzy membership value, NT_N using:

$$NT_N(Ratio, difference) = SI_N(Ratio) \times \mu_N(difference) \tag{9}$$

, where $SI_N(Ratio)$ is the Shadow Image Detection fuzzy set membership function, as defined in (6). $\mu_N(difference)$ is the difference in Non-Transparent Window pixel's membership function. *difference* = |Blue or Green component for sampled pixel of Star on image "Flat_FB_Blight" - The same coordinate sampled pixel of Star in image "Flat_FB_Flight"|, defined in [11].

Step 10: Color Shifting security thread Detection: Detect Color Shifting Security in RM *N*, where *N* = 10, 20 or 50. Perform Color Shifting security thread Detection function [11] and determine the Color shifting security fuzzy membership value, CSS_N using:

$$\begin{aligned}CSS_N(Ratio, y) = {} & \mu_N(Ratio)\big(\mu_{BLUE}(y) \times \mu_{RED}(y) \\ & + \mu_{GOLD}(y) \times \mu_{GREEN}(y) \\ & + \mu_{RED}(x)\mu_{GREEN}(y)\big)\end{aligned} \tag{10}$$

, where $\mu_N(Ratio)$ is the Color Shifting security thread Bounding Box Ratio membership function: $\mu_{BLUE}(y)$, $\mu_{RED}(y)$, $\mu_{GOLD}(y)$, $\mu_{GREEN}(y)$ are Color shifting of Blue, Red, Gold and Green color membership function defined in [11].

Step 11: Colored Glossy Patch Detection: Detect Colored Glossy Patch in RM *N*, where *N* = 10, 20 or 100. Perform Colored Glossy Patch Detection function [11] and determine the Color glossy patch fuzzy membership value, CGP_N using:

$$CGP_N(Ratio) = \begin{Bmatrix} 0 & if\ Ratio \le a \\ \frac{Ratio-a}{b-a} & if\ \mathrm{a} \le Ratio \le b \\ \frac{c-Ratio}{c-b} & if\ b \le Ratio \le c \\ 0 & if\ Ratio \ge c \end{Bmatrix} \tag{11}$$

, where $Ratio = \mathrm{H_{CGP}}/\mathrm{W_{CGP}}$ is the colored glossy patch bounding box's height ($\mathrm{H_{CGP}}$) to width ($\mathrm{W_{CGP}}$). *N* is the number of Ringgit value.

$a = 2\mathrm{Th_{CGP(min)}} - \left(\frac{\mathrm{Th_{CGP(max)}} - \mathrm{Th_{CGP(min)}}}{2}\right)$,

$b = \left(\mathrm{Th_{CGP(min)}} + \frac{\mathrm{Th_{CGP(max)}} - \mathrm{Th_{CGP(min)}}}{2}\right)$,

$c = 2\mathrm{Th_{CGP(max)}} - \left(\frac{\mathrm{Th_{CGP(max)}} - \mathrm{Th_{CGP(min)}}}{2}\right)$.

$\mathrm{Th_{CGP(min)}}$ and $\mathrm{Th_{CGP(max)}}$ are the minimum and maximum threshold of "colored glossy patch" height to width ratio.

Step 12: Text and Logo Detection: Detect Text and Logo in RM *N*, where *N* = 1, 5, 10, 20, 50 or 100. Perform Text and Logo Detection function [11] and determine the Text and Logo fuzzy membership values, T_N and L_N using:

$$T_N(Ratio) = \begin{Bmatrix} 0 & if\ Ratio \le a \\ \frac{Ratio-a}{b-a} & if\ \mathrm{a} \le Ratio \le b \\ \frac{c-Ratio}{c-b} & if\ b \le Ratio \le c \\ 0 & if\ Ratio \ge c \end{Bmatrix} \tag{12}$$

, where $Ratio = \mathrm{H_{RT}}/\mathrm{W_{RT}}$ is the Rectangle Text bounding box's height ($\mathrm{H_{RT}}$) to width ($\mathrm{W_{RT}}$). *N* is the number of Ringgit value.

$a = 2\mathrm{Th}_{\mathrm{RT(min)}} - \left(\frac{\mathrm{Th}_{\mathrm{RT(max)}} - \mathrm{Th}_{\mathrm{RT(min)}}}{2}\right)$,

$b = \left(\mathrm{Th}_{\mathrm{RT(min)}} + \frac{\mathrm{Th}_{\mathrm{RT(max)}} - \mathrm{Th}_{\mathrm{RT(min)}}}{2}\right)$,

$c = 2\mathrm{Th}_{\mathrm{RT(max)}} - \left(\frac{\mathrm{Th}_{\mathrm{RT(max)}} - \mathrm{Th}_{\mathrm{RT(min)}}}{2}\right)$.

$\mathrm{Th}_{\mathrm{RT(min)}}$ and $\mathrm{Th}_{\mathrm{RT(max)}}$ are the minimum and maximum threshold of "Rectangle Text" bounding box height to width ratio.

$$L_N(Ratio) = \begin{Bmatrix} 0 & if\ Ratio \leq a \\ \frac{Ratio-a}{b-a} & if\ \mathrm{a} \leq Ratio \leq b \\ \frac{c-Ratio}{c-b} & if\ b \leq Ratio \leq c \\ 0 & if\ Ratio \geq c \end{Bmatrix} \tag{13}$$

, where $Ratio = \mathrm{H}_L/\mathrm{W}_L$ is the Logo bounding box's height (H_L) to width (W_L). *N* is the number of Ringgit value.

Step 13: Two Color Fluorescent Element Detection: Detect Two Color Fluorescent Element in RM *N*, where *N* = 1, 5, 10, 20, 50 or 100. Perform Two Color Fluorescent Element Detection function in [11] and determine the Two color fluorescent element membership value, $TCFE_N$ using:

$$TCFE_N(Ratio) = \begin{Bmatrix} 0 & if\ Ratio \leq a \\ \frac{Ratio-a}{b-a} & if\ \mathrm{a} \leq Ratio \leq b \\ \frac{c-Ratio}{c-b} & if\ b \leq Ratio \leq c \\ 0 & if\ Ratio \geq c \end{Bmatrix} \tag{14}$$

, where $Ratio = H_{TCFE}/W_{TCFE}$ is the shadow image bounding box's height ($\mathrm{H_{TCFE}}$) to width ($\mathrm{W_{TCFE}}$). *N* is the number of Ringgit value.

$a = 2\mathrm{Th}_{\mathrm{TCFE(min)}} - \left(\frac{\mathrm{Th}_{\mathrm{CFE(max)}} - \mathrm{Th}_{\mathrm{CFE(min)}}}{2}\right)$,

$b = \left(\mathrm{Th}_{\mathrm{TCFE(min)}} + \frac{\mathrm{Th}_{\mathrm{TCFE(max)}} - \mathrm{Th}_{\mathrm{TCFE(min)}}}{2}\right)$,

$c = 2\mathrm{Th}_{\mathrm{TCFE(max)}} - \left(\frac{\mathrm{Th}_{\mathrm{TCFE(max)}} - \mathrm{Th}_{\mathrm{TCFE(min)}}}{2}\right)$.

$\mathrm{Th}_{\mathrm{TCFE(min)}}$ and $\mathrm{Th}_{\mathrm{TCFE(max)}}$ are the minimum and maximum threshold of "Two-color flouresent element" bounding box height to width ratio.

Step 14: Decision making Apply fuzzy logic based Weighted Specific (FLWS) Malaysian Banknote Counterfeit Detection algorithm below:

(i) **Keep a record of the output of the inferred security features** from steps 6 through 13 in the form of x_y *(SI_y, WP_y, PS_y, NT_y, CSS_y, CGP_y, T_y, L_y and $TCFE_y$)*, where *x* denotes the security feature for a specific Malaysian banknote and y denotes the value of that read Malaysian banknote.

For instance, in the example of reading a RM1 banknote, the banknote reader was able to recognise *SI*, *PS*, and *NT* very well but was unable to or detected *TCFE* and *T*. The result for the sample used to draw conclusions is $SI_1 = 0.9$, $PS_1 = 0.8$, $NT_1 = 0.7$, $TCFE_1 = 0.2$, and $T1 = 0.1$.

(ii) **Conduct a series of** *M* (advise 1,000 turns or more is best) **experiments** to determine the accuracy for each security feature for a specific Malaysian Banknote(WS_{SI}, WS_{WP}, WS_{PS}, WS_{NT}, WS_{CSS}, WS_{CGP}, WS_T, WS_L and WS_{TCFE}). Each security feature's normalized accuracy is as follows:

$$\mathrm{ACC}\ (\mathrm{WS}_{x,\mathrm{RM}y}) = \frac{SuccessfulAtt}{M} \tag{15}$$

, where *x* is the security feature for a particular Malaysian Banknote, *y* is the particular read Malaysian Banknote value and *SuccessfulAtt* is the number of attempts that a particular security feature successfully detected by the banknote reader.

(iii) **Determine the Experimented Weightage Specific WS** for each of these security features by:

$$\mathrm{WS}_{x,\mathrm{RM}y} = \frac{\mathrm{ACC}\ (\mathrm{WS}_{x,\mathrm{RM}y})}{\sum_{n=1}^{\mathrm{MNSF_{RM}}y} \mathrm{ACC}\ (\mathrm{WS}_{x,\mathrm{RM}y})_n} \tag{16}$$

, where *x* is the security feature for a particular Malaysian Banknote, *y* is the particular read Malaysian Banknote value and MNSF is the number of Security Features selected for testing the particular *y*-value Malaysian banknotes.

For instance, in the example to obtain the Weighted Specific of Security Features in RM1, *y* is 1. *x* is SI, PS, NT, TCFE and TL. $\mathrm{MNSF_{RM1}}$ is 5. $\mathrm{ACC}\left(\mathrm{WS_{SI,RM1}}\right) = 1.0$, $\mathrm{ACC}\left(\mathrm{WS_{PS,RM1}}\right) = 0.8$, $\mathrm{ACC}\left(\mathrm{WS_{NT,RM1}}\right) = 0.6$, $\mathrm{ACC}\left(\mathrm{WS_{TCFE,RM1}}\right) = 0.4$, and $\mathrm{ACC}\left(\mathrm{WS_{TL,RM1}}\right) = 0.2$. Hence $\mathrm{WS_{SI,RM1}} = 0.333$, $\mathrm{WS_{PS,RM1}} = 0.267$, $\mathrm{WS_{NT,RM1}} = 0.2$, $\mathrm{WS_{TCFE,RM1}} = 0.133$ and $\mathrm{WS_{T,RM1}} = 0.067$.

(iv) **Determine the de-fuzzified output**:

$$D_{FLWS} = \frac{\sum_{n=1}^{MNSF_{RMy}} (x_y^n) \times \mathrm{WS}_{x,RMy}^n}{\sum_{n=1}^{MNSF_{RMy}} \mathrm{WS}_{x,RMy}^n} \tag{17}$$

For example, continue from (i) and (iii),

$$D_{FLWS} = \frac{(0.9\times0.33)+(0.8\times0.27)+(0.7\times0.2)+(0.2\times0.13)+(0.1\times0.07)}{0.333+0.267+0.2+0.133+0.067}$$
$$= 0.69$$

(v) **Banknote counterfeit detection decision making** is based on a set of rules:

IF CS = =1 AND $D_{FLWS} \geq \mathrm{THRESHOLD_{RM1}}$, THEN output "It is a real RM1 banknote".
ELSE IF CS= =5 AND $D_{FLWS} \geq \mathrm{THRESHOLD_{RM5}}$, THEN output "It is a real RM5 banknote".
ELSE IF CS= =10 AND $D_{FLWS} \geq \mathrm{THRESHOLD_{RM10}}$, THEN output "It is a real RM10 banknote".
ELSE IF CS= =20 AND $D_{FLWS} \geq \mathrm{THRESHOLD_{RM20}}$, THEN output "It is a real RM20 banknote".
ELSE IF CS= =50 AND $D_{FLWS} \geq \mathrm{THRESHOLD_{RM50}}$, THEN output "It is a real RM50 banknote".
ELSE IF CS==100 AND $D_{FLWS} \geq \mathrm{THRESHOLD_{RM100}}$, THEN output "It is a real RM100 banknote".
ELSE Output: "It is not a Malaysian banknote".

, where CS is colour sensor output (1 =RM1, …., 100 = RM100)
$\mathrm{THRESHOLD_{RM1…RM100}}$ is the acceptable Threshold value set for deciding the real banknote. Normally set to at least half or up to two-third (meaning at least half or two-third of the selected Security Features successfully detected for the Malaysian banknote).

For example, refer to (iv), if the CS =1 and $\mathrm{THRESHOLD_{RM1}}$ set is 0.667 (two-third of the selected security features for RM1 are detected), then $D_{FLWS} = 0.6866 \geq \mathrm{THRESHOLD_{RM1}} = 0.667$, "It is a real RM1 banknote".

III. RESULTS AND DISCUSSION

The experimental findings for the FLWS Malaysian banknote counterfeit detection algorithm will be covered in this part. The related dataset and threshold used in the algorithm can be referred to ref. [11]. A. Parameter Setup and Optimization in paper [11]. Training was carried out with extracting the watermarks of 1,000 pieces of real banknotes for each RM1, RM5, RM10, RM20, RM50, RM100 category to define the assigned weightage for their corresponding security features based on the success/failure to detect the corresponding security features. The security features for RM1, RM5, RM10, RM20, RM50, RM100 and the corresponding success/failure are listed in Table I. Table II calculated out the assigned weights (WS_{SI}, WS_{WP}, WS_{PS}, WS_{NT}, WS_{CSS}, WS_{CGP}, WS_{T}, WS_{L} and WS_{TCFE}) using Eq. (15) for the corresponding banknotes according to data from Table I.

The acceptable Threshold value selected to determine the real banknote in decision-making, as demonstrated in Step 14, is 0.66 (indicating that the Malaysian banknote's selected security features were effectively identified in at least two-thirds of the cases.). Experimental test was further carried out with 1,000 pieces of real Malaysian banknotes and 1,000 pieces of fake Malaysian banknotes for each type of Malaysian Banknotes. The four possible outcomes for the banknote identification scenario are listed in Table III.

In summary, the recommended banknote reader obtained around 100%, 100%, 100%, 97.50%, 100%, and 100% accuracy for RM1, RM5, RM10, RM20, RM50, and RM100, detection respectively. Overall, the system has an accuracy of up to 99.58% in recognising the correct banknote value and counterfeit detection.

False Positive and False Negative cases are given special consideration since they could result in the visually impaired person losing their business's credit. However, for RM20, there still exist 50 banknote detection cases related to False Negative class. After further investigating these 50 False Negative cases, it is found that around 50 samples of real RM20 aging banknotes with poor and faded color quality were used in the experimental testing for the counterfeit banknote reader. Coloured Glossy Patch, Two Colour Fluorescent elements, and Colour Shifting security watermarks were weakly detected in these 50 pieces of banknotes. Watermark Portrait security feature also hardly detected in these 50 pieces real RM20 banknotes due to the watermarks captured is less embossed. Since this is the issue of the real banknotes' quality, the issue is still awaiting to be solved. In the worst- case scenario, omitting the related watermark extraction/consideration (Coloured Glossy Patch, Two Colour Fluorescent elements, Colour Shifting security and Watermark Portrait security) or assigning a lighter weightage for these watermarks in the total RM20 counterfeit detection would be the optimum solution.

The proposed FLWS Malaysian banknote readers' detection accuracy and processing speed are also compared with three state-of-the-art methods: 1) MobileNet model using RMSprop Loss Function (learning rate = 0.0001) at TensorFlow's Keras API [10], 2) VGG16 model using 2D Convolution Layer (32 neural) at TensorFlow's Keras API [9] and 3) Fuzzy Logic Weighted Averaging (FLWA) algorithm [11]. MobileNet and VGG16 models are deep learning models that are used for image classification tasks.

These models were used in a Jupiter notebook to detect real and fake Malaysian banknotes, follow these steps:

1. Collect and prepare a dataset of images of real and fake notes. This dataset should be split into training and testing sets.
2. Import the necessary libraries, such as TensorFlow and Keras, which will be used to build and train the MobileNet model and VGG16 model.

Table I: Chosen security features on Malaysian Banknotes.

No.	Security Features	Success/Failure Detection (from 1000 Notes)					
		RM1	RM5	RM10	RM20	RM50	RM100
1.	Shadow Image (SI)	948/52	893/107	—	—	—	—
2.	Watermark Portrait (WP)	—	—	715/285	781/219	754/246	832/168
3.	Perfect See-through Register (PS)	746/254	714/286	956/44	927/73	—	836/164
4.	Non-transparent Window (NT)	905/95	872/128	—	—	—	—
5.	Colour Shifting Security Thread (CSS)	—	—	727/273	792/208	736/264	—
6.	Coloured Glossy Patch (CGP)	—	—	754/246	796/204	—	873/127
7.	Text (T)	836/164	914/86	1000/0	927/73	1000/0	832/168
8.	Logo (L)	917/83	1000/0	918/82	925/75	936/64	836/164
9.	Two Colour Fluorescent Element (TCFE)	954/46	1000/0	836/164	791/209	1000/0	1000/0

Table II: Assigned weight security for Malaysian Banknote.

No.	Weight Security (WS_x)	Assigned Weighting Specific ($WS_{x,\mathrm{RM}y}$)					
		RM1	RM5	RM10	RM20	RM50	RM100
1.	WS_{SI}	0.1787	0.1655	—	—	—	—
2.	WS_{WP}	—	—	0.1211	0.1315	0.1704	0.1597
3.	WS_{PS}	0.1406	0.1324	0.1619	0.1561	—	0.1605
4.	WS_{NT}	0.1706	0.1617	—	—	—	—
5.	WS_{CSS}	—	—	0.1231	0.1334	0.1663	—
6.	WS_{CGP}	—	—	0.1277	0.1340	—	0.1679
7.	WS_T	0.1576	0.1695	0.1693	0.1561	0.2259	0.1676
8.	WS_L	0.1728	0.1854	0.1554	0.1557	0.2115	0.1597
9.	WS_{TCFE}	0.1797	0.1854	0.1416	0.1332	0.2259	0.1919
Total		1	1	1	1	1	1

Table III: Confusion matrix banknote detection results for FLWS Algorithm.

Outcome \ *N*	RM1	RM5	RM10	RM20	RM50	RM100
True positive (The predicted RM *N* banknote is real, and it actually is a real RM *N* banknote)	1000	1000	1000	950	1000	1000
True negative (The predicted RM *N* banknote is fake, and it actually is a fake RM *N* banknote)	1000	1000	1000	1000	1000	1000
False positive (The predicted RM *N* banknote is real, and it actually is a fake RM *N* banknote)	0	0	0	0	0	0
False negative (The predicted RM *N* banknote is fake, and it actually is a real RM *N* banknote)	0	0	0	50	0	0

3. Use the MobileNet and VGG16 architecture, which is a pre-trained model, as a starting point for your model.
4. Use the training data to fine-tune the model by training it on the dataset of real and fake notes images with batch size = 32 and epochs = 20.
5. Use the model to make predictions on new images of real and fake notes.

Experimental setup for method 1: It is understood that the model MobileNet with Loss Function RMSProp was selected with its best accuracy of about 96.80% in the ref. [10]. Convolutional Neural Networks using MobileNet model with Loss Function RMSProp (0.0001) optimisation technique being trained with Malaysian banknotes captured with front light, flat positioned (1,000 different attempts for each RM1, RM5, RM10, RM20, RM50 and RM100) and tested with another one-thousand real (RM1, RM5, RM10, RM20, RM50 and RM100) and one-thousand fake (RM1, RM5, RM10, RM20, RM50 and RM100) banknotes. The average time to load the model and build up the interpreter objects (Training time) was 810 seconds, and the average inference time while modelling detecting banknotes (Testing time) was 1 second. The overall test Accuracy is 72.95%.

Experimental setup for method 2: Total of one-thousand different attempts for each (RM1, RM5, RM10, RM20, RM50 and RM100) Malaysian banknotes captured with front light, flat positioned as the dataset for training the model. VGG16 model using 2D Convolution Layer (32 neural) at TensorFlow's Keras API being trained and tested with 1000 real (RM1, RM5, RM10, RM20, RM50 and RM100) and 1000 fake (RM1, RM5, RM10, RM20, RM50 and RM100) banknotes. The average time to load the model and build up the interpreter objects (Training time) was 600 seconds, and the average inference time while modelling detecting banknotes (Testing time) was 1 second. The overall test Accuracy is 78.83%. The accuracy and required processing time for the experimented methods and the proposed FLWA and FLWS Malaysian banknote readers were summarised in Table IV to Table VII below.

Table IV: Accuracy & processing time for Method 1 MobileNet Model.

Accuracy						Processing Time	
		True positive	True negative	False-positive	False-negative	Training Time (Per 1000 banknotes)	Banknote Detection Time (Per banknote)
MobileNet model using RMSprop Loss Function (learning_rate =0.0001) at TensorFlow's	RM1	570	1000	0	430	810 Second	1 Second
	RM5	130	1000	0	870	810 Second	1 Second
	RM10	340	1000	0	660	810 Second	1 Second
	RM20	370	1000	0	630	810 Second	1 Second
	RM50	990	1000	0	100	810 Second	1 Second
	RM100	690	1000	0	310	810 Second	1 Second

Table V: Accuracy & processing time for Method 2 VGG16 Model.

Accuracy						Processing Time (second)	
		True positive	True negative	False-positive	False-negative	Training Time (Per 1000 banknotes)	Banknote Detection Time (Per banknote)
VGG16 model using 2D Convolution Layer (32 neural) at TensorFlow's Keras API	RM1	1000	40	960	0	600	1
	RM5	1000	1000	0	0	600	1
	RM10	960	1000	0	40	600	1
	RM20	200	1000	0	800	600	1
	RM50	260	1000	0	740	600	1
	RM100	1000	1000	0	0	600	1

Table VI: Accuracy & processing time for FLWA Malaysian Banknote counterfeit detection.

Accuracy						Processing Time (second)	
		True positive	True negative	False-positive	False-negative	Banknote Detection Time (Per 1000 banknotes)	Banknote Detection Time (Per banknote)
FLWA Malaysian Banknote Counterfeit Detection Algorithm	RM1	978	1000	0	22	11,480	11.48
	RM5	974	1000	0	26	11,480	11.48
	RM10	877	1000	0	123	11,480	11.48
	RM20	903	1000	0	97	11,480	11.48
	RM50	1000	1000	0	0	11,480	11.48
	RM100	964	1000	0	36	11,480	11.48

Table VII: Accuracy & processing time for FLWS Malaysian Banknote counterfeit detection.

Accuracy						Processing Time (second)	
		True positive	True negative	False-positive	False-negative	Weight enrolment Time (Per 1000 banknote)	Banknote Detection Time (Per banknote)
FLWS Malaysian Banknote	RM1	1000	1000	0	0	840	11.48
	RM5	1000	1000	0	0	840	11.48
	RM10	1000	1000	0	0	980	11.48

Counterfeit Detection Algorithm	RM20	950	1000	0	50	980	11.48
	RM50	1000	1000	0	0	700	11.48
	RM100	1000	1000	0	0	840	11.48

Fast banknote recognition systems are a benefit of the MobileNet and VGG16 models. Initially, they were methods for identifying the denomination of banknotes. In comparison to FLWA and FLWS model, they do not have feature extraction methods to extract banknote watermarks, which results in lesser accuracy in Malaysian banknote counterfeit detection. They also need a lot more enrolment information than other parallel approaches need in order to execute the banknotes detection more accurately.

It was discovered that the FLWS increased the accuracy of FLWA with the precise weightage assignment on each of the watermarks, with a better level of attention consideration, when compared to the results provided in Tables VI and VII. The proposed FLWS model has the advantages of much higher accuracy than FLWA model since the weight assignment in the model is more specific with the different levels of emphasis under consideration. However, FLWS model has the disadvantage of slightly complex algorithm than FLWA since it requires an enrolment process to get the specific weights for each security feature.

IV. CONCLUSION

A brand-new Ringgit Counterfeit Detection method (FLWS) based on fuzzy logic image processing has been developed and put to the test. Due to the watermark extraction approaches incorporated into it, experimental findings demonstrate that the developed FLWS outperforms the cutting-edge MobileNet model, VGG16 model, and FLWA model for Malaysian banknote counterfeit detection in terms of accuracy. Given that varying levels of emphasis are taken into consideration, the suggested FLWS model has the advantage of being substantially more accurate than the parallel FLWA model. The FLWS model, however, has the drawback of having a significantly more complicated algorithm because it needs an enrolment process to obtain the precise weights for each security features. Future extends may investigate several essential aspects to enhance the proposed algorithms. This includes covering more tests on worn and heavily faded banknotes to cater to those dynamic issues and more security elements like security fibres and Intaglio watermarks. Due to the lack of high-resolution UV imaging techniques to capture these micrometre-sized particles seen on the banknotes, security fibres cannot be covered in the current investigation. Intaglio watermarks were also left out of the current study because of the heightened printing impact when touched. To extract intaglio watermarks, a unique mechanism was needed. The Malaysian banknote counterfeit detection algorithm will be able to be employed in real-time with good counterfeit detection accuracy owing to the addition of these two security components, making banknote detection more resilient and reliable.

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