Thai Banknote Image Recognition with Convolutional Neural Network (CNN)

Chomtip Pornpanomchai, Krissanapong Palakham

Faculty of Information and Communication Technology (ICT), Mahidol University

999 Phuttamonthon 4 Road, Salaya, Nakhon Pathom, 73170, Thailand

(**E-mail:** chomtip.por@mahidol.ac.th, krissanapong.pal@student.mahidol.ac.th)

Abstract

Nowadays, a banknote is most frequently used around the world that represents a currency in order to pay, exchange, collect as well as donate to poor people. Although many people are using online technology such as internet banking and mobile banking, many people are also using the banknote because it is an easy way to use and very convenient. However, many people have a physical impairment which is blindness. Blind people cannot see and identify how much money they have. The Thai Banknote Recognition is an image recognition application by using GUI as a thing to recognize. The Thai Banknote Recognition Database stored data of 1,213 images of banknotes including 20, 50, 100, 500, and 1,000 Baht that have an accuracy of 97.05, 96.13, 97.6, 95.35, and 96.07 percent respectively. The average access time is about 1.3659 seconds per image.

I. Introduction

Nowadays, more than two million currencies are used by several countries around the world. A banknote, which was used in many nations for trading, making purchases, and displaying income, is one item that represents cash. Most people have healthy bodies that allow them to distinguish between different banknotes depending on their value or number. However, there are about 39 million blind people in the world. [1] Many people who go blind lose their eyesight, one of the most important parts of our body. Due to their inability to recognize, locate, identify, and differentiate between environmental objects, people are unable to even identify the value of banknotes, and the only thing they can see is a black image. In addition, 80% of blind people are lived in the continue developing country, and using money are also continuously changing; [1] Thailand is one of them.

Thailand is a country in the South-East Asia Region with an estimated population of 66 million. By a large number of populations in Thailand, there are approximately 369,013 people who are blinded. However, everyday life in Thailand is challenging for blind people because of unaccommodated pavement and walking streets. [2] Therefore, blindness is increasing this challenge as well as banknote recognition that they do not know although touching it by hand. Thailand banknotes are issued in five denominations including 20 Baht, 50 Baht, 100 Baht, 500 Baht, and 1,000 Baht with different features, such as sizes, colors, identified numbers, watermarks, and textures as well as general values. [3]

Figure 1 *Example of Thai Banknotes Series 17*

Currently, blind people keep different value banknotes in the distributed pocket in order to identify them. However, they must be assisted by a third person to classify it by telling them. Artificial Intelligence (AI) improvements and technology developments are enabled to use in advanced technical performance in order to recognize the actual value of each banknote or currency for making blind people acknowledge.

The banknote recognition has several methodologies to detect and recognize whether neural networks, Markov model, Principal Component Analysis (PCA), Speed-Up Robust Features (SURF), K-Nearest Neighbor (KNN), or Fuzzy Logic. [1]

Therefore, the primary objective of this research is to develop a computer system that will enable blind persons to recognize the actual value of each banknote. People who are blind would recognize the amount of money they possess. Additionally, it can be used by regular people with the developed technology for recognizing a banknote, such as an automatic teller machine (ATM).

II. Literature Review

Several researchers and scientists worldwide used to develop the methodology of banknote recognition in order to distinguish each country's banknote, fake banknote searching, and implementation for blind people. They applied many techniques to proceed with their experiment; the details are as follows:

a. Speed Up Robust Features (SURF)

SURF is one of the most popular features which can be used to generate scale-invariant and rotation-invariant interest points with detectors and descriptors. [4] Hasanuzzman, Yang, and Tian used the SURF technique to develop banknote recognition for assisting impaired people. The experiment achieved 100% recognition accuracy for all seven classes, as shown in Table 1. [4] In another experiment, Larisa, Mónica, Guillermo, and Ismael used the SURF technique to recognize the EURO banknote for blind people blending with a Haar-like feature. Banknote detection and value recognition accuracy were 84% and 97.5%, respectively. [1] Sanchez also used this technique to recognize banknotes for blind people via smartphone. The experiment achieves 98% of recognition with a 100% true recognition rate and 0% false recognition rate. [5]

Ground Truth	No. of images	False Positive	True Positive
$1	20	0	100%
$2	20	0	100%
$5	20	0	100%
$10	20	0	100%
$20	20	0	100%
$50	20	0	100%
$100	20	0	100%

Table 1 *A summary table of the experiment of the SURF technique*

b. Haar-like Features

Haar-like features identify the interest zone instead of pixel scanning with the scalar values that represent the different averages between two rectangles. [1] [6] Larisa, Mónica, Guillermo, and Ismael used this technique for the EURO banknote recognition experiment to increase the modification by approximately 10% of the hit rate detector by using the SURF technique as a recognition algorithm. Increased performance provides high accuracy for banknote recognition including 84% and 97.5% of banknote detector and banknote value recognition respectively. [1]

c. Convolutional Neural Network (CNN)

CNN is a powerful deep learning technique that built several neurons with learnable weights and biases. Imad, Ullah, Hassan, and Naimullah used this technique to develop Pakistani banknote recognition for blind people. The experimental accuracy that recognized seven banknotes of Pakistani is successfully at 96.85%. [7]

d. Hidden Markov Models (HMM)

HMM has employed banknote surfaces as a random process that can read all values with different denominations to distinguish the value of a banknote. [8] [9] Hassanpour and Hallajian used this method to distinguish 101 different denominations from 23 countries. In the experiment, the performance results of applying this methodology to 23 countries' banknotes can be indicated as 95% accuracy. [8] Abbas and Anisheh also used this method with the Fourier-Mellin and Support Vector Machine to recognize the different denominations from 23 countries. They applied several experiments with 40% torn, worn, and rotated banknotes from the database. In the experiment, the proposed techniques achieved the result of 98.7% accuracy. [9]

e. Support Vector Machine (SVM)

SVM is a classifier derived from statistical learning which finds the maximum margin hyperplane to separate training data into two groups. The SVM has advantages in solving main problems including high dimensional data and high generalization performance as well as finding the correctly optimal hyperplane. [9] [10] Chi-Yuan, Wen-Pin, and Shie-Jue used this technique with multiple-kernel to recognize the counterfeit banknote. The experiment has four rounds applied to a banknotes data set that achieved 93.548% accuracy. [10] Bo-Yuan, Mingwu, Xu-Yao, and Ching also used this technique to recognize part-based serial numbers in banknotes. In the experiment, they separated results into two parts including baseline recognition results containing 98.90% with Linear kernel and 99.31% with RBF kernel, and part-based recognition results containing 99.27% with Linear kernel and 99.43% with RBF kernel. [11]

f. K-Nearest Neighbor (KNN)

KNN is a methodology that classified objects based on the nearest training point by declaring distances based on Euclidean Distance. [12] Hardani, Luthfianto, and Tamam used this classification method to identify the authenticity of the Rupiah banknote. The result of this experiment showed an accuracy rate of 100% for k=1, 77.78% for k=3, and 55.56% for k=5. [13] Raho, Al-Khiat, and Al-Hamami also used this methodology to recognize cash currencies. The experiment applied this model to 100 banknotes with a success accuracy of 91% and 9% failure. [14]

III. Methodology and Material

This part provides several methodologies for processing banknote recognition. The description contains the system conceptual diagram and system structure chart that are processed on MacBook Pro (13-inch, 2020, Two Thunderbolt 3 ports), 1.4 GHz Quad-Core Intel Core i5 Processor, RAM 8 GB 2133 MHz LPDDR3, Graphics Intel Iris Plus Graphics 645 1536 MB with MATLAB 2020a Software for coding. Other materials are iPhone 11, 64 GB, and iPad Air Generation 5^{th}, 256 GB to prepare images. The description of methodologies is as follows:

The Thai Banknote Recognition System starts with finding some banknotes for all prices including 20, 50, 100, 500, and 1,000 Baht. Then, use a phone or tablet that can take a picture for the banknote. In this experiment, we took 1,213 images covering all prices including 238 images of 20 Baht, 233 images of 50 Baht, 250 images of 100 Baht, 237 images of 500 Baht, and 255 images of 1,000 Baht. After we took pictures, we perform the Convolutional Neural Network (CNN) by using MATLAB software to process both training and testing. We keep the final result in the Thai Banknote Recognition in a database and also display it to users. The Thai Banknote recognition system conceptual diagram is shown in Figure 2.

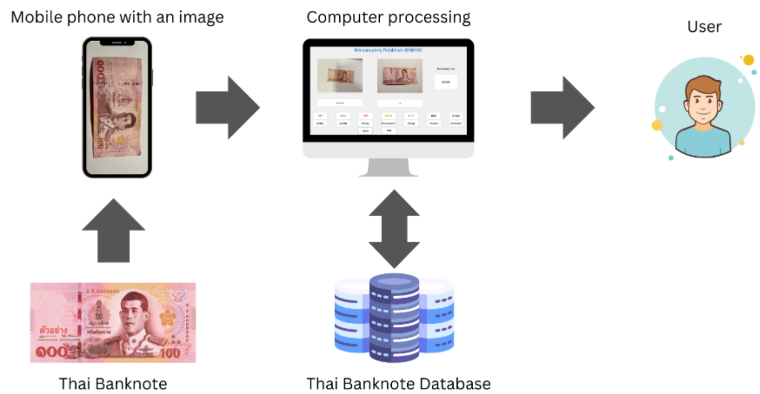

Figure 2 *The Thai Banknote recognition system conceptual diagram*

According to the process of Thai Banknote recognition, we provide the structure chart of this process as shown in Figure 3. The process until we put the data into a computer system, we use MATLAB to perform the step-by-step process in order to get a final result.

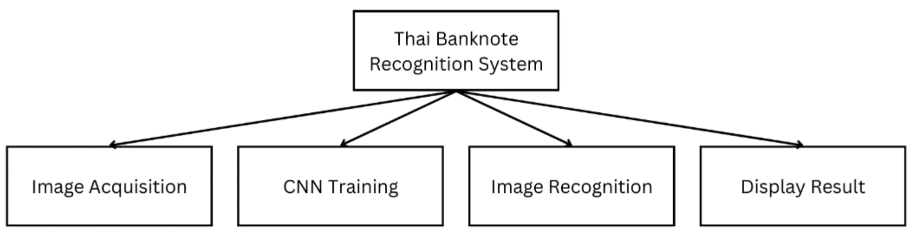

Figure 3 *The Thai Banknote recognition system structure chart*

1. **Image Acquisition** – We start with image acquisition that used the module captured banknotes that are laid on an A4 paper and ground. All photos that are used in this project are taken by iPhone 11 mobile phone and iPad Air Generation 5^{th} Tablet with took both front and back of the banknote. The image acquisition includes image resizing to resize the received image. For example, the 1000 Baht banknote has 3024*4032 pixels, we have to resize it into 224*224 pixels for processing in the same size picture. However, each picture has a different size, but it has to resize into 224*224 pixels. All images are taken from 22 August to 8 September 2022 and used for this research.

2. **Convolutional Neural Network (CNN) Training** – This research employed the CNN training called "ResNet50" in MATLAB software for training and testing the banknote. The ResNet-50 is the 50 layers that received data as 224*224 in order to reduce computational costs by enabling the training of data with fewer data sets. [15] The output of ResNet50 is selected from the highest percentage of feature matching. The banknote recognition system is performed by separating into 2 parts including train and test data. The training data is 80 percent of all images, and the test data is 20 percent of all images or the remaining train data. The processing time of training data is about $1.3873*10^2$ seconds to train all data.

3. **Image Recognition** – This process starts by taking other pictures to try to recognize that the received image price has the same as the output price. The processing time of recognition is 1.3659 seconds to recognize the image output.

4. **Display Result** – This process is to display the result of banknote recognition. We perform a GUI for this project in order to receive and display both input images and output images as shown in Figure 4. The GUI parts that are really used in this research are contained as follows:
    a. The window of the input image as shown in Figure 4, label 1
    b. The window of the output image as shown in Figure 4, label 2
    c. The display of processing time to recognize as shown in Figure 4, label 3
    d. The display of input filename image as shown in Figure 4 label 4
    e. The display of output banknote price as shown in Figure 4 label 5
    f. The button to get an input image as shown in Figure 4 label 6
    g. The button to recognize a banknote image as shown in Figure 4 label 7
    h. The button to clear both input and output as shown in Figure 4 label 8
    i. The button to exit the GUI as shown in Figure 4 label 9

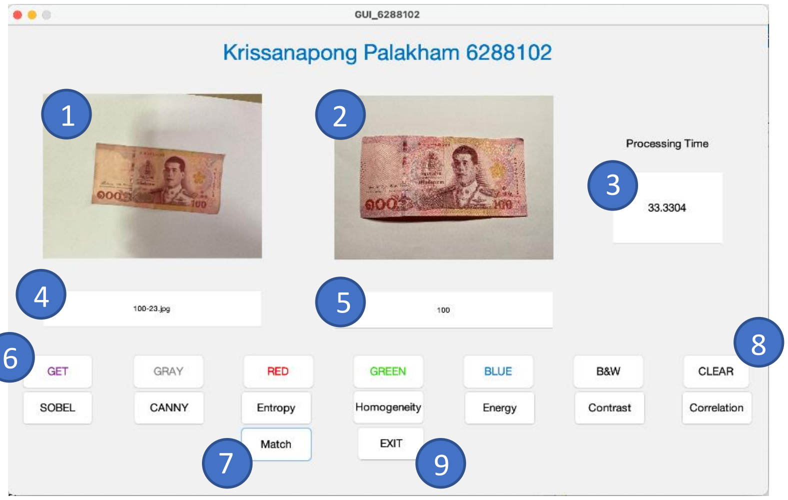

Figure 4 *The GUI of the Banknote Recognition System*

IV. Experiment and Result

The experiment of this research was conducted on 1,213 images which are 833 mobile phone images and 360 tablet images which is easily accessed. The experiment of the recognition system is shown in Table 2.

Bank price	**Testing Number**	**Matched**	**Mismatched**
20 Baht	238	231	7
50 Baht	233	224	9
100 Baht	250	244	6
500 Baht	237	226	11
1000 Baht	255	245	10
Total	1,213	1,170	43

Table 2 *Experimental table of Banknote Recognition*

V. Conclusion

In this research, Thai Banknote Recognition fulfilled the research objectives by using the CNN model to recognize a banknote price for blind people. The computer systems are assisted and useful to perform, process as well as recognizing a banknote correctly. The ResNet50 in MATLAB allows us to build a deep learning technique in order to recognize a banknote and finish this research with high-quality output. The statistics that represent a performance are matched and unmatched images. The output of this experiment matched 1,170 images and mismatched 43 images which is a low rate of mismatched that can be really implemented by users. Moreover, the processing time of training data is about $1.3873*10^2$ seconds to train all data and the processing time of recognition data is about 1.3659 seconds to recognize each output. The accuracy of each banknote including 20, 50, 100, 500, and 1,000 Baht contained an accuracy of 97.05, 96.13, 97.6, 95.35, and 96.07 percent respectively.

VI. Acknowledgement

The authors would like to thank everyone who supported us at the Faculty of Information and Communication Technology (ICT), Mahidol University.

VII. References

[1] D. D. Larisa, C. P. Mónica, P.-F. Guillermo and L. L. Ismael, "Euro Banknote Recognition System for Blind People," *Sensors 2017*, vol. 17, no. 1, pp. 1-13, 20 January 2017.

[2] W. Jenchitr and S. Raiyawa, "Refractive errors: the major visual impairment in Thailand," *Rangsit Journal of Arts and Sciences*, vol. 2, no. 2, pp. 133-141, 2012.

[3] Bank of Thailand, "Circulating Banknotes," [Online]. Available: https://www.bot.or.th/English/Banknotes/HistoryAndSeriesOfBanknotes/pages/current_series_of_banknotes.aspx. [Accessed 16 September 2022].

[4] H. M. Faiz, Y. Xiaodong and T. YingLi, "Robust and Effective Component-based Banknote Recognition by SURF Features," *WOCC*, pp. 1-6, 2011.

[5] S. Ruiz and A. Gustavo, "A Computer Vision-Based Banknote Recognition System for the Blind with an Accuracy of 98% on Smartphone Videos," *Journal of The Korea Society of Computer and Information*, vol. 24, no. 6, pp. 67-72, June 2019.

[6] T. Mita, T. Kaneko and O. Hori, "Joint Haar-like Features for Face Detection," *Proceedings of the Tenth IEEE International Conference on Computer Vision* , vol. 2, no. 1, pp. 1619-1626, November 2005.

[7] M. Imad, F. Ullah, M. A. Hassan and N. , "PakistaniCurrency Recognition to Assist Blind Person Based on Convolutional Neural Network," *Journal of Computer Science and Technology Studies (JCSTS),* vol. 2, no. 2, pp. 12-19, 2020.

[8] H. Hassanpour and E. Hallajian, "Using Hidden Markov Models for Feature Extraction in Paper Currency Recognition," *Computer Science,* pp. 1-5, 2007.

[9] A. Yaseri and S. M. Anisheh, "A Novel Paper Currency Recognition using Fourier Mellin Transform, Hidden Markov Model and Support Vector Machine," *International Journal of Computer Applications,* vol. 61, no. 7, pp. 17-22, January 2013.

[10] Y. Chi-Yuan, S. Wen-Pin and L. Shie-Jue, "Employing multiple-kernel support vector machines for counterfeit banknote recognition," *Applied Soft Computing,* vol. 11, no. 1, pp. 1439-1447, 2011.

[11] F. Bo-Yuan, R. Mingwu, Z. Xu-Yao and S. Y. Ching, "Part-Based High Accuracy Recognition of Serial Numbers in Bank Notes," *Artificial Neural Networks in Pattern Recognition, Lecture Notes in Computer Science,* vol. 8774, p. 204–215, 2014.

[12] B. T. Rodel Emille, E. R. Arboleda, A. Andilab and R. M. Dellosa, "Implementation Of Template Matching, Fuzzy Logic And K Nearest Neighbor Classifier On Philippine Banknote Recognition System," *International Journal of Scientific & Technology Research,* vol. 8, no. 8, pp. 1451-1453, August 2019.

[13] D. N. K. Hardani, T. Luthfianto and M. T. Tamam, "Identify The Authenticity of Rupiah Currency Using K Nearest Neighbor (K-NN) Algorithm," *Jurnal Ilmiah Teknik Elektro Komputer dan Informatika (JITEKI),* vol. 5, no. 1, pp. 1-7, June 2019.

[14] G. I. Raho, A. Al-Khiat and A. H. Al-Hamami, "Cash Currencies Recognition Using k-Nearest Neighbor Classifier," *International Journal of Web & Semantic Technology (IJWesT),* vol. 6, no. 4, pp. 11-21, October 2015.

[15] A. Çınar, M. Yıldırım and Y. Eroğlu, "Classification of Pneumonia Cell Images Using Improved ResNet50 Model," *Traitement du Signal,* vol. 38, no. 1, pp. 165-173, February 2021.