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Thai Currency Classification Application for Visually Impaired Persons

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Abstract

This research presents an application designed to assist visually impaired individuals in identifying Thai banknotes and coins. The application utilizes image processing and machine learning techniques, specifically a Convolutional Neural Network with ResNet101 architecture, to accurately classify 11 types of Thai currency. It is designed for offline use on smartphones, providing real-time audio and text output to enhance accessibility and understanding for users with visual impairments. The dataset includes 2,593 images of Thai banknotes and coins, split into 80% for training and 20% for testing. The application employs the trained model to conduct real-world tests using a smartphone camera, testing with actual banknotes and coins, achieving an average accuracy of 92.73%.

Keywords: *Banknotes; coins; smart app; classification; currency; Thai banknote; Thai currency; mobile app*

1. Introduction

Currently, individuals with visual impairments face significant challenges in carrying out essential activities such as financial transactions, including making and receiving payments. The inability to visually identify coins or banknotes leads to difficulties in managing daily financial activities and also impacting their privacy in spending. Although applications have been developed in other countries to aid in identifying coins and banknotes, such as the currency of Hong Kong by Ng et al., (2020) and Ethiopian money by Aseffa et al., (2022), in Thailand, the development has been focused on Thai banknotes only, as seen in the research by Sirikham et al., (2009). However, there is still a lack of precise tools for recognizing both Thai banknotes and coins.

To address these needs, we have developed an application using deep learning technology, specifically employing Convolutional Neural Networks (CNN), trained on a large dataset of Thai banknotes and coins to improve accuracy in identifying and classifying these currencies. Testing the accuracy of popular models such as ResNet50, ResNet101, ResNet152, MobileNet, and VGG16 revealed that ResNet101 was the most effective for this task due to its superior ability to recognize specific features of banknotes and coins.

This research has developed an application to classify Thai banknotes and coins, using a smartphone camera to scan the desired currency and providing real-time feedback in both text and Thai voice. This allows users to independently recognize and differentiate currency types. This development not only helps visually impaired individuals gain greater independence in managing their finances but also demonstrates the effective use of technology to solve social problems.

1.1 Related research.

At present, numerous research studies are focused on classifying various foreign currencies using different methods, both to assist visually impaired individuals and to detect counterfeit banknotes. However, studies specifically aimed at helping visually impaired individuals accurately identify Thai currency, particularly in both banknotes and coins, are still relatively scarce. In this regard, researchers have reviewed related academic articles and the summary is presented in Table 1.

Table 1 Summary of Research on Coin and Banknote Classification Methods

Classification Method	Research Title	Authors	Type of Currency	Accuracy	Advantages	Limitations
Convolutional Neural Network (CNN)	An Intelligent Banknote Recognition System by using Machine Learning with Assistive Technology for Visually Impaired People	Ng et al., (2020)	Hong Kong	80-100%	- Assists visually impaired in accurate banknote identification - Offline processing, no internet dependency - Accessible via audio and vibration feedback for the blind	- Limitations in recognizing worn or old banknotes - Requires high-resolution camera on smartphones
	Ethiopian Banknote Recognition Using Convolutional Neural Network and Its Prototype Development Using Embedded Platform	Aseffa et al., (2022)	Ethiopia	96.4%	- Accurate, practical for real-world use	Not specified
CNN (YOLO-v3)	YOLO-v3 Based Currency Detection and Recognition System for Visually Impaired Persons	Joshi et al., (2020)	India	95.71% - 100%	- Accurate, fast operation	Not specified
CNN (YOLO-v4)	Graph elements of banknotes of the Republic of China detection and recognition based on deep learning algorithm	Wang et al., (2021)	Yuan	91.83%	- Accurate detection	Not specified
Faster R-CNN on Raspberry Pi 4	Real-time Bangladeshi Currency Detection System for Visually Impaired Person	Sarker et al., (2019)	Bangladesh	97.8%	- High accuracy in banknote classification - Practical in various environments - Enhances independence for the visually impaired	Not specified
CNN & Visible-light Line Sensor	Multi-National Banknote Classification	Pham, Lee, & Park (2017)	Yuan, Euro, Yen, Won, Ruble, Dollar	100%	- High accuracy	- Limited by the need for pre-classification by size
Enhanced CNN in Quaternion Wavelet Domain	Banknote Classification in Quaternion Wavelet Domain	Huang, & Gai (2020)	Dollar, Euro, Ruble, Yuan	99.28%	- High accuracy in multi-national banknote classification - Efficient in complex image recognition - Real-time classification	- Requires high computational resources - Complexity in real-world deployment
CNN for Portrait Detection and Classification	Banknote Portrait Detection Using Convolutional Neural Network	Kitagawa et al., (2017)	Multi-national banknotes with portraits	60.03%	- Accurate and quick detection of portraits on banknotes - Applicable to various countries' banknotes	- Potential for detection errors - Requires training data improvement

Table 1 Cont.

Classification Method	Research Title	Authors	Type of Currency	Accuracy	Advantages	Limitations
Faster R-CNN and ResNet	Deep Feature-Based Three-Stage Detection of Banknotes and Coins for Assisting Visually Impaired People	Park et al., (2020)	Jordan and Korea	Not specified but mentioned improved detection in all environments	- Effective detection in diverse environments including folded banknotes and reflective lighting	- Potential errors in coin detection - Further improvements needed for detecting small objects like coins
Multispectral Sensors for ATM	Fake Banknote Detection Using Multispectral Images	Kang, & Lee (2016)	Korean and US banknotes	Not specified	- Efficient in detecting counterfeit banknotes - Applicable to multiple countries	- Requires adequate training data - Limited processing capability for real-time ATM operation
Morphology	Morphology-Based Banknote Fitness Determination	Lee et al., (2019)	Euro, Ruble	Not specified	- Detects banknote dirtiness	- Requires high-quality banknote images and complex processing
Image Processing & VC++	A Kind of Automatic Banknote Sorting Device Based on Vision	Zhou (2018)	Chinese banknotes	Not specified	- Works with industrial cameras, suitable for flat banknotes in small batches	- Requires image angle adjustment to determine banknote size
Accelerated-KAZE (AKAZE) Algorithm	HOMER: Cryptography based Currency Detection System for Visually Impaired People	Jangir et al., (2020)	Indian banknotes	90%	- Enhances banknote identification for the blind - Effective and accurate detection - Practical in real-world scenarios	Not specified
Texture Features & MLSVMs	Banknote Dirty Degree Identification Method Based on Texture Features of Banknote Images and Multi-Layer Support Vector Machines	Sun et al., (2021)	Chinese banknotes	<= 51%	- Accurate in identifying banknote dirtiness - Uses complex techniques for efficient classification	- Requires complex image processing and data analysis - May not be accurate in all situations
Camera & Microcontroller	Banknote and Coin Speaker Device for Blind People	Sirikham et al., (2009)	Thai banknotes and coins	80%	- Works with Thai banknotes and coins - Aids the blind in identifying monetary value	- Accuracy decreases with new and old banknotes of different colors - Requires controlled lighting conditions
Support Vector Machine (SVM)	Parameters Learning of BPS M7 Banknote Processing Machine for Banknote Fitness Classification	Kongprasert, & Chongstitvatana (2019)	Thai 100 Baht notes	87.29% - 87.51%	- Increases accuracy in classifying suitable and unsuitable banknotes	- Requires detailed testing and adjustment of SVM model parameters for optimal accuracy

Table 1 Cont.

Classification Method	Research Title	Authors	Type of Currency	Accuracy	Advantages	Limitations
Template Matching with Image Processing	Automatic South African Coin Recognition Through Visual Template Matching	Sooruth, & Gwetu (2018)	South African Coins	91.67%	- Utilizes image processing techniques to extract three key features: radius, color, and texture - Radius calculated via Circular Hough Transform - Color determined using K-Means clustering - Texture extracted from Local Binary Patterns - Capable of recognizing coins regardless of their rotation	- Potential limitations in recognizing coins with very similar characteristics - Requires high-quality image data for accurate feature extraction

Table 1 shows that research developed to assist visually impaired individuals in recognizing Thai currency, including both coins and banknotes, is still relatively limited, with accuracy levels below 90%, which is not highly precise. This is in contrast to the classification of foreign currencies for the visually impaired, where developments have achieved accuracies of 90% and above.

Therefore, the development of an application for individuals with visual impairments has been undertaken, enabling the classification of different types of Thai coins and banknotes. The application is designed for use on smartphones, providing audio output and the capability to operate without an internet connection, facilitating real-time display and interaction. This research encompasses related theories, procedural steps, experimentation, discussion, and the summarization of results, as detailed in the subsequent sections.

1.2 Theory

1.2.1 CNN

According to Saha (2018), a Convolutional Neural Network (ConvNet/CNN) is a type of deep learning algorithm specifically effective for processing images. It assigns importance to different aspects or objects within an image through learnable weights and biases, allowing it to distinguish between them. This makes ConvNets highly efficient, requiring less preprocessing than other classification algorithms. Unlike traditional methods where filters are manually engineered, ConvNets are capable of learning these features autonomously with adequate training. The architecture of ConvNets is inspired by the human brain's visual cortex, where each neuron responds to stimuli within a restricted field known as the receptive field. These receptive fields overlap, ensuring comprehensive coverage of the visual area, mimicking the way the human brain processes visual information.

1.2.2 ResNet101

ResNet101 (Kalshetty, & Parveen, 2023) is a commonly used deep neural network architecture for image classification tasks. ResNet101 is part of the Residual Networks (ResNet) family, which is a type of Convolutional Neural Network (CNN) designed to efficiently handle very deep network architectures. The ResNet architecture, including ResNet101, is highly popular due to its ability to train networks with many layers, up to several hundred, effectively. Details about the architecture are discussed in the following section**.**

ResNet101 architecture

The ResNet101 architecture consists of a total of 101 layers, and it is known for its use of residual blocks that include skip connections or shortcuts. These shortcuts allow data from the input layer of a block to be added directly to its output layer. This design mitigates the problem of performance degradation (where accuracy plateaus and then decreases during training as the network depth increases) by allowing the training of deeper networks.

The main components of ResNet101 as shown in Figure 1, can be described in sections as follows:

1. Initial Layers:

Single Convolution Layer: The network begins with a 7x7 convolutional layer that has 64 filters and a stride of 2.

Max Pooling: This is followed by a 3x3 max pooling layer with a stride of 2.

2. Residual Blocks:

The core of ResNet1 0 1 consists of multiple residual blocks, each containing three layers:

1x1 Convolution (Dimension Reduction): Used to reduce the dimensionality.

3x3 Convolution: The main convolutional layer that processes the data.

1x1 Convolution: Increases the dimensionality back to match the residual (shortcut) connection.

These blocks are arranged in groups with varying numbers of blocks and filters.

3. Final Layers:

Global Average Pooling: Positioned before the final classification layer.

Fully Connected Layer: A dense layer with a softmax activation function that maps the output to a probability distribution over the desired classes.

The advantages of ResNet101 are as follows:

1. Deep Network Structure: Capable of modeling complex patterns due to its depth.

2. Residual Blocks: Help avoid the problem of vanishing gradients through the use of skip connections, enabling the training of deep networks.

3. Versatility: Efficient in various tasks beyond image classification, including object detection and segmentation.

1.2.3 TensorFlow Lite

According to TensorFlow's official documentation, TensorFlow Lite is optimized for mobile and embedded devices, enabling efficient execution of machine learning models directly on devices such as smartphones (TensorFlow, n.d.). This capability is crucial for applications requiring real-time processing without connectivity to server-based computing resources. An application that uses TensorFlow Lite for smartphones can be a powerful tool for a wide range of applications. TensorFlow Lite is a lightweight version of the TensorFlow machine learning library designed for use on mobile devices and other resource-constrained devices.

1.2.4 Confusion matrix for multiclass classification

The confusion matrix for multi-class classification (Jayaswal, 2021) is a method used to assess the accuracy of a classification model. It is presented as a table that displays the number of correct and incorrect predictions made by the model, subdivided by each class. Each row of the matrix represents instances in an actual class, while each column represents instances in a predicted class. The main diagonal of the matrix shows the number of correct predictions for each class, and the off-diagonal elements indicate misclassifications, as shown in Figure 2.

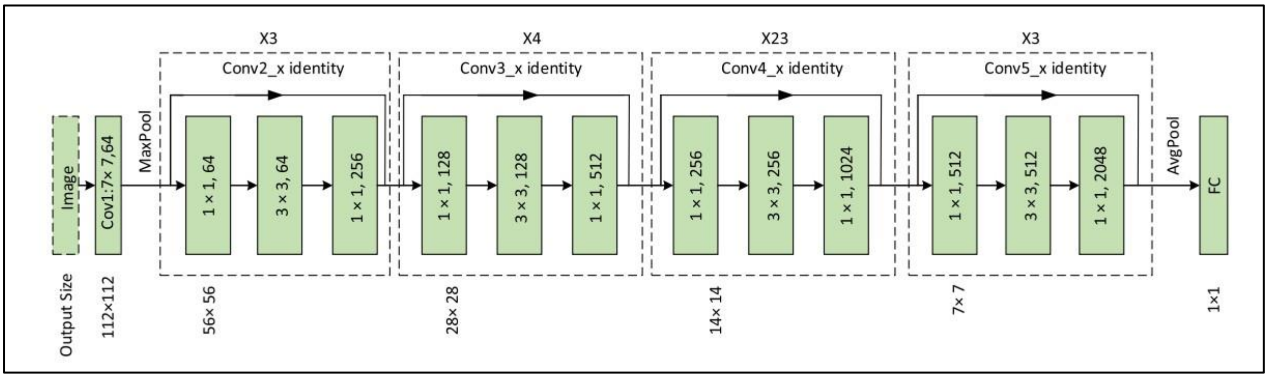


Figure 1 Architecture of ResNet101
Source: Kalshetty, & Parveen, 2023

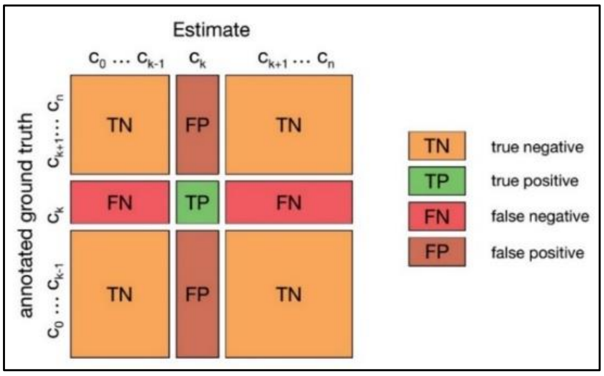


Figure 2 Confusion matrix for multiclass classification
Source: Padmanabhan, & Dubey, 2019.

In Figure 2, the Confusion matrix for multi-class classification is displayed. The following explanations can be given for the values of TP, TN, FP, and FN:

True Positive (TP) is the model correctly predicts the positive class (both prediction and actual values are positive).

True Negative (TN) is the model correctly predicts the negative class (both prediction and actual values are negative).

False Positive (FP) is the model incorrectly predicts the negative class as positive (predicted positive, actual negative).

False Negative (FN) is the model incorrectly predicts the positive class as negative (predicted negative, actual positive).

Jayaswal (2021) provides a detailed explanation of various performance metrics such as the confusion matrix, precision, recall, and F1 score, which are crucial in evaluating the effectiveness of classification models. The formulas for calculating Overall Accuracy, Precision, Recall, and F1 score as shown in equations (1)-(4) are as follows:

$$\text{Overall Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

$$\text{F1 score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

The formulas for calculating Macro Average (Macro avg.) and Weighted Average (Weighted avg.), precision, recall, and F1 score are shown in equations (5)-(10).

1. Macro Average (Macro avg.):

$$\text{Macro Precision} = \frac{(\text{Precision\_Class1} + \text{Precision\_Class2} + ... + \text{Precision\_ClassN})}{N} \tag{5}$$

$$\text{Macro Recall} = \frac{(\text{Recall\_Class1} + \text{Recall\_Class2} + ... + \text{Recall\_ClassN})}{N} \tag{6}$$

$$\text{Macro F1 Score} = \frac{(\text{F1 Score\_Class1} + \text{F1 Score\_Class2} + ... + \text{F1 Score\_ClassN})}{N} \tag{7}$$

2. Weighted Average (Weighted avg.) as shown in equations (8)-(10):

$$\text{Weighted Precision} = \frac{(\text{Precision\_Class1} * \text{Support\_Class1} + ... + \text{Precision\_ClassN} * \text{Support\_ClassN})}{\text{Total Support}} \tag{8}$$

$$\text{Weighted Recall} = \frac{(\text{Recall\_Class1} * \text{Support\_Class1} + ... + \text{Recall\_ClassN} * \text{Support\_ClassN})}{\text{Total Support}} \tag{9}$$

$$\text{Weighted F1 Score} = \frac{(\text{F1 Score\_Class1} \times \text{Support\_Class1} + ... + \text{F1 Score\_ClassN} \times \text{Support\_ClassN})}{\text{Total Support}} \tag{10}$$

Where:

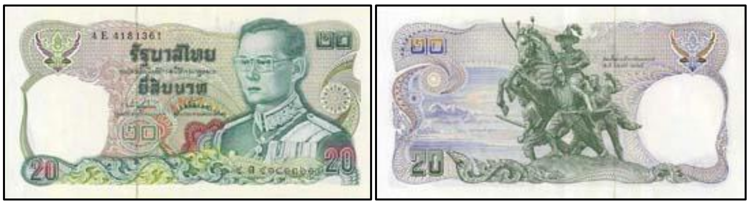
- N is the number of classes in the classification.
- Precision_ClassX, Recall_ClassX, F1 Score _ClassX are the Precision, Recall, and F1 Score values for Class X.
- Support_ClassX is the number of examples in Class X.
- Total Support is the sum of the number of examples across all classes.

1.2.5 Thai currency

The Thai currency used in this study consists of current banknotes and coins, detailed as follows.

Thai Banknotes

According to information from the Bank of Thailand (2023), the current Thai banknotes in circulation include the 20 Baht, 50 Baht, 100 Baht, 500 Baht, and 1,000 Baht notes. The 20 Baht note is the smallest, predominantly green in color, as shown in Figure 3. The 50 Baht note is slightly larger than the 20 Baht note and is primarily blue, as depicted in Figure 4. The 100 Baht note is larger than the 50 Baht note and predominantly red, as shown in Figure 5. The 500 Baht note is larger than the 100 Baht note, primarily purple in color, as depicted in Figure 6. The 1,000 Baht note is the largest, predominantly brown, as shown in Figure 7.



(a) (b)

Figure 3 Thai 20 Baht banknote, front (a) and back (b)

(a) (b)

Figure 4 Thai 50 Baht banknote, front (a) and back (b)

(a) (b)

Figure 5 Thai 100 Baht banknote, front (a) and back (b)

(a) (b)

Figure 6 Thai 500 Baht banknote, front (a) and back (b)

(a) (b)

Figure 7 Thai 1,000 Baht banknote, front (a) and back (b)

(a) (b)

Figure 8 Thai 25 Satang coins, front (a) and back (b)

(a) (b)

Figure 9 Thai 50 Satang coins, front (a) and back (b)

(a) (b)

Figure 10 Thai 1 Baht coin, front (a) and back (b)

(a) (b)

Figure 11 Thai 2 Baht coin, front (a) and back (b)

(a) (b)

Figure 12 Thai 5 Baht coin, front (a) and back (b)

(a) (b)

Figure 13 Thai 10 Baht coin, front (a) and back (b)

Thai Coins

According to the Royal Thai Mint (2024), Thai coins come in a variety of sizes, shapes, and designs, making them an interesting and diverse form of currency. According to Thailand Circulation (2024), the current circulating coins in Thailand are available in denominations of 25 satang, 50 satang, 1 Baht, 2 Baht, 5 Baht, and 10 Baht. The 25 satang and 50 satang coins are small, round, and brass-colored, as shown in Figures 8 and 9, respectively. The 1 Baht coin is slightly larger and thicker, as illustrated in Figure 10. The 2 Baht coin is larger and thicker than the 1 Baht coin, as depicted in Figure 11. The 5 Baht coin, made of nickel-clad steel, is larger and thicker than the 2 Baht coin, as shown in Figure 12. The largest and thickest coin is the 10 Baht, made from nickel-clad brass, as illustrated in Figure 13.

2. Objectives

The objectives of this research are as follows.

1) To develop an application for individuals with visual impairments, enabling them to classify different types of Thai coins and banknotes.

2) To design the application for use on smartphones, providing both audio output and the ability to operate without an internet connection, allowing for real-time display and interaction.

3. Experimental

Process of Smart Thai Coin and Banknote Application

The working process of the Smart Thai Coin and Banknote Application, as depicted in Figure 14, consists of the following crucial steps:

1) Install Application: This step is performed during the initial installation of the application on the device.

2) Open Camera: When the application is launched, the camera automatically opens, enabling users to utilize the camera functionality.

3) Test with Thai Coins and Banknotes: Users can use the application to test and identify various types of Thai coins and banknotes. They can capture images of the coins or banknotes using the camera.

4) Display Text and Sound: Upon detecting a Thai coin or banknote, the application displays relevant text information on the screen and provides real-time voice output, indicating the type of coin or banknote. This functionality operates without the need for an internet connection.

5) End Process: Users can close the application or terminate the process when they have finished using it.

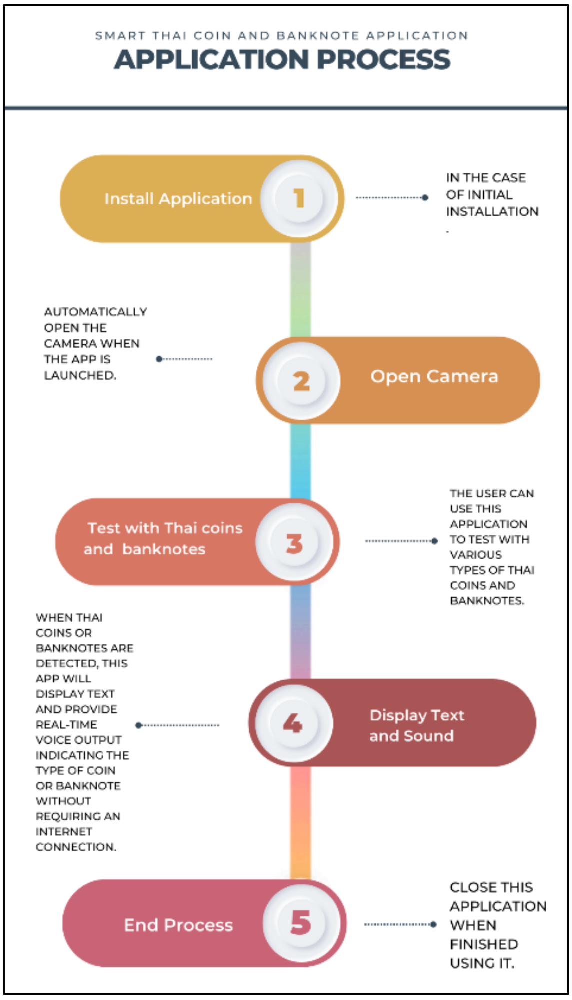


Figure 14 Application process

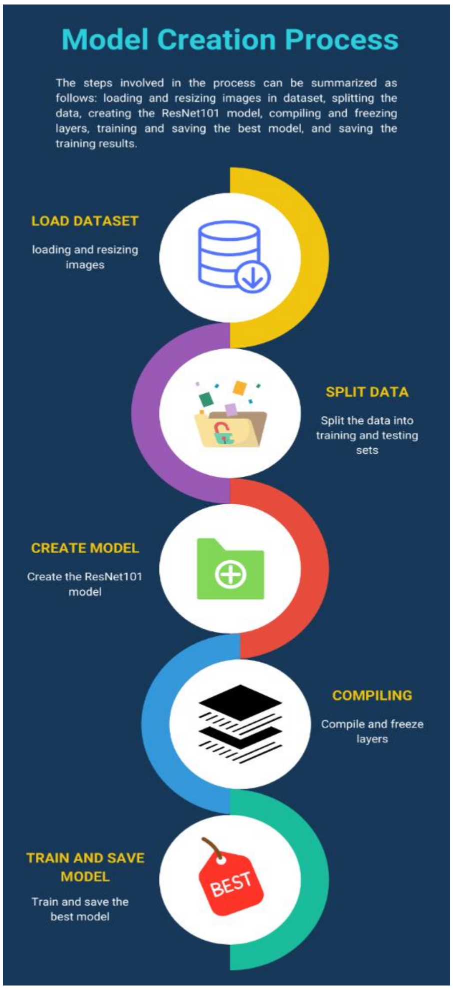


Figure 15 Model creation process

Figure 15 illustrates the steps involved in creating the model, which consists of 5 main steps, as explained in detail below.

1. Load the dataset. The first step is to load the images from the dataset and resize them to the desired size. This is done using OpenCV to load and convert the images from Blue, Green, Red (BGR) to Red, Green, Blue (RGB) and resize them to 224x224 pixels.

2. Split the data. Divide the data into 80% training set and 20% test set.

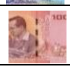
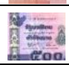
3. Create a model using the ResNet101 model.

4. Compile after the model is created.

5. Train and Save the Model In this step, training of the ResNet101 model starts using the previously separated training and testing datasets. This model is trained to learn and improve the accuracy of its predictions. The batch size was set to 32. The learning rate was set to 0.001 for 150 epochs. The results of model training were saved as a Comma-Separated Values (CSV) file. Additionally, the training results were saved as a graph in an image file format to provide a clear summary of the training outcomes. The pandas library is used to read and manipulate data in a tabular format, and matplotlib.pyplot is used to create clear and informative graphs to visualize the training results.

Table 2 presents a summary of images used to train the ResNet101 model. There are sample images of the 11 classes used to train the ResNet101 model. The classes consist of the following coin and banknote denominations: .25 represents a 25 Satang coin, .50 represents a 50 Satang coin, 1 represents a 1 Baht coin, 2 represents a 2 Baht coin, 5 represents a 5 Baht coin, 10 represents a 10 Baht coin, 20 represents a 20 Baht banknote, 50 represents a 50 Baht banknote, 100 represents a 100 Baht banknote, 500 represents a 500 Baht banknote, and 1,000 represents a 1,000 Baht banknote.

Table 2 Summary of Images Used to Train the ResNet101 Model

No.	Class name	Sample image (224x224 pixels)	Number of images
1	25 Satang		177
2	50 Satang		268
3	1 Baht		250
4	2 Baht		219
5	5 Baht		255
6	10 Baht		241
7	20 Baht		291
8	50 Baht		200
9	100 Baht		249
10	500 Baht		243
11	1,000 Baht		200
Summary of images			2,593

From Table 2, each row represents the class and the number of images used for testing to build the model as follows: 177 images of 25 Satang coin, 268 images of 50 Satang coin, 250 images of 1 Baht coin, 219 images of 2 Baht coin, 255 images of 5 Baht coin, 241 images of 10 Baht coin, 291 images of 20 Baht banknote, 200 images of 50 Baht banknote, 249 images of 100 Baht banknote, 243 images of 500 Baht banknote, and 200 images of 1,000 Baht banknote. The total number of images and banknotes used for testing to build the model is 2,593 images.

4. Results

In this study, we investigated and compared the average accuracy of various models such as ResNet50, ResNet101, ResNet152, MobileNet, and VGG16 using a dataset consisting of a total of 2,593 images, categorized into 11 classes. The classes include 25 Satang with 177 images, 50 Satang with 268 images, 1 Baht with 250 images, 2 Baht with 219 images, 5 Baht with 255 images, 10 Baht with 241 images, 20 Baht with 291 images, 50 Baht with 200 images, 100 Baht with 249 images, 500 Baht with 243 images, and 1,000 Baht with 200 images. Each class was divided into training and testing sets with a ratio of 80:20 respectively. The training process was conducted over a total of 150 epochs, with a learning rate set at 0.001 and a batch size of 32.

Table 3 presents the average accuracy values for each model used in classifying types of Thai currency, ranging from 0.25 to 1,000 Baht, using a test dataset comprising 2,593 images as mentioned in Table 2. It is observed that ResNet101 has the highest average accuracy of approximately 98.83%, indicating that this model is the most effective among those compared for this dataset. ResNet50 has a slightly lower average accuracy than ResNet101, at about 98.72%, which still represents a very high level of accuracy. ResNet152 has an average accuracy of around 98.03%. MobileNet shows a credible average accuracy of approximately 96.28%, indicating good performance, although not as high as the ResNet models. VGG16 has the lowest average accuracy at approximately 93.24%.

Table 3 The average accuracy values of the models compared with the created dataset (Thai coins and Banknotes)

No	Model	Average Accuracy (%)
1	ResNet50	98.72
2	ResNet101	98.83
3	ResNet152	98.03
4	MobileNet	96.28
5	VGG 16	93.24

The test results from Table 3 show that the ResNet101 model has the highest average accuracy of 98.83% compared to the other models in the table, so we use this model. We tested it with the Thai banknote dataset from IEEE Dataport (Meshram et al., 2020) to develop the model and evaluate its performance by calculating the average accuracy. The results obtained from this dataset were then compared with the results from the newly created dataset. As shown in Table 4, we divided 80% of the training data and 20% of the testing data from the entire dataset.

Table 4 Average accuracy of the Thai banknote model compared to generated and existing datasets

No	Model	Created data set (%)	Existing data set (%)
1	ResNet50	96.87	91.01
2	ResNet101	97.96	91.85
3	ResNet152	96.89	89.23
4	MobileNet	93.61	87.47
5	VGG 16	90.10	77.54

Table 4 shows the average accuracy of the model compared with the newly created dataset and the existing dataset. (Thai banknotes only) as follows:

- The dataset generated by the ResNet101 model has the highest average accuracy of 97.96%, which is higher than the average accuracy of the existing dataset of 91.85%.

- The ResNet50 model has an average accuracy comparable to the created dataset at 96.87% and shows good accuracy with the existing dataset at 91.01%.

- The ResNet152 model scores an average accuracy with the created dataset at 96.89% and with the existing dataset at 89.23%.

- The MobileNet model records an average accuracy with the created dataset at 93.61% and with the existing dataset at 87.47%.

- The VGG16 model has the lowest average accuracy among the group with the created dataset at 90.10% and with the existing dataset at 77.54%.

The analysis indicates that the ResNet models, particularly ResNet101, perform better in classifying Thai banknotes than the other models, even though there are some variations when comparing the newly created dataset and the existing dataset. The differences in accuracy between these two datasets may stem from the diversity of samples and the distribution of data within each dataset.

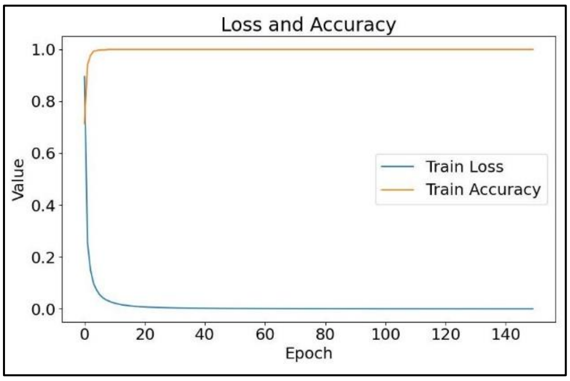


Figure 16 Loss and accuracy

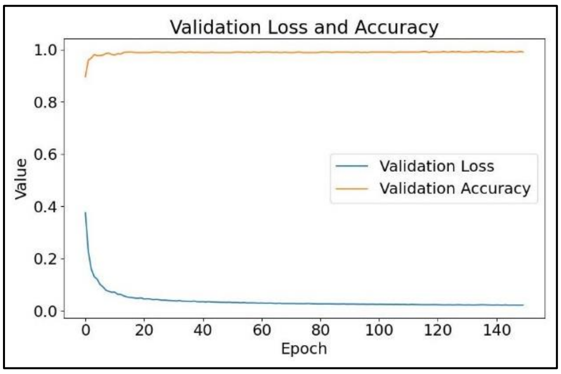


Figure 17 Validation loss and accuracy

Table 5 Precision, recall, F1-Score, and support values

No	Class	Precision	Recall	F1-Score	Support
1	0.25	1.00	1.00	1.00	177.00
2	0.5	1.00	1.00	1.00	268.00
3	1	1.00	1.00	1.00	250.00
4	2	1.00	1.00	1.00	219.00
5	5	1.00	1.00	1.00	255.00
6	10	1.00	1.00	1.00	241.00
7	20	1.00	1.00	1.00	291.00
8	50	0.99	1.00	1.00	200.00
9	100	1.00	0.99	1.00	249.00
10	500	1.00	1.00	1.00	243.00
11	1,000	0.99	1.00	0.99	200.00
Accuracy		1.00	1.00	1.00	1.00
Macro average		1.00	1.00	1.00	2,593.00
Weighted average		1.00	1.00	1.00	2,593.00

From the results presented in Figure 16 and Figure 17, it can be concluded that the model generated demonstrates excellent predictive performance. Starting from epoch 9, the accuracy of the model is consistently high, reaching 1 or 100%, and the loss steadily decreases, approaching 0, in the validation data from epoch 119 onwards. The validation accuracy measures at 0.9904 or approximately 99.04%, which falls within the average range of 99.04-99.23%. Furthermore, the loss in the training process consistently decreases, reaching a minimum value of 0 in each training cycle. The val_loss value approaches 0 and the val_acc value approaches 1, indicating that the model has effective prediction ability. and can be used to classify Thai coins and banknotes. Next are the test results for precision, recall, F1 score, and support values, shown as in Table 5

Table 5 shows the Precision, Recall, F1-Score, and Support values for each class according to Thai currency classification ranging from 25 and 50 satang, 1, 2, 5, 10, 20, 50, 100, 500 and 1,000 Baht. Using the ResNet101 model, it can be explained as follows.

- Precision indicates the correctness of predictions when the model identifies an example as belonging to a particular class—whether that example truly belongs to that class.

- Recall refers to the rate at which the model correctly identifies examples of a particular class compared to the total number that should have been identified as that class.

- F1-Score is the harmonic mean of Precision and Recall, providing an overall picture of the model's accuracy and coverage in classifying examples into that class.

- Support is the actual number of test data examples for each class.

For most classes, the Precision, Recall, and F1-Score values are a perfect 1.00, indicating perfect accuracy and completeness in predictions, except for classes 50, 100, and 1,000, which have Recall and/or F1-Score values of 0.99, still reflecting very high accuracy. The overall model accuracy, Macro average, and Weighted average all score 1.00, suggesting the model performs exceptionally well overall.

Figure 18 displays the confusion matrix from a study using the ResNet101 model, which shows its performance across 11 different class categories representing various denominations of Thai currency: 0.25, 0.50, 1, 2, 5, 10, 20, 50, 100, 500, and 1,000 Baht. The matrix is explained as follows:

- The horizontal axis (x-axis) represents the labels predicted by the model.

- The vertical axis (y-axis) represents the actual labels from the test data.

- Each cell in the matrix shows the number of predictions made by the model for each class combination.

- The cells on the main diagonal (from the top left to the bottom right) represent the number of True Positives (TP), where the model's predictions match the actual labels. These cells are darker than the others, indicating higher values, and signal the model's accuracy.

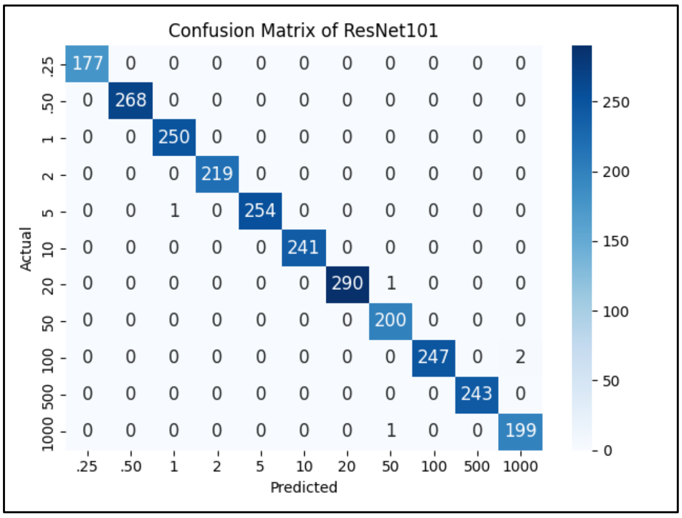


Figure 18 Confusion matrix

- The cells off the main diagonal indicate the number of misclassifications by the model (False Positives and False Negatives). For example, there are zero instances where the model confused the 0.25 class with any other class, which is consistent for most classes.

- The majority of the matrix shows a high number of TPs (dark cells on the diagonal) and very few to zero misclassifications (light cells off the diagonal), suggesting high precision and recall rates for the model.

The model performs exceptionally well with a high degree of accuracy in correctly predicting the class labels. The small number of misclassifications shown in the matrix indicates very few errors, which is excellent for such a multiclass classification problem.

Table 6 The values of TP, FP, TN, and FN for each class, calculated from the confusion matrix

No.	Class	TP	FP	TN	FN
1	0.25	31	0	488	0
2	0.50	60	0	459	0
3	1	54	1	464	0
4	2	37	0	482	0
5	5	46	0	472	1
6	10	49	0	470	0
7	20	61	0	457	1
8	50	36	2	481	0
9	100	59	0	458	2
10	500	47	0	472	0
11	1,000	34	2	482	1

Table 6 presents the values of True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN) for each type of Thai currency, divided into 11 classes, as calculated from the confusion matrix in this study. This table demonstrates the high accuracy of the model, with very low numbers of FP and FN across each class. For instance, it is observed that the classes for 0.50, 2, 10, and 500 have no FP or FN values at all. This indicates the model's effectiveness in accurately classifying different denominations of Thai currency. For classes 1, 5, 20, 50, 100, and 1,000, where the number of FP and FN is less than or equal to 2, which is very low.

This research has chosen the ResNet101 model due to it having the highest Average Accuracy to be used in application development. The data that was created was used to train and develop into a ‘best_model_101.h5’, which was then converted into a ‘best_model_UseThis_float.tflite’ file for use with the developed Android application on smartphones. After converting the model to .tflite, it was used with Android Studio to create an APK application and installed on a Smartphone operating on the Android system to conduct real-time tests with actual images of banknotes and coins. These tests used a different set of data from that used for training and testing during the model creation, covering 11 types of currency as shown in Figures 19-20. The detection was performed through the phone's camera in real-time, displaying results both in text and via voice through the smartphone. The test results for 11 types of currency, both coins and banknotes, were tested 20 times each and recorded in Table 7 to determine whether the classification was correct or incorrect.

Table 7 displays the real-time application testing results on a smartphone. This table shows that the application can correctly identify Thai banknotes, achieving a 100% correctness rate for the 50, 100, and 500 Baht notes. For lower denominations, such as the 25 and 50 Satang coins, the correctness rates are the lowest at 75% and 85%, respectively. It's noted that coin testing in real usage has more errors than banknote testing due to factors like the very small size and similar colors of coins, such as the 25 and 50 Satang, which are close in color and size, leading to classification errors. Also, the smartphone's camera may not focus clearly on very small coins at close range, and at a greater distance, predictions can be incorrect. Similarly, the 5 Baht coin can be mistaken due to its color resembling that of the 1 Baht coin. Environmental conditions, lighting, proximity, and background also affect the real-time coin recognition through the camera during actual use. Overall, the application has an average accuracy rate of 92.3% in this testing.

Table 7 The results of the app's real-time usage testing on a smartphone

No.	Class Name	Correct	Percent
1	25 Satang	15	75
2	50 Satang	17	85
3	1 Baht	20	100
4	2 Baht	17	85
5	5 Baht	18	90
6	10 Baht	20	100
7	20 Baht	20	100
8	50 Baht	20	100
9	100 Baht	19	95
10	500 Baht	19	95
11	1,000 Baht	19	95
	Accuracy (%)		**92.73**

Based on the related literature, the research includes a study by Sirikham et al., (2009) which classified Thai currency using a microcontroller. Therefore, this study compared the accuracy results of classifying all types of Thai currency. The comparative results are displayed in Table 8. This table lists the accuracy percentages for each type of Thai banknote. The newly developed method showed an average accuracy of 92.73%, which is higher than the 83.64% accuracy of Sirikham et al., (2009) method. The tests revealed that the new method was highly effective in classifying 1 Baht coins and 10, 20, and 50 Baht banknotes with a 100% accuracy rate. The 100, 500, and 1,000 Baht banknotes achieved an impressive 95% accuracy. The 50 Satang and 2 Baht coins were identified with an 85% accuracy rate, while the 25 Satang coin had the lowest accuracy at 75%, slightly less than Sirikham et al., (2009) method. Coins proved to be more challenging due to their small size and similar coloring, leading to less clear capture by the camera at close ranges, which contributed to real-time operational errors. In contrast, banknotes with their distinct colors and larger size were more accurately captured by the camera, resulting in significantly fewer classification errors.

Table 8 Results of comparing the accuracy of Thai currency classification between the developed method and the other method (Sirikham et al, 2009)

No.	Class Name	Created Method	Other Method
1	25 Satang	75	80
2	50 Satang	85	80
3	1 Baht	100	80
4	2 Baht	85	80
5	5 Baht	90	100
6	10 Baht	100	100
7	20 Baht	100	80
8	50 Baht	100	80
9	100 Baht	95	80
10	500 Baht	95	80
11	1,000 Baht	95	80
	Accuracy (%)	92.73	83.64

Figures 19 – 20 illustrate examples of the application in use, installed on a smartphone. The application operates independently of internet connectivity, enabling users to function offline. It utilizes a digital camera to scan Thai coins and banknotes. Figure 19 shows the application distinguishing 25 Satang, 50 Satang, and 1, 2, 5, and 10 Baht coins. Figure 20 illustrates the classification of various types of banknotes. Besides textual output, the application also provides audio feedback, aiding visually impaired users in understanding and utilizing the application effectively.

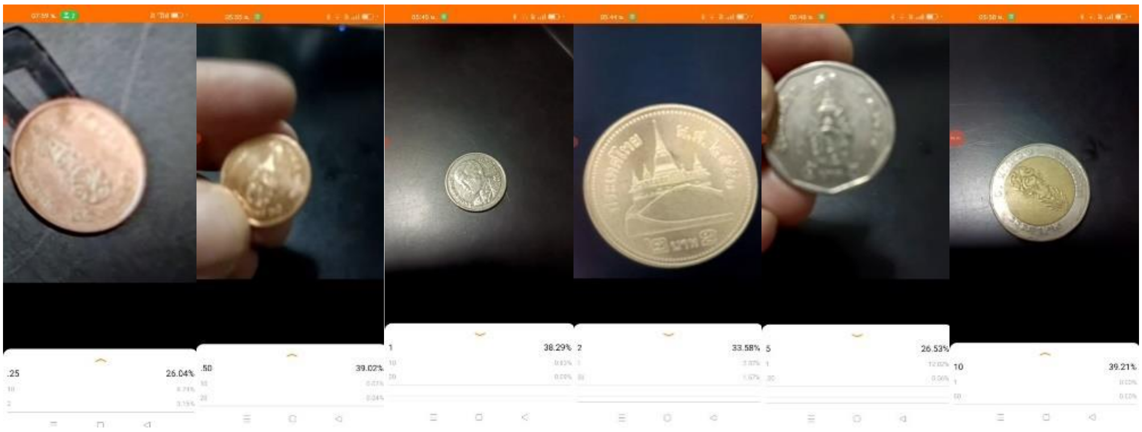


Figure 19 The testing with .25, .50, 1, 2, 5, and 10 Baht coins

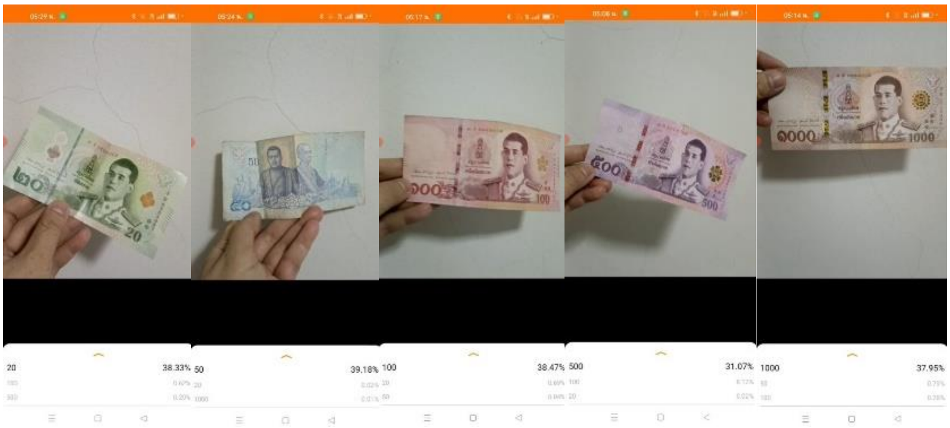


Figure 20 The testing with 20, 50, 100, 500, and 1,000 Baht banknotes

5. Discussion

From testing and real-world usage, the following issues were encountered and suggestions are as follows.

1) In real-use testing, the most common errors occur in coin detection, which results in a higher rate of mistakes compared to banknotes, despite the training and testing data being highly accurate. This is due to the problem of the coin being very small. The appearance of the coin cannot be clearly focused at close range. In addition, the colors of the coins are similar. For example, 25 and 50 satang coins are small and have very similar colors. This causes errors in actual testing, etc. Therefore, it is necessary to improve the training dataset further for accuracy in actual use

2) This research did not investigate counterfeit coins or banknotes. This makes the visually impaired unable to inspect. Therefore, further development is needed to enhance usability.

3) There should be a multilingual application with audio display output that can be used conveniently. Additionally, it should support more currencies to facilitate use by foreigners in the future.

6. Conclusion

This research developed a smartphone application to assist visually impaired individuals in identifying Thai currency, including coins and banknotes, using a Convolutional Neural Network with ResNet101 architecture because it yielded the highest average accuracy compared to ResNet50, ResNet152, MobileNet, and VGG16 architectures. For testing, the data was divided into 80% for training and 20% for testing from the total data set. Then, it was compared with an existing dataset to find the most accurate testing set. Here, the newly created test set was more accurate and thus, the model from this test set was used with the newly developed Android application to conduct real-time tests without the need for an internet connection. Using a smartphone with the developed application installed, the camera was pointed at actual banknotes and coins (which are different from the sets used for training and testing) for testing. This application showed high accuracy in real-world tests with an average accuracy of 92.73%, displaying both text and audio results, making it more accessible. However, there are still errors in classifying certain types of coins, such as the 25 Satang, 50 Satang, 5 Baht and 2 Baht coins, due to their small size and similar colors. The camera cannot focus clearly at close range, making it hard to see patterns or text, resulting in more errors than with banknotes. This research highlights the need for the development of a more diverse training dataset to improve accuracy in future testing.

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