Bhutanese Currency Classification

CSA301 Deep Learning
Bachelor of Science in Computer Science
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1 Abstract

The human visual system could be used for recognizing and authenticating currency notes. However, the observation powers of human eyes are limited, and it is often difficult for people to recognize genuine currency without any technological assistance. Moreover, due to the similarities in paper texture between several categories, blind people have trouble distinguishing paper cash. Therefore, deep learning has been employed to identify different Bhutanese currency (Ngultrum banknotes) and to display its equivalent value to other currencies. This project mainly focus on Ngultrum banknotes which ranges from Nu.1 to Nu.1000. In this project, the model use Convolutional Neural Network (CNN) model to extract the features of paper currency, so that the model can more accurately recognize the denomination of the currency, both front and back. And the model was able to achieve a training accuracy score of 99.49(%) and a validation accuracy score of 82.34(%).

Keyboards: Bhutanese Currency; Deep Learning; CNN; Image Classification

2 Introduction

Ngultrum is the locally and officially accepted currency of Bhutan which is used for all economic trades at professional and local level. The currency code of Bhutan is BTN and the symbol is Nu. The 100 cents make up 1 Ngultrum and Cents in Bhutan are called Chhertum. Nu.1, Nu.5, Nu.10, Nu.20, Nu.50, Nu.100, Nu.500 and Nu.1000 are the banknotes acceptable in the country.

The notes have something related to Bhutanese culture imprinted on them. The reverse of the note has a dzong picture. For example, obverse of a Nu.500 note has a picture of His Majesty Ugyen Wangchuck with a Raven Crown and the reverse has a picture of majestic Punakha Dzong. This pattern is followed for all value notes, each of them having a different picture.

2.1 Problem Statement

Due to the similarities in paper texture between several categories, blind people have trouble distinguishing paper cash. These people have a really difficult time dealing with money. In order to find a solution to this problem, this project aims to develop a technical solution using deep learning to build a model that can classify Bhutanese currency.

2.2 Aims

The aim of the project is to develop a model using Deep Learning to identify different Bhutanese currency especially new Ngultrum banknotes. After the currency value is identified the information of the currency and its equivalent value to other currency will be displayed.

2.3 Scope and Limitations

2.3.1 Scope

This project will be used to classify new Bhutanese currency, focusing on Ngultrum and not Chhertum. The Ngultrum banknotes will range from Nu.1, Nu.5, Nu.10, Nu.20, Nu.50, Nu.100, Nu.500 and Nu.1000. For training the model the number of sample required is a minimum of 500 samples of each banknotes with both obverse and reverse images.

2.3.2 Limitations

1. It may be difficult to find old Ngultrum bank notes for this project. Some may be torn and some very old to the point that it may be difficult for the model to identify correctly. Therefore the old notes will be excluded for this project.

2. Since each banknote has a unique serial number it is important to make sure that the model learn from various different banknotes. Therefore a large number of banknotes of the same value must be collected.

3. The model will also not include Chhertum, or coins, as it is no longer in use nor a large number of samples can be found to train the model.

2.4 Significance

This project will help its users to identify Bhutanese currency and will be provided information related to the identified currency. Blind people will be able to identify their currency and it can help foreigners and tourist as well to learn to identify the local currency and its value on their own.

With rapid development of technology, Bhutan is moving towards online transaction and we see less paper currency being used. Projects like this can help digitally conserve information for future references.

3 Related Work

The human visual system could be used for identifying and authenticating various currency notes. However, the observation powers our human visual system are limited and it is difficult to recognize genuine currency notes without any technological assistance. Therefore various deep learning techniques are implemented to improve the accuracy of various currency recognition and their results are quite promising in terms of accuracy and precision. Many works have been proposed in identifying currency notes in the preceding years.

Similar works has been proposed by Qian Zhang, et al[1] using various deep learning approaches such as CNN, SSD, MLP. They have used CNN, PCA + BPNN and FNN methods to perform currency recognition so as to make the experimental results more accurate through layer-by-layer extraction of currency features. The author have first obtain the video of each image data and then it is filtered to select the images that meets the experimental requirements into the data set. These images are used for data augmentation to increase the size of the data-set. After that, they have trained the model to perform the currency classification based on the extracted features. They have reported an accuracy of 96.6%, 99.6%, and 92.5% for each respective methods[1].

Suyash, Mahesh and Bahrani[2] proposed to develop an Indian currency recognition system by using image processing and deep learning techniques. After their research, they adopted transfer learning techniques to train a pre-trained model and convolution neural network (CNN) algorithm to extract features of the currency note. They furthermore experimented for higher accuracy by using transfer learning models like EfficientNet, Xception, VGG16, MobileNet, and many others with different hyper-parameters like an epoch, batch size, and learning rate. After training 6-7 models, they used MobleNet as their model for classifying the images as it gave the highest accuracy for their dataset. Their model achieved the highest percentage of accuracy (98.71%) in batch size of 16.

According to Jadhav, Sharma and Bhandari[3], from 2019 International Conference on Innovative Trends and Advances in Engineering and Technology, the most crucial approach based on an image processing technique is bank note identification. In their work, numerous methodologies and procedures have been studied and tested for the classification of bank notes from various nations using independent picture data sets for each nation. Deep learning is the best technique in the era of big data, where processing massive amounts of data is necessary for every real-world application. So in their work[3] in Currency identification and forged banknote detection they determined that it is best to use Deep Learning.

Their main objective was to identify fake money notes from Saudi Arabia and India. The photographs were captured using the camera, and in the image was converted to gray scale, features were then extracted from the captured images. On the basis of their differences and discontinuities, real and fake cash images were distinguished from one another. The traits that were extracted were utilized to identify counterfeit money. The decision weather a note is fake or real was made by comparing the values of the two notes[3]. Unlike this paper, this project is to build a model that can detect and classify the currency. it is unsure if being able to classify the currency can also identify forged banknotes.

Another paper by Qian Zhang and Wei Qi Yan on Currency Detection and Recognition Based on Deep Learning[4], from 2018 15th IEEE International Conference on Advanced Video and Signal Based Surveillance, is most similar to our project.

In this paper by Qian Zhang and Wei Qi Yan[4], they mainly useed Single Shot Multi-Box Detector (SSD) model based on deep learning as the framework, employ Convolutional Neural Network (CNN) model to extract the features of paper currency, so that they can more accurately recognize the denomination of the currency, both front and back. Their main contribution is through using CNN and SSD, the average accuracy of currency recognition was up to 96.6%.

Unlike Jadhav, Sharma and Bhandari[3], in the work by Qian Zhang and Wei Qi Yan[4], they state that at present, their research can only target currency recognition, and it is impossible to identify the authenticity of the currency[4]. They had trained the

SSD framework, tested on four different models and finally selected the best one. These models were based on empirical methods which gave them satisfactory results.

4 Methodology

4.1 System Overview

The following is the system overview for the process of building a classification model for new Bhutanese Currency.

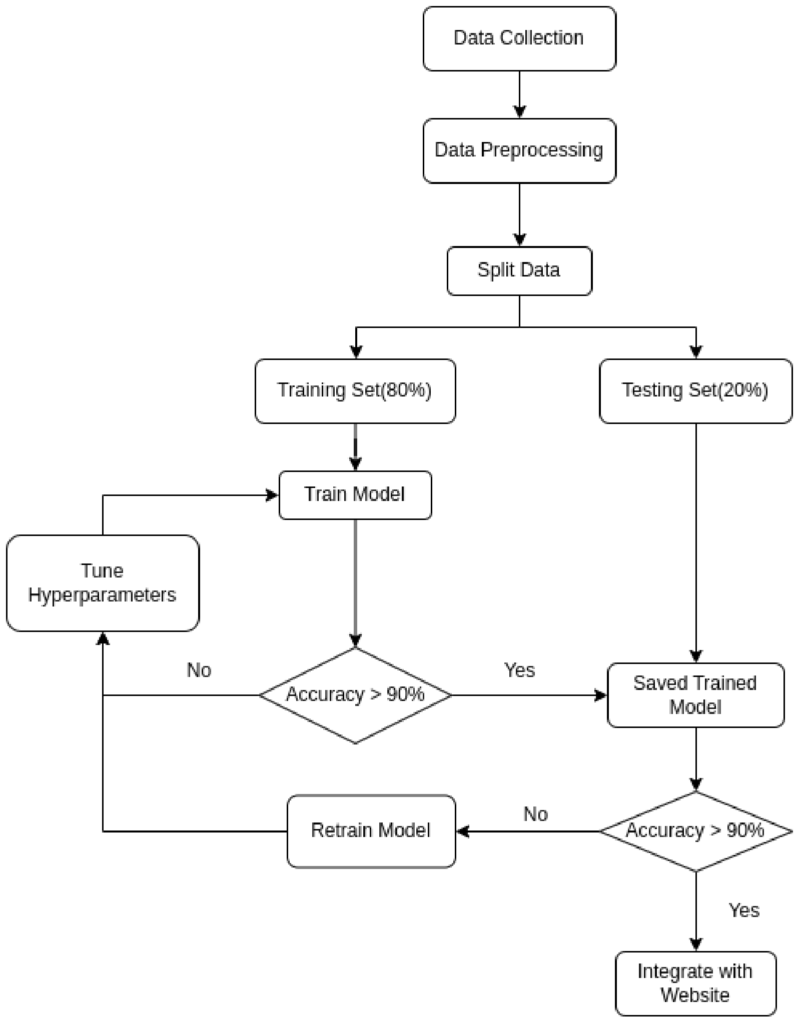

Figure 1: Flow chart for the Proposed Method

The process of building the model to classify currency will start with the collection of data, which will be used from kaggle. After which the dataset will be processed with the necessary features and conversion of the images into pixel data stored into csv files. Then with the set up a structure for the dataset, into the training and testing sets.

The model will then be trained with the training set and checked for accuracy. If we obtain high accuracy we will test the model with the testing set. If the model has low accuracy then the model will be trained again after tuning the hyper-parameters until the desired accuracy is obtained. Finally after the model is completed, it will be integrated with the website.

4.2 Algorithm

Convolution Neural Network
A CNN architecture-based approach is proposed for currency recognition. A three convolution layers CNN is developed to identify the new Bhutanese currency as shown in Fig.2. CNNs [5] are particularly useful for image classification, image recognition, and computer vision (CV) applications because they provide highly accurate results, especially when a large amount of data is involved. As the object data passes through the CNN's numerous layers, it also picks up the features of the item over time. The requirement for manual feature extraction is eliminated by this direct learning. The steps involved in image classification are the input layer, hidden layers, and output layer.

The following is the diagrammatic representation of the CNN architecture that will be used:

Table 1: CNN architecture

Layer	Filter no.	Filter size	Padding	Activation
Conv2D	32	(3, 3)	same	relu
MaxPooling		(2, 2)		
Conv2D	64	(3, 3)	same	relu
MaxPooling		(2, 2)		
Conv2D	64	(3, 3)	same	relu
MaxPooling		(2, 2)		
Conv2D	64	(3, 3)	same	relu
MaxPooling		(2, 2)		
Conv2D	64	(3, 3)	same	relu
MaxPooling		(2, 2)		
Flatten				
BatchNormalization				
Dense	64			relu
Dropout	0.2			
Dense	8			softmax

As for the image dimension, 224 x 224 will be used as input. The channel will be taken as 3 considering the accuracy for RGB is greater that grayscale.For this project, there are 4 convolution layers including the input layer with relu activation function and a filter size of three on each. Between each convolution layer, there will be max-pooling layer in order to reduce over-fitting in the model. Followed by a flattening layer whose output will be input for the fully connected layer. The final layer, the output layer will have softmax function since this is a multi-class classification problem. The number of nodes in the output layer will be 8 since there are a total of 8 classes of new Bhutanese currency.

4.3 Dataset

For this project, the model will be trained using an existing dataset of Bhutanese currency from kaggle[6]. There are a total of 8 different classes of currency; Nu.1, Nu.5, Nu.10, Nu.20, Nu.50, Nu.100, Nu.500, and Nu.1000.

The dataset contains a total of 8,000 images:

- 8 classes of Bhutanese currencies, all a class of the new paper currency.
- 1000 images each will be split over training (80%) and testing (20%) sets.

4.4 Evaluation Metrics

The accuracy of the model in deep learning technology can be assessed using a confusion matrix. It is used to describe the model's performance based on test data where the true values are known. It is also be used to calculate recall, precision, accuracy, and the f1-score using the following from the confusion matrix:

- True Positive (TP): when the trained model correctly predicts the positive class.
- True Negative (TN): when the model correctly predicts the negative class.
- False Positive (FP): when the model incorrectly predicts the positive class.
- False Negative (FN): when the model incorrectly predicts the negative class.

The **Accuracy** is ratio of correctly predicted class to the total instances. This way of finding accuracy is best known when there is an equal number of instances in each class in the dataset. The given equation is used to find the accuracy:

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

The **Precision** is used to compare True Positive(TP) and False Positive(FP) entities, it is calculated from the confusion matrix using following formula:

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

TP are for entities that are correctly categorized, while FP are the entities that are incorrectly classified. The **Recall** is used to compare the TP entities to FP entities that are not labelled at all, it is given by the formula:

$$\text{Recall} = \frac{TP}{(TP + FN)}$$

The **F1-Score** is a solution when there is a point where output estimation with recall and precision is no longer possible. It takes the precision and recall values and averages them, the formula is:

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

4.5 Experimental Setup

1. Programming language
   Python 3.9, Django will be used to develop the website which also uses Python language.

2. Deep learning Library
   The following libraries will be used to train the model for classification in this project:

   - **Tensorflow**: TensorFlow is a free and open-source machine learning and artificial intelligence software library. It can be used for a variety of applications, but focuses particularly on deep neural network training and inference. Will be used for data preprocessing and model building.
   - **Keras**: Keras is an open-source software library that provides a Python interface for artificial neural networks. Keras acts as an interface for the TensorFlow library, will be used to build the classification model.
   - **OpenCV**: OpenCV is a library of programming functions mainly aimed at real-time computer vision. Will be used to take in image input.
   - **Numpy**: Numpy is a Python library that adds support for huge, multi-dimensional arrays and matrices, as well as a vast number of high-level mathematical functions to operate on these arrays. Will be used to manage the 2D dataset and necessary conversion for preprocessing.

3. Platform
   Google Colab: Colab allows anybody to write and execute arbitrary python code through the browser, and is especially well suited to machine learning, data analysis and education with high GPU computing.

5 Results and Discussions

With the current architecture of the model and dataset, the model was able to achieve a training accuracy score of 99.49% and a validation accuracy score of 82.34% as give in the figure below. The model requires around 13 epochs with a batch size of 32. As for the input type of the image, the colour used is RGB.

```
160/160 [==============================] - 118s 737ms/step - loss: 0.0252 - accuracy: 0.9949
Train Accuracy: 99.49%
40/40 [==============================] - 53s 1s/step - loss: 0.9239 - accuracy: 0.8234
Validation (Seen) Accuracy: 82.34%
```

Figure 2: Accuracy of train set and validation set

The following are the classification report and the confusion matrix of the test set.

Table 2: Classification Report

	Precision	Recall	F1-score	Support
Nu. 1	0.95	0.98	0.97	200
Nu. 10	0.74	0.96	0.84	200
Nu. 100	0.85	0.92	0.88	200
Nu. 1000	0.98	0.92	0.95	200
Nu. 20	0.90	0.76	0.82	200
Nu. 5	0.93	0.88	0.90	200
Nu. 50	0.96	0.91	0.94	200
Nu. 500	0.99	0.93	0.96	200
Accuracy			0.91	1600
Macro avg	0.91	0.91	0.91	1600
Weighted avg	0.91	0.91	0.91	1600

In order to test the model, a total of 1600 dataset was used and the model achieved an accuracy of 91%. For each class, 200 images were tested and as seen in Table 1 most of the precision, recall, f1 score and support scores are above 88%. Therefore the model was trained without much overfitting.

Table 3: Confusion Matrix

Nu. 1	196	4	0	0	0	0	0	0
Nu. 10	2	193	3	1	1	0	0	0
Nu. 100	0	7	183	0	4	4	2	0
Nu. 1000	2	6	2	184	3	2	1	0
Nu. 20	3	24	18	1	151	2	1	0
Nu. 5	1	12	5	0	5	175	2	0
Nu. 50	1	9	1	0	0	6	182	1
Nu. 500	1	5	3	2	3	0	1	185
	Nu. 1	Nu. 10	Nu. 100	Nu. 1000	Nu.20	Nu. 5	Nu. 50	Nu. 500

6 Conclusion

In this project deep learning was used to classify Bhutanese currency, specifically by using CNN, a type of artificial neural network. The CNN architecture contains 4 layers including the input layer and a fully connected layer for feature abstraction and classification. With the help of callbacks and hyper parameter fine tuning the model with the highest accuracy was achieved, with 99.49% train accuracy and 91% test accuracy.

After analysis, the group found that when the currency is in a clear state on the entire screen and the angles are parallel, the recognition speed is faster, and the precision is higher. When the currency is at a very obvious angle or appears on the image far away, the accuracy of the recognition will decrease slightly, but if the dataset is fully trained and well taken, the model for currency classification can be conducted well.

The aim of this project is to build a model that can detect and classify the currency. it is unsure if being able to classify the currency can also identify forged banknotes. But with the current model, it is possible to help visually impaired people to classify the paper currency. With further training of the model, it can be integrated with mobile applications to make it more convenient and practical.

References

[1] Q. Zhang, W. Q. Yan, and M. Kankanhalli, “Overview of currency recognition using deep learning,” *Journal of Banking and Financial Technology*, vol. 3, no. 1, pp. 204–211, 2022.

[2] S. M. Bahrani, “Deep learning approach for indian currency classification,” *International Journal of Engineering Applied Sciences and Technology*, vol. 5, no. 6, pp. 335–340, 2020.

[3] M. Jadhav, Y. kumar Sharma, and G. Bhandari, “Currency identification and forged banknote detection using deep learning,” in *2019 International Conference on Innovative Trends and Advances in Engineering and Technology (ICITAET)*. IEEE, 2019, pp. 178–183.

[4] Q. Zhang and W. Q. Yan, “Currency detection and recognition based on deep learning,” in *2018 15th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS)*. IEEE, 2018, pp. 1–6.

[5] V. Veeramsetty, G. Singal, and T. Badal, “Coinnet: platform independent application to recognize indian currency notes using deep learning techniques,” *Multimedia Tools and Applications*, vol. 79, no. 31, pp. 22 569–22 594, 2020.

[6] Y. Jamtsho, N. Dema, and S. wangmo, “Bhutanese currency; new bhutanese currency,” https://www.kaggle.com/datasets/yjvision/bhutanese-currency, 2021.