Currency Recognition and Calculation System using Machine Learning Techniques

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Abstract: - Different currencies are being processed in money exchange shops and banks around the globe on a daily basis, where money exchange and transfer takes place. Identifying different currency is a difficult task and can lead to financial loss. There are approximately 180 currencies being used around the world, and each of them differ in color, size and texture. Thus, to correctly identify different currencies, a currency recognition systems needs to be designed. In this paper, we propose the design of an AlexNet based currency recognition system to recognize different international currency notes. We use 10-fold Cross Validation to obtain the cross-validation results of the AlexNet model. The features for the Alex model is extracted from the images back and front of each currency note. We also explore and implement deep learning models to compare the performance of the AlexNet model.

Key-Words: - Convolution Neural network, Deep Learning, AlexNet, feature extraction.

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1 Introduction

Technologies have now become a vital component that has been used in this modern world. Over the last twenty years, there have been numerous complaint that has been made to banks and other currency agencies about the uprising use of fake money and the slow efficiency of money exchange. These impacts have resulted in an urgent need to developing a currency recognition system using machine language to be used around the globe. Many countries around the globe have developed their own currency recognition to prevent them from the uprising fake currency being used and the efficiency of the money exchange in banks and other retails shops. Bangladesh as a classic example is one of the very countries that had already being used to it and has a positive outcome thus far [1].

Moreover, the pacific island countries are also facing the same problems. Ideas have now been urgently put forward to find an alternative solution to tackle the problem. Since most currencies are differing from each other in size, texture, and color across the region. There is a need to develop machine recognition for each one differently. While one recognition machine can gather for more than fifty (50) plus currencies but it could work much even faster if there are only one or less than five currencies on average to be recognized. Thus this project will use the Fiji currency as a trial to train and test the model and will then further to gather for other currency upon implementation of the project.

In any engineering problem, multiple solutions and approached are presented as responses and resolutions. Given the objective of this project which is to implement the system model using the Raspberry pie with Python and later to train and test the architecture design model upon hard ware implementation. In the next section we present a brief literature review.

2 Background

In today's modern world many devices use Deep learning language such as Convolution neural network. Most of the industries are now shift from machine language to Deep learning language to gather for the fast-growing rate of technologies around the globe. This has encountered many changes that can be seen all around us by the use of technologies in comparison to the past centuries. Robots have already been used in most industries to carry out the task that should be done by a human. Traffic lights and other electronic devices are also programs to ensure there is efficiency in everything that we gather for as the edge of technologies keeps on rising tremendously.

However, there's numerous language technique that can gather for that uprising technology that gives confidence to the designer to gather for the use of deep learning neural network. Deep learning was the neuron network comprising multiple layers, which can learn multiple images from the dataset. This mainly used in the field of images, speech and vision recognition. Deep learning works by estimating the weights of the layers using the propagation algorithms. Even though the process was must complicated. It was applied in the field of image recognition and image processing. The performance of deep learning is more efficient in solving problems with big data. Comparing to other machine learning techniques the performance of deep learning, it is much better when solving problems with bigger data [1].

Furthermore, the Convolution Neural Network (CNN) consists of multiple convolution layers has applied to solve problems with difficult texture information. Compare to other neural network CNN was very easy to train with backpropagation, this due to the fact that CNN has very sparse convolution layers [2]. By using the connection and the weights, the feature can obtain. CNN regenerates the input images using two types regions of interest (ROI's) such as averaging and sampling. CNN has good performance when the quality of image recognition can affect by the camera noise, compression, and saturation [3]. In the medical field, CNN was proposing and used to detect interstitial lung disease and lymph node and it found that CNN has higher performance and medical imaging and classification [4].

The Convolution neural Network was also used in the reversed vending machine were the empty beverages containers for recycling and by using the CNN it considers to be one of the powerful image's classification. AlexNet Network the training size of the images are to be resized to 227 x 227, it has 5 convolution layers and followed by the max polling layers, 2 global layers and softmax at the end [5]. In relation to the image processing, using the verification of diverse currency notes Shahbaj Khan et al. [6], implies the need for converting the image from RGB to Grayscale to ease the difficulties in the preprocessing extraction for security thread. In the process, the currency edges can be identified using the Sobel operator and edge-base segmentation. The desired output will correspond by testing the dataset. S. Surva et al. [7] implies another technique through image smoothening and image adjusting. In the process, the currency image is being tested by a median filter, which detects the size, color, and texture against the original currency. This process is significant because it removes all the noises and reads the patterns in both x and y directions. While Sushma R G et al. [8] implies that there is no need for additional light to be used for high-resolution images as it equalized all the noises. Where the RGB to grayscale and RGB to YCBCr on focus on the region of interest for the image of the use currency. Furthermore, R. Bhavani et al. [9] discuss another method using the extraction techniques point detector SURF which combines and descriptor. The process implies image, preprocessing, feature extraction, classification, and results. And B Vanajakshi et al. [10] recommend that the JPEG format of an image be used, which goes into two stages namely image analysis and image processing techniques. There are two methods used to get a better result such as image smoothened and image adjusted. Vishu R et al. [11], there are five steps that are recommended such as preparation of dataset, prepare train, set feature projection, features construct classification model and prediction of unseen samples [12]. This paper focuses mainly on features extraction and detection of different currency notes. Next we describe the methodology section.

3 System Design and Implementation

The currency recognition and calculation system can be modeled as a discrete event system. This refers to the system that can operate different tasks with respect to a different time interval. Currency recognition and calculation operate at a different time interval. The mathematical model of this system involves the following images resizing, extraction, classification, verification, feature calculation. The Alex-net model was used for currency detection; Figure1 shows the model consists of two steps, the training and the test stages, using the training data, the Alex net model is trained and the accuracy done by comparing labels of the data that are used for training.

Figure 1 shown below represents the overall process for currency recognition using the Alex-Net model.



Fig. 1 Currency recognition system diagram

The AlexNet model therefore, the weight and Biases are also updated using the error back propagation and reference it with accuracy after learning the training data. The testing data are now applied to the model and the detected result can be analyzed while accuracy can also be calculated.

3.1 Alex-Net model

Alex-Net model was representation of the CNN model, and it has three advantage which is the higher performance, less training and strong robustness. For the currency recognition we choose to use the Alex net model, Alex net model are used for both training larger data in deep network and also smaller training data in shallower network. The Alex-Net model it consists of the input layer 5 convolutional layers, followed by max pooling layer and 3 convolutional layer and the soft max.

3.2 Input layer

The input layer of the Alex-Net model is where the images was resized this was done by specifying the images size in this case is 227 by 227 by 3. This number equals to the height, weight and the Red Green Blue (RGB).

3.3 Convolution Layer

Feature extraction from the input images are done in the convolution layers of the Alex-Net model it the relationship are preserves between pixels and also learning the images features from small portion squares from the input image. The convolution layers will learn all the feature from the data. The equation below expresses the convolution layer. Can be expressed as equation below.

$$h_{i,j} = \sum_{k=1}^{m} \sum_{l=1}^{m} w_k, lx_i + k - 1, j + l - 1$$
(1)

Where m = kernel width and the height, h = out of the convolution, x = input, w = weights.

3.4 Batch Normalization Layer

The batch Normalization works by normalizing the activations of each channel and gradient propagation inside of the network. The used of batch Normalize layer will speed up the training and also reduce the sensitivity to the initialization of the network.

3.5 Pooling Layer

There are two types of pooling the max pooling and the average-pooling, the max pooling is widely used because of the accuracy and more precisely. This pooling helps the Alex-Net model to translation of these features (example, if the 5 dollars appear to be two images as 10 dollar the Alex-Net will recognize it as 5 dollar). Below was mathematical model for the pooling layer, can be expressed equation below.

$$h_{i,j} = \max\{x_i + k - 1, j + l - 1 \, \nabla 1 \le k \\ \le m \text{ and } 1 \le l \le m\}$$
(2)

3.6 Fully Connected Layers

Fully connected layers work by combining all the features learnt by all the convolution kernels. If all the feature actually presents from the input images the fully convolution layers neurons will now be activated, and this will provide a representation of what are existing in the input images, and the output layer will now correctly classify the input images. And can be expressed equation below.

$$X^{l} = f\left(W^{l}XX^{l-1} + b^{l}\right) \quad (3)$$

Where W^l is weight matrix, b^l is bias vector, f(.) is the activation function for nonlinear.

3.7 Deep learning model

Deep learning is also the techniques used for images processing, which is very important for the following problems such as motion detection, and facial recognition. Study has been taken and proven that Deep learning is one of the successful in Natural languages Processing [13]. It ranges from simple problems to most complex tasks. Using the Neural network toolbox provided in the MATLAB.

Figure 2 shown below presents the overall training and test step.



Fig. 2 System flow diagram

Computer simulation results and discussion are presented next.

4 Computer Simulation Results

To validate our proposed currency recognition system, we have chosen to use two Fiji money and the United of America money; the currency collected are group into eleven classes. For Fiji currency there were five classes, we used the 5FJD, 10FJD, 20FJD, 50FJD and 100FJD, and for United Stages currency there were seven classes which are 1USD, 2USD, 5USD, 10USD, 20USD, 50 USD and 100USD. Each currency will have both the front and the back, during capturing the currency we make sure that the currency notes are flat and can be seen from the camera. The front and the back of the currency were just stored in databases. Table 1 below shows the dataset used for training and test the model Alex Net.

Table 1 USA	and Fiji currenci	es used as dataset
Currency	USA Dollars	Fiji Dollars
\$ 1	200	0
\$ 2	200	0
\$ 5	200	200
\$ 10	200	200
\$20	200	200

\$50	200	200
\$100	200	200
Total images	1400	1000

Table 2 shows the summary of the dataset used for training and test for Fiji and USA currency, there were total of three training and test were done for this project, first we using the Fiji currency for training the Alex-Net model and testing it, second we using the USA currency for training and testing the model, lastly using both Fiji and USA currency for training and testing. And analysis of result was done respectively.

Table 2 Currency system training			
Number of Training	Country	Number of training images	
	Fiji	800	
1			
	USA	1120	
2			
	USA & Fiji	1920	
3			

Features were extracted from the Fiji and USA currency using the SURF in the MATLAB, with the images size of 227 x 227 x 3 RGB images. The features were in the three-dimension, the features extraction was done for both Fiji and USA currency, for the Fiji currency, features were extracted from the following banknotes 5 FJD, 10 FJD, 20 FJD, 50FJD, 100FJD and USA currency features were extracted from the following banknotes 1 USD, 2 USD, 5 USD, 10 USD, 20 USD, 50 USD, 100 USD this for both front and back, and using the MATLAB function (zscore) to standardized it from (-4 to 4). This was done to get some of the hidden information from the dataset set. Table 3 shows the size of the features extracted.

Table 3 Features extraction dataset			
Currency	Fiji	USA	
	Matrix size	Matrix size	
1	0	454 x 681	
2	0	454 x 681	
5	454 x 681	454 x 681	

10	454 x 681	454 x 681
20	454 x 681	454 x 681
50	454 x 681	454 x 681
100	454 x 681	454 x 681
Total	2270 x 681	3178 x 681

We analyze the model Accuracy and the loss function by evaluating the selected CNN Alex-Net model. For the currency recognition system, we examine both the front and the back of the currency notes.

Figure 3 shown below presents the results obtained by the Alex-Net model that was fully trained and the accuracy was very high, and there was not overfitting during the training. We can see from the graph the accuracy from the validation accuracy was stabilize at the end and this shows the model was fully trained.



Fig. 3 Validation of the currency recognition system

The loss function graph shows the model performance, how the model will perform for the new dataset that there will be no difference from the result we obtained for the training of the model and the result the model will be predicted. This shows that the data been fully trained in the model. Figure 4 shown below presents the loss function graph for the Alex-Net model, from the loss function graph we can see that it decreasing to almost zero.



After proper training of the Convolution Neural network Alex-Net model of the proposed system, we got satisfactory results. For features extracted the convolution layers play an important role in features extraction and classification of currency samples. A summary of the paper is presented next.

6 Conclusion

We used the currency both front and back for the Fiji and the USA currency, the Alex-Net model was trained, three different models were tested and finally selecting the Alex-Net CNN as the best model.

The system model accuracy reached 96 %, after properly carrying out training process on the proposed system to recognize currencies. The obtained results were satisfactory, for currency recognition detecting the front and the back, however we need to improve our system recognition accuracy percentage. In the future, we consider applying Deep Learning and Fast R CNN for the currency recognition.

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