BANGLADESHI BANK NOTE DETECTION USING DEEP CONVOLUTION NEURAL NETWORK

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APPROVAL

This Project titled "**Bangladeshi Bank Note Detection using Deep Convolutional Neural Network**", was submitted by Faria Farzana Mukta ID: 181-15-1969, Md. Nieamul Kabir ID: 181-15-1924 & Md. Firoz Hossain ID: 181-15-1883 to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 20 February 2022.

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We hereby declare that this project has been done by us under the supervision of **Md. Sabab Zulfiker, Lecturer (Sr. Scale), Department of CSE, Daffodil International University**. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

This report presents a Bangladeshi Banknote detection system using a Deep Convolutional Neural Network. This project is usually designed for people who do not recognize or cannot see the Bangladeshi banknotes. Visually impaired humans face trouble in figuring out and spotting the unique types of banknotes due to a few reasons. Many projects like this have been followed before this project was completed. Some of the works of others are also mentioned in this paper. The detection system is also capable of identifying the Bangladeshi Banknotes that are rumpled, decrepit, or may be worn. The detection system consists of image preprocessing, image evaluation, and image recognition. In this project, 3000 images have been used. There are 50 taka, 100 taka, 200 taka, 500 taka, 1000 taka. This project has been completed using CNN, Vgg16, Transfer learning, and transfer learning-based improved CNN model. The system can identify five banknotes used in Bangladesh with an accuracy of 91% by Deep CNN, 95% by Improved Deep CNN, and 81% by VGG16. Visually impaired human beings might be capable of using it effortlessly in day-by-day transaction

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CHAPTER 1
INTRODUCTION

1.1 Introduction

The transaction of money is an imperative part of human civilization. There are many visually impaired human beings around the world, especially in the growing globe. According to information by the World Health Organization [1], the general variety of visually impaired human beings withinside the globe is 285 million. 39 million of those human beings are blind and 246 million of them are affected by vision-associated problems. About 90% of the total visually impaired population lives withinside the developing world and most significantly 82% of them are elderly 50 years or more. In Bangladesh, there are approximately 750,000 visually impaired humans. Among them, 80% of the visually impaired humans stay in rural areas. One of the fundamental issues suffered via way of means by the visually impaired character is picking out paper currencies due to the similarity of paper size and texture among unique banknotes. Detecting the cost of bank currency is an essential element if they're to carry out a financial interest like several other human beings. A convolutional neural network (CNN) is a much simpler technique that does not require any additional equipment and can be easily integrated into many platforms. Datasets may be extended and modified according to want without a good deal of complexity. Also, the usage of CNN to categorize pictures is less difficult and greener than different function extraction and image processing methods. Designing a simple and cost-effective CNN model that can detect eight different types of Bangladeshi banknotes in real-time and can be used across multiple platforms. We have used a custom CNN version and a VGG16 pre-trained version at first. We then combined the concept of each model and used transfer learning. Our improved CNN version offers better accuracy than the other models.

1.2 Motivation

Normally a visually impaired or blind person has a hard time moving. If they do not know the money then financial transactions are more difficult. Many people think that they are a burden on society. They are often ignored in society. There are many such people in our country. In the present age, many technologies have come out which will not be a burden to these people and society. One of them is that knowing money is very important for our daily life. If a person does not understand the value of a note, then financial transactions are difficult for him. It is even more difficult for blind people. In such a situation, it is very important to know the banknote. This is our report on how a visually impaired person can identify Bangladeshi Bank Notes. The VGG16 version had effectively overcome the limitations of image processing. A synthetic dataset was used to train and test the model. Deep CNN functions as a typical extractor. The motivation at the back of this study is to discover a method to enforce an image popularity system to understand Bangladeshi banknotes for visually disabled humans. By using this system, visually impaired humans can trust in recognizing currencies. Also, they can create their own microfinance business enterprise and feature notion in monetary dealings.

1.3 Rationale of the Study

This study was conducted to identify Bangladeshi Banknotes using images from a dataset and learn how to classify any Bangladeshi banknotes. We have trained our model to identify Bangladeshi banknotes. We have labored on this research to assist visually impaired or blind human beings in addition to society. The researcher gets assistance from our study that which methodology offers faster output and better accuracy.

The major hassle faced by visually impaired human beings is understanding paper currencies. Especially in Bangladesh, now no longer sufficient studies and improvement has been performed to clear up the issue. Due to the similarity of paper size and texture between specific Bangladeshi banknotes, it is pretty difficult to identify the notes for people who are visually impaired. A system must be advanced a good way to assist them to recognize banknotes easily. Visually impaired human beings don’t need to be a burden to society. They additionally need to make a contribution to their family. They want self-belief in the monetary dealings, now no longer relying on others.

1.4 Research Questions

Various questions came to our minds earlier than beginning the research. The work is focussed on establishing an Image Detection System for visually impaired people to detect Bangladeshi paper currency. The maximum essential questions concerning this study were:

- What dataset should we use?
- What methodology should we apply?
- What framework will we use?
- How we'll achieve higher accuracy as the system will be used in financial dealings?

1.5 Main Objective

- Creating a system that can easily identify Bangladeshi banknotes.
- Identify the Bangladeshi 50taka,100taka,200taka,500taka,1000taka bank notes.
- Using this system to reduce the workload and time needed to identify banknotes that can be used in other tasks instead.

1.6 Report Layout

The following is how we organized our project report:

- Chapter One contains the introduction of our research, motivation for this study, objectives, and expected outcome of this study.
- Chapter Two includes the background of the research, related works, research summary, and difficulties encountered during this research.

●Chapter Three includes the research methodology, the proposed systems, datasets, the implementation procedure, data preprocessing, and the improved model

●Chapter Four includes Experimental Results and Discussion including experimental setup, confusion matrix, performance, and comparative analysis.

●Chapter Five includes the Conclusion and Future Scope of this project.

CHAPTER 2
BACKGROUND

2.1 Introduction

We have used CNN, VGG16, improved deep CNN architecture, and Transfer Learning in our research work.CNN is a kind of specialized neural network that works for image datasets. CNN is typically used for image detection and classification.CNN is an effective algorithm for image processing.VGG is a convolutional neural network structure that has been around for a long time. It is an item recognition model that may support as many as nineteen layers.

2.2 Related Works

When compared to other currency detection algorithms, the CNN model is more efficient while also being easier to apply. CNN gives high accuracy to any image recognition type problem.CNN is better than all other algorithms. Some strategies required additional hardware. The use of a limited number of currencies is another constraint of existing efforts. We addressed the flaws of the present literature in our proposed method to achieve better results.

Abburu et al.[5], presented a currency identification machine that recognizes both the origin and value of 20 different currencies using image processing. This method works by first identifying the country by utilizing previously set sections of a subject, and then extracting the currency fee by using factors such as size, color, or textual content on the note, depending on how much the banknotes within the same nation differ. However, this method is incapable of identifying damaged notes.

Zhang and Yan [13], The Single Shot Multi-Box Detector (SSD) model is being used as the architecture, and the CNN model is used to acquire the characteristics of New Zealand dollars. This research is limited to only three banknotes, making it ineffective for analyzing a system.

The researchers used a variety of approaches to solve this issue. Jia Feng et al.[10] proposed a method for detecting Chinese currency in real time. For their experiments, they constructed a modified Kohonen Network to recognize Chinese paper currency. The technology described could be used to a real-world currency sorting system.

Vision-based banknote recognition systems have been proposed by a number of academics. Costa et al.[12] develop a computer vision system that uses a camera to consistently recognize banknotes. Using a cell phone camera, Solymár et al.[11] caught the Hungarian notes. Because of the multiple electrical components involved and the sensor's limitations, prior research based on sensor-based systems have lower accuracy. As a result, the vision-based system was chosen as one of the most practical and accurate methods of image capture.

Chowdhury et al. [6], proposed using deep learning and image processing to create an automatic currency identifier for Indian banknotes. They used innovative classification approaches. For the extracted features, the k-NN model was utilized, and the pre-processed currency images were placed into the CNN version for identification. There are currently just a few methods for identifying Bangladeshi paper currency. A Bangladeshi banknote identification algorithm for cellular devices was reported by Rahman Sarker et al.[4]. To recognize Bangladeshi currency, they used the widely used ORB feature descriptor. Most Bangladeshi banknotes have an image of Bangabandhu Sheikh Muzibur Rahman on one side, which is nearly identical to all notes. For increasing accuracy, this system was designed in this sort of manner that it'll most effectively discover the aspect of the banknote that is unique in every note and dismiss the comparable facet.

In this research, we used the CNN model to classify Bangladeshi banknotes in real-time with a visual and aural output, resulting in higher consistent identity accuracy and faster processing time.

2.3 Research Summary

After analyzing the prevailing project works and papers we found that numerous opportunities for deep learning Or D-CNN algorithms may be used to carry out Banknote detection. These current works have numerous obstacles and we are able to restore that with our challenge. The maximum possible choice for us is the open-supply ImageNet like VGG16, Transfer gaining knowledge of Convolutional Neural networks that have publicly available documentation and codes. For this work, We needed more data to expand our dataset. In that case, our advanced CNN version may be very beneficial to conquer the limitations

2.4 Scope of the Problem

This study makes a specialty of locating a manner to develop Bangladeshi currency detection devices for visually impaired humans. This project's motive is to construct a system for extracting capabilities from images to discover Bangladeshi banknotes. The system additionally desires to extract some traits to perceive if there's not anything withinside the picture. Our project turned into additionally categorized all of the images.

2.5 Challenges

To develop one of these devices for visually impaired human beings we want to create a reliable system with better accuracy and usability. Some of the demanding situations can also additionally be available in the improvement of this research primarily based on totally system:

- Time Complexity: As the supposed device is an actual-time detection system, we want to recognize with maximum priority to lessen the processing time of the detection.
- Data collection: We have confronted a lot of problems to customize our information. We needed to take all the images for unique banknotes individually. This took a massive quantity of time from us.
- Data transfer: There are obstacles to how a whole lot of information may be saved from a cell device as we've taken the images from our cell. We additionally wanted to switch the images from our cell to our laptop through the USB cable. It took a long time to switch all of the images due to the fact we had a huge variety of images on our cell phones.
- Hardware obstacles: There may be bottlenecks in our processing hardware wherein they were lag at the back of the captured images. This can without difficulty be rectified by including extra-strong hardware like CPU, HDD, or GPU in our architecture

- Preprocessing of the datasets for the powerful analysis.
- Getting sufficient statistics to teach the neural networks properly.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Introduction

Our project goal is to recognize Bangladesh Bank Note. We have used CNN(Convolutional Neural Network) and Transfer Learning in order to solve the problem. We are using CNN algorithm which we have implemented using the Tensorflow framework. For the Training dataset, we used a custom and existing dataset of images

3.2 Proposed System

Our project goal is to identify banknotes for that we have used custom CNN, Transfer learning and transfer learning-based improved CNN model, VGG16 is used as a pre-trained model to recognize banknotes. Finally, we compared these three models and improved CNN outperforms the other models. At first, we have used a custom CNN model with four different filters and used ReLU and Softmax activation layer. Next, we have used a pre-trained model as VGG-16 to extract the features from images, train this pre-trained model, and evaluated the performance. Finally, we build our transfer learning-based improved CNN model where the pre-trained VGG-16 model worked as a feature extractor and custom CNN worked as a trainable model.

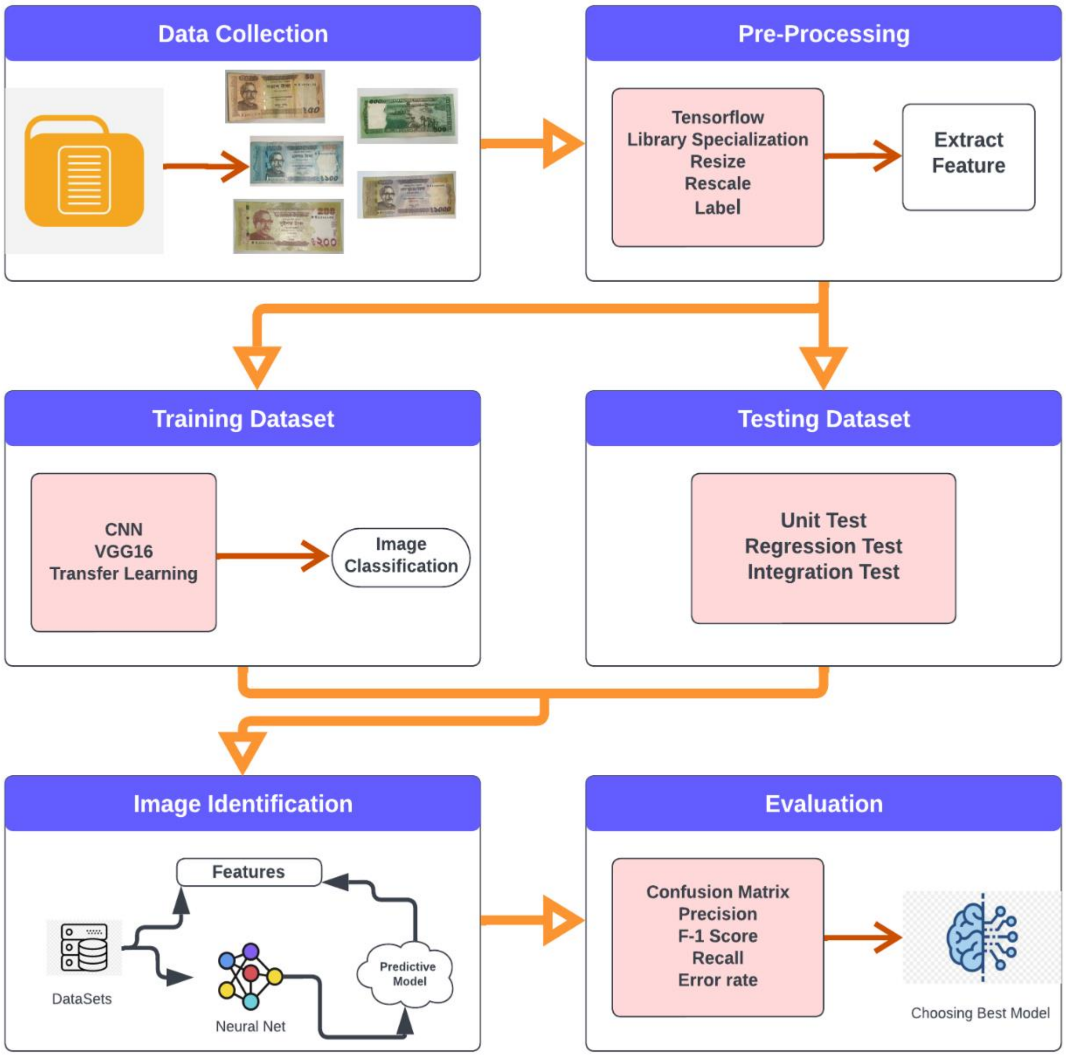

Figure 1: Working method of the proposed methodology.

3.3 Dataset

The initial step of implementing our model was collecting data. Our model was based on an image dataset. We were collecting raw data, collecting takas, and taking images by our own mobile devices. Banknotes(taka) were collected from banks and many stationary shops. After capturing the image which was raw data. We reduced pixel size for easy to load data in our model. The collection was made up of 3000 images, 400*300 above pixel size pictures. There were 5 classes in the dataset.

3.4 Implementation Procedure

3.4.1 Data preprocessing

Data pre-processing is very important for every dataset. Because our dataset contains different sizes of images. If the images have different sizes will cause a problem while training them. So in order to avoid that problem, we have transformed and resized the images so that all the images are of the size where we used an image size of 50. Also, as we used the CNN model for training our dataset, it requires a lot of images. We had enough data to train our dataset. In the data pre-processing part we have also labeled our image and used 3 channel color images (RGB). This helped us a lot to get better performance and quality images to train the dataset.

3.4.2 Convolutional Neural Networks (CNNs)

ConvNets (CNN) are multi-layer neural networks used for image processing and object detection. CNNs have multiple layers that analyze and extract features from data.

Convolution Layer: CNN includes a convolution layer, which filters a picture. Convolution layer with multiple filters to perform the convolution process.

ReLU(Rectified Linear Unit): A ReLU layer is utilized by CNNs to execute operations on objects. A corrected function map is the result. When the pooling layer's flattened matrix is given as an input, a very connected layer comes up that classifies and labels the images.

Pooling Layer: In the pooling Layer, the characteristic map is corrected and despatched to a pooling layer. Pooling is a downsampling method that reduces the dimensions of the characteristic map. The pooling layer flattens the two-dimensional arrays from the pooled characteristic map right into a single linear vector this is lengthy and continuous.

Fully Connected Layer: When the pooling layer's flattened matrix is used as an input, a fully connected layer comes up that classifies and labels the images.

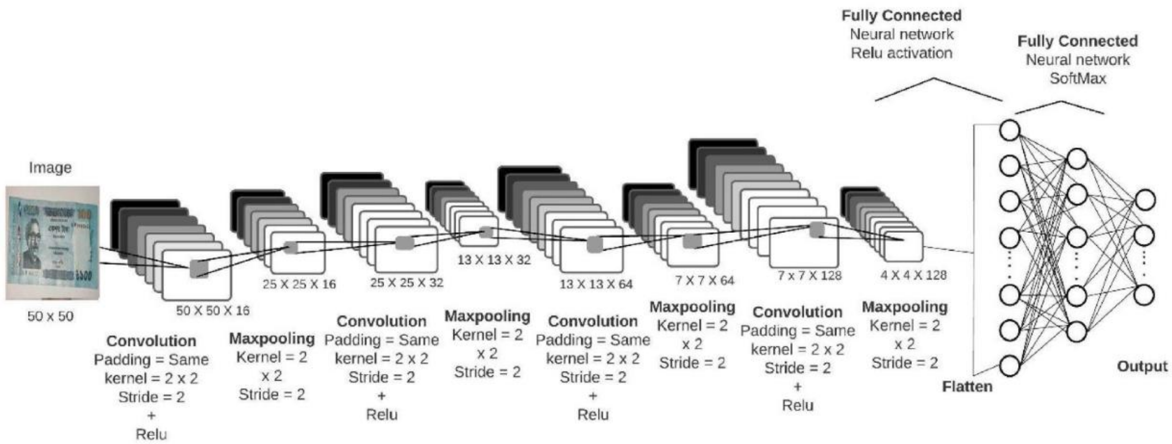

Figure: Working method of CNN

3.4.3 Transfer Learning

Transfer learning is the method of applying a formerly discovered version to a new problem. It is now pretty famous in deep learning due to the fact it may educate deep neural networks with fairly little data. When a machine learning model that has already been trained is used to resolve a unique but related problem, that is referred to as transfer learning. For examples, if we trained a simple classifier to predict whether an image has a backpack, we might utilize the model's information to find different gadgets like sunglasses. The weights learned via way of means of a network at "task A" are transferred to a new "mission B.

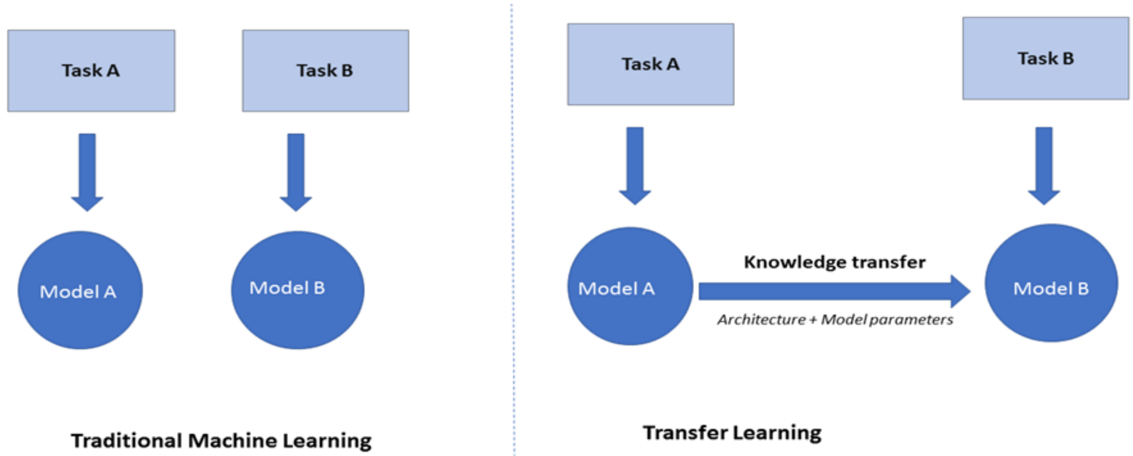

Figure: Working method of Transfer Learning

3.4.4 Pre-Trained Model (VGG16)

This is a pre-trained model for implementing our research. If we need to improve, we have optimized the parameters and changed the pre-trained model to VGG16 without fine-tuning. Even after reducing the epochs, we still get better results than performance after training with VGG16.

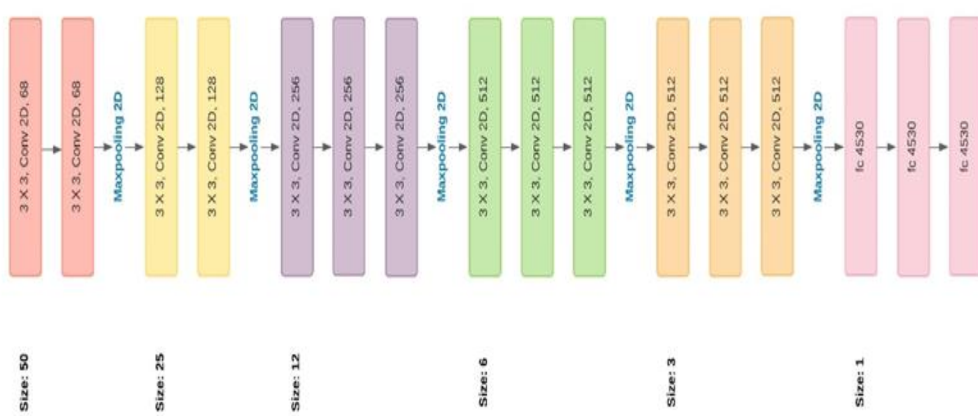

Figure: VGG16 model's architecture.

3.4.5 Improved Model

If we need to improve, we have optimized the parameters and changed the pre-trained model to VGG16 without fine-tuning. Even after reducing the epochs, we still get better results than performance after training with VGG16. As VGG16 requires much time for training, it will require more GPU and ram. So, we might run out of memory. Currently, almost every Nvidia GPU supports tensor cores which can speed up neural network training by 2x-3x. They also require less GPU memory.

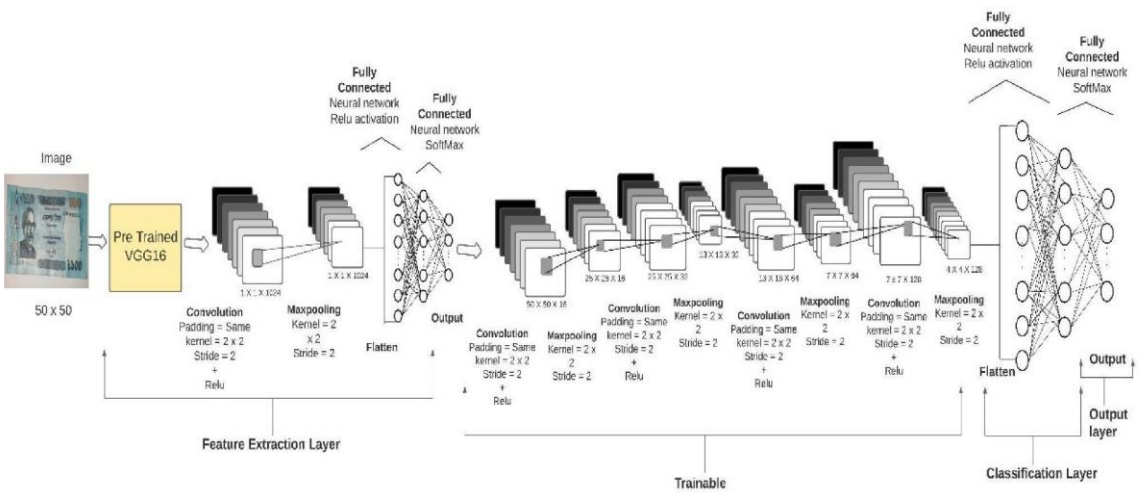

Figure: Workflow of improved CNN model.

3.4.6 Model Tuning.

Basically tuning is a trial and error process that changes some hyperparameters. For improving our improved CNN model, we have increased the batch size to 32. In the case of our dataset, we did not change any confusing classes. After using the epoch to 15, we get some great improvements in our model.

3.4.7 Model Training

In our research model training is most important for implementation. We have used the Keras and Tensorflow framework to implement the CNN model without fine-tuning the pre-trained

VGG16 model. There we have used a batch size of 128 and trained for 15 epochs. Here we had 5 classes. The learning rate, batch size, picture filtering, and number of epochs are all hyper-parameters from a configuration file that are used to train the model. The model's training parameters, as well as the model architecture, are kept for future assessment and modification for superior outcomes. The training and validation datasets are loaded within the training loop. The Adam Optimizer with Cross-Entropy Loss is used to train the model. At each epoch on the validation set, the model is evaluated, and the model with the highest validation accuracy is saved to storage for future evaluation and usage. Once the training is complete, the training and validation error and loss, as well as a plot of error and loss overtraining, are saved.

3.4.8 Experimental Environment

The experiment is conducted on a personal computer where the microprocessor is Intel(R) Core(TM) i5-7200U CPU @ 2.50GHz 2.71 GHz with NVIDIA HD Graphics

620 4GB, 8 GB ram, and Windows 10 operating system. The model is executed on an open-source platform Google Colab Notebook. The model is implemented on the Tensorflow and Keras framework.

CHAPTER 4
RESULTS AND DISCUSSIONS

4.1 Performance Evaluation

With different performance metrics, we have evaluated the performance of the models. These are the matrix we have used accuracy, precision, recall, f1-score. Because the number of right predictions is divided by the total number of predictions in the dataset, accuracy is calculated. The highest level of accuracy is 1.0, while the lowest level is 0.0. Precision can be visible as a measure of quality and recall as a measure of quantity. An f1-score is considered best when it is 1, while the model is a complete failure when it is 0.

4.2 Model Evaluation

In order to calculate a confusion matrix, we need to know about TP, FP, TN, and FN.

TP (True Positive) = Correctly predicted classes.

FP (False Positive) = Predicting negative classes as positives.

TN (True Negative) = Predicting negative classes as negatives.

FN (False Negative) = Predicting negative classes as positives.

Using the above variables, we have calculated the values of accuracy, f1-score (micro), precision (micro).

Accuracy for a multiclass confusion matrix is the average number of correct predictions.

Here, accuracy = $\frac{(\text{Total TP} + \text{Total TN})}{(\text{Total TP} + \text{Total TN} + \text{Total FP} + \text{Total FN})}$

F1-Score is the harmonic mean of precision and recall. For multiclass confusion matrices, we use the micro f1-score.

Here, f1-score = $\frac{2 * \text{Total TP}}{(2 * \text{Total TP} + \text{Total FP} + \text{Total FN})}$

Precision means the fraction of positive samples which were correctly predicted as positive. Here, we have used micro-precision.

Here, precision = $\frac{\text{Total TP}}{(\text{Total TP} + \text{Total FN})}$

Error rate indicates the fraction of incorrect predictions.

Here, error rate = 1- accuracy.

We have trained the model to find the accuracy, f1-score, recall, and precision of the model for our dataset. It took 3ms/1s for each epoch.

4.2.1 Confusion Matrix

Detecting bank note has become very popular among researchers. In order to get the best out of our model, we have trained our model with multiple classes of images and used it as the final layer of our CNN model.

Confusion matrices were utilized to evaluate the performance of our model. Here in Figure M1, we have shown the confusion matrix of the custom CNN model after training the model with our given images. The diagonal part indicates the number of images it has been detected correctly

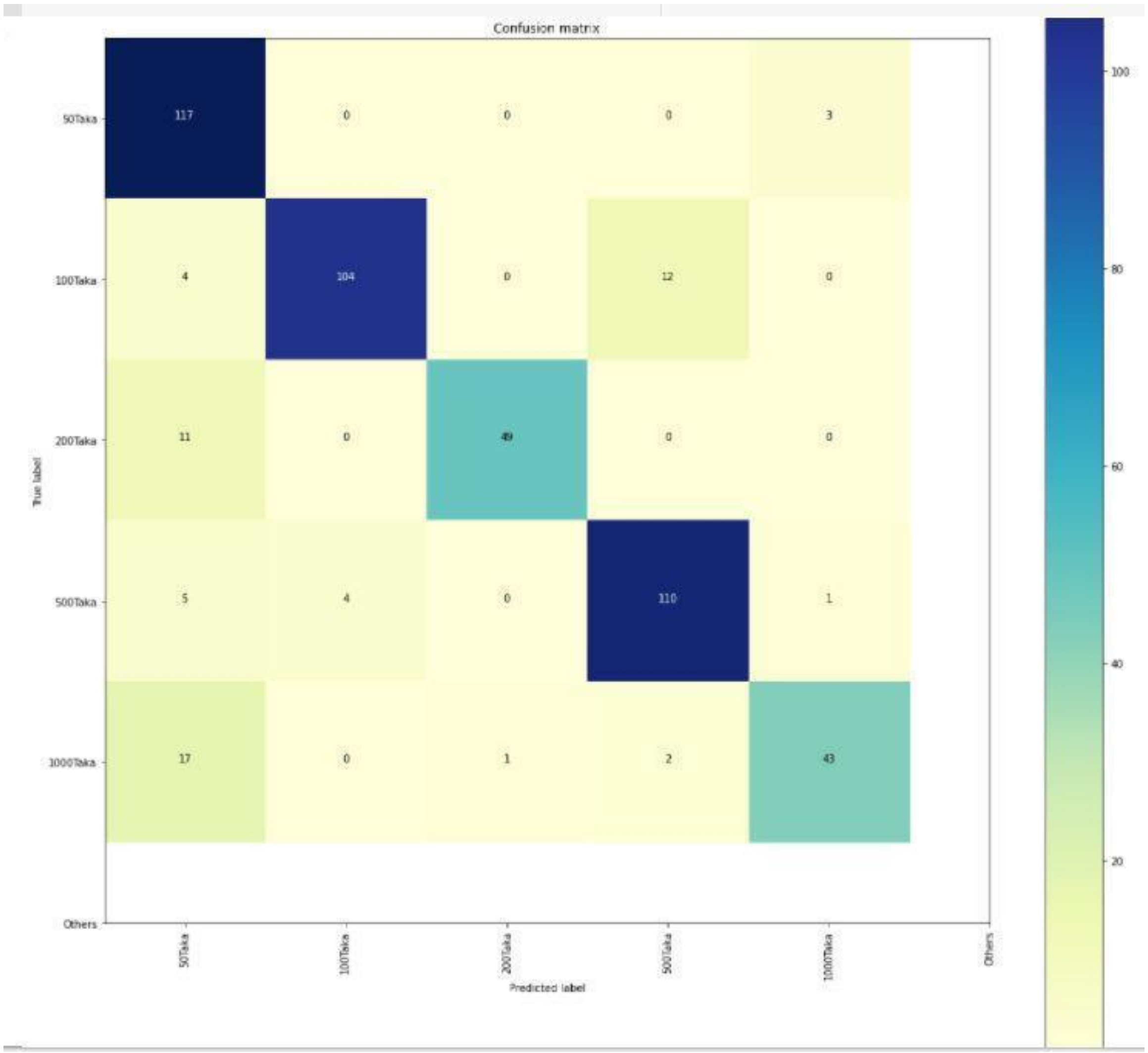

Figure M1: Confusion matrix of Custom CNN

Here in this Figure M2, we have shown the confusion matrix of the VGG16 model after training the model with our given images. The diagonal part indicates the number of images it has been detected correctly.

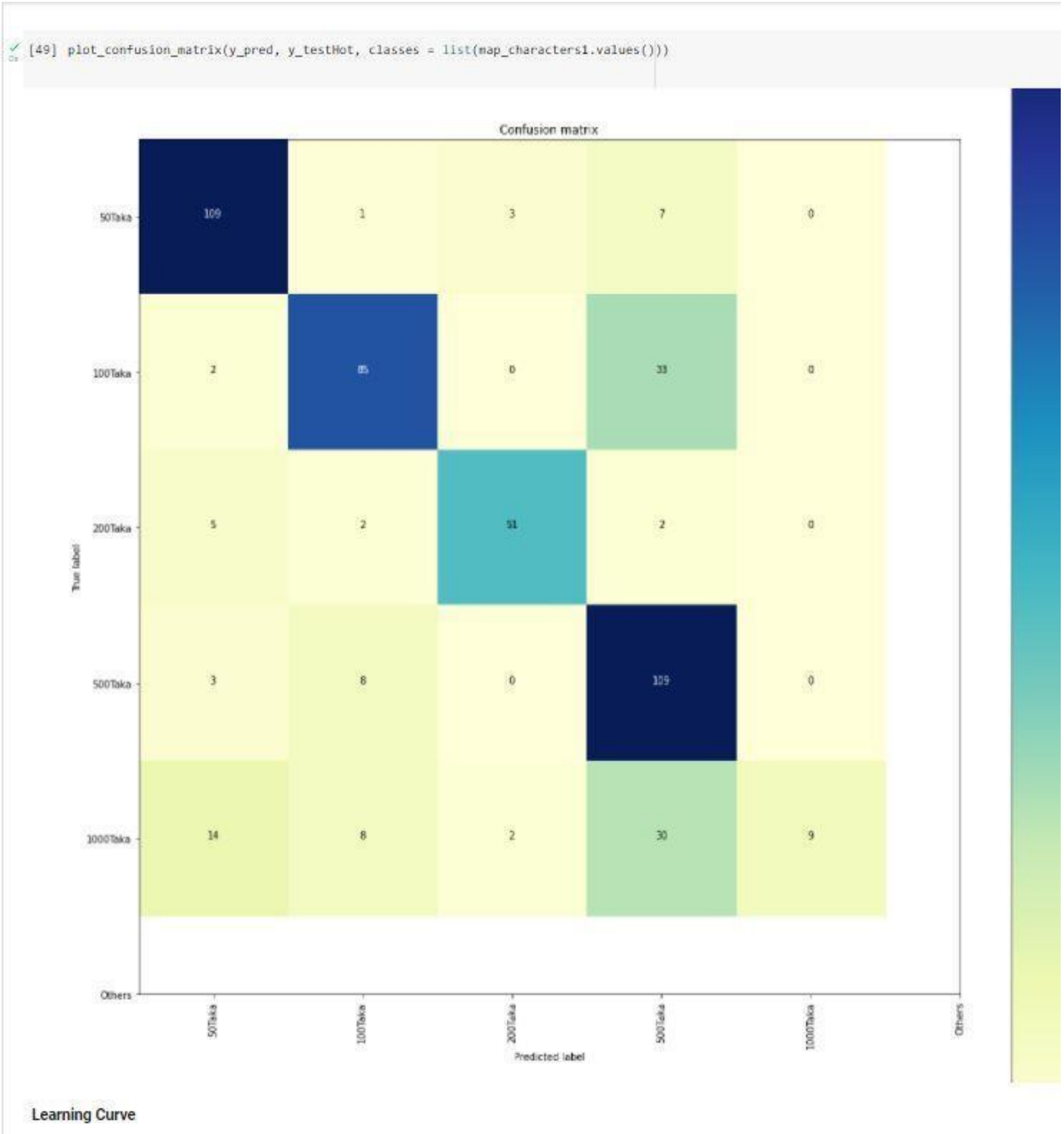

Figure M2: Confusion matrix of VGG16

Here in Figure M3, we have shown the confusion matrix of our improved CNN model after. training the model with our given images. The diagonal part indicates the number of images it has been detected correctly

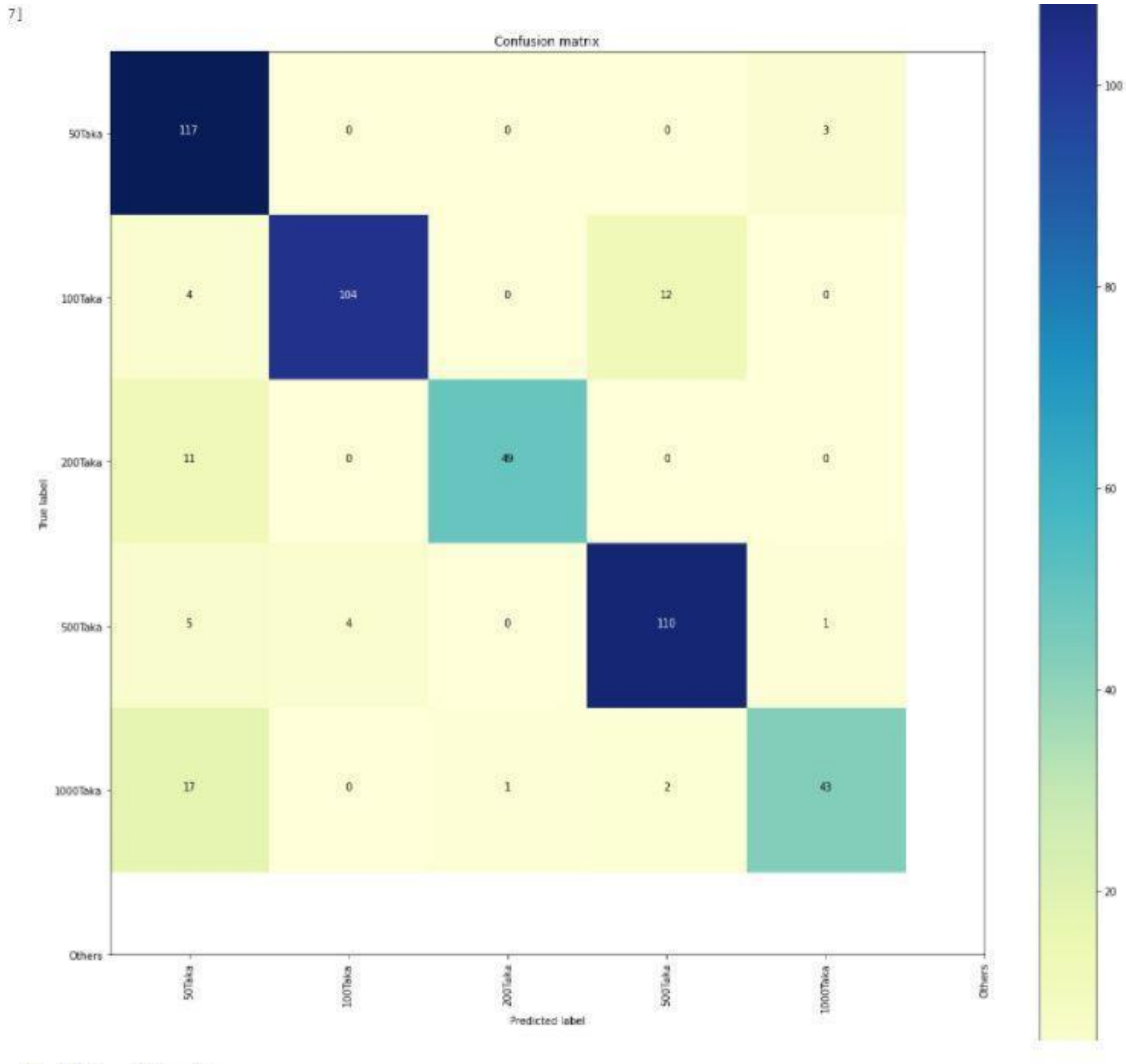

Figure M3: Confusion matrix of Improved CNN

4.2.2 Performance Matrix

Table 1: Performance after training with Custom CNN

Epoch	**Train loss**	**Valid loss**	**Accuracy**	**Error rate**	**time**

1	1.5768	1.5711	0.2600	0.740	53ms
2	1.4964	1.6806	0.3450	0.655	36ms
3	1.1356	2.4293	0.5250	0.475	36ms
4	0.9997	2.9840	0.5840	0.416	36ms
5	0.8434	3.1795	0.6630	0.337	36ms
6	0.7329	3.4874	0.7070	0.293	62ms
7	0.6031	4.6805	0.7940	0.206	36ms
8	0.4914	4.9048	0.8270	0.173	35ms
9	0.4600	3.5629	0.8410	0.159	36ms
10	0.4013	4.9801	0.8650	0.135	36ms
11	0.3392	4.9031	0.8820	0.118	36ms

12	0.3219	5.1660	0.8890	0.111	36ms
13	0.2889	5.8469	0.9010	0.099	40ms
14	0.2835	6.3136	0.9100	0.090	37ms
15	0.2561	5.6842	0.9140	0.086	36ms

In Table 1, though the accuracy was not bad, the model had huge validation loss. So, our model has rooms for improvement.

Table 2: Performance after training with VGG16

Epoch	Train loss	Valid loss	Accuracy	Error rate	time
1	1.5592	1.5911	0.3040	0.69 6	34s
2	1.3686	1.6264	0.5010	0.499	33s
3	1.2528	1.6649	0.6030	0.397	33s
4	1.1623	1.7066	0.6580	0.342	33s

5	1.0860	1.7530	0.6670	0.333	33s
6	1.0237	1.8001	0.7060	0.294	33s
7	0.9679	1.8462	0.7100	0.290	33s
8	0.9210	1.8845	0.7420	0.260	33s
9	0. 8779	1.9272	0.7590	0.241	33s
10	0.8385	1.9716	0.7690	0.231	33s
11	0.8060	2.0119	0.7880	0.212	33s
12	0.7747	2.0511	0.7980	0.202	33s
13	0.7474	2.0872	0.8080	0.192	33s
14	0.7226	2.1287	0.8180	0.182	33s
15	0.7009	2.1570	0.8120	0.188	33s

In Table 2, our training loss as well as our accuracy improved with other performance factors.

Table 3: Performance of Improved CNN

Epoch	Train loss	Valid loss	Accuracy	Error rate	time
1	1.3092	2.0286	0.4750	0.525	1s
2	0.8293	2.6641	0.6900	0.310	1s
3	0.6131	3.2799	0.7780	0.222	1s
4	0.4658	3.8958	0.8440	0.156	1s
5	0.3630	4.3356	0.8700	0.130	1s
6	0.3143	4.4193	0.8940	0.106	1s
7	0.2763	4.8384	0.9090	0.091	1s
8	0.2394	5.1271	0.9280	0.072	1s
9	0.2205	5.1721	0.9290	0.071	1s
10	0.2243	5.5884	0.9230	0.077	1s
11	0.1753	5.9592	0.9350	0.065	1s
12	0.2014	5.4956	0.9360	0.064	1s

13	0.1746	6.2210	0.9430	0.057	1s
14	0.1465	6.4558	0.9490	0.051	1s
9	0.1357	6.4164	0.9540	0.046	1s

In Table 3, our training loss as well as our accuracy improved with other performance factors.

4.3 ACC, Precision, Recall, and f1 score

	ACC	precision	recall	f1-score	support
50Taka	91%	0.76	0.97	0.85	120
100Taka		0.96	0.87	0.91	120
200Taka		0.98	0.82	0.89	60
500Taka		0.89	0.92	0.90	120
1000Taka		0.91	0.68	0.78	63
Others		0.00	0.00	0.00	0
micro avg		0.88	0.88	0.88	483
macro avg		0.75	0.71	0.72	483
weighted avg		0.89	0.88	0.88	483

Figure: ACC,Precision, recall, and f1-score of custom CNN.

The above ACC, Precision, recall, and f1-score of custom CNN is shown in the table,here 50 Taka, 100 Taka, To 200 Taka, 500 Taka, 1000 Taka notes have been used.And different values of their accuracy, precision, recall, f1-score are shown.Here the value of accuracy is 91%.Here the maximum value of precision is 0.76 and the maximum value is 0.96.Here the maximum value of recall is 0.68 and the maximum value is 0.97.Here the maximum value of the f1-score is 0.78 and the maximum value is 0.91.Their support value is also shown.Also shown are micro avg, macro avg, weighted avg values in the table above.Micro avg, macro avg, weighted avg values are the same.

	ACC	precision	recall	f1-score	support
50Taka	91%	0.82	0.91	0.86	120
100Taka		0.82	0.71	0.76	120
200Taka		0.91	0.85	0.88	60
500Taka		0.60	0.91	0.72	120
1000Taka		1.00	0.14	0.25	63
Others		0.00	0.00	0.00	0
micro avg		0.75	0.75	0.75	483
macro avg		0.69	0.59	0.58	483
weighted avg		0.80	0.75	0.72	483

Figure: ACC,Precision, recall, and f1-score of VGG16 model.

The above ACC, Precision, recall, and f1-score of the VGG16 model are shown in the table, here 50 Taka, 100 Taka, To 200 Taka, 500 Taka, 1000 Taka notes have been used. And different values of their accuracy, precision, recall, f1-score are shown. Here the maximum value of precision is 0.60 and the maximum value is 1.00. Here the maximum value of recall is 0.14 and the maximum value is 0.91. Here the maximum value of the f1-score is 0.25 and the maximum value is 0.88. Their support value is also shown. Also shown are micro avg, macro avg, weighted avg values in the table above. Micro avg, macro avg, weighted avg values are the same value.

	ACC	precision	recall	f1-score	support
50Taka	91%	0.76	0.97	0.85	120
100Taka		0.96	0.87	0.91	120
200Taka		0.98	0.82	0.89	60
500Taka		0.89	0.92	0.90	120
1000Taka		0.91	0.68	0.78	63
Others		0.00	0.00	0.00	0
micro avg		0.88	0.88	0.88	483
macro avg		0.75	0.71	0.72	483
weighted avg		0.89	0.88	0.88	483

Figure 11: ACC,Precision, recall, and f1-score of improved CNN model.

The above ACC, Precision, recall, and f1-score of the improved CNN model are shown in the table, here 50 Taka, 100 Taka, To 200 Taka, 500 Taka, 1000 Taka notes have been used. And different values of their accuracy, precision, recall, f1-score are shown. Here the value of accuracy is 91%. Here the maximum value of precision is 0.76 and the maximum value is 0.96. Here the maximum value of recall is 0.68 and the maximum value is 0.97. Here the maximum value of the f1-score is 0.78 and the maximum value is 0.91. Their support value is also shown. Also shown are micro avg, macro avg, weighted avg values in the table above. Micro avg, macro avg, weighted avg values are the same.

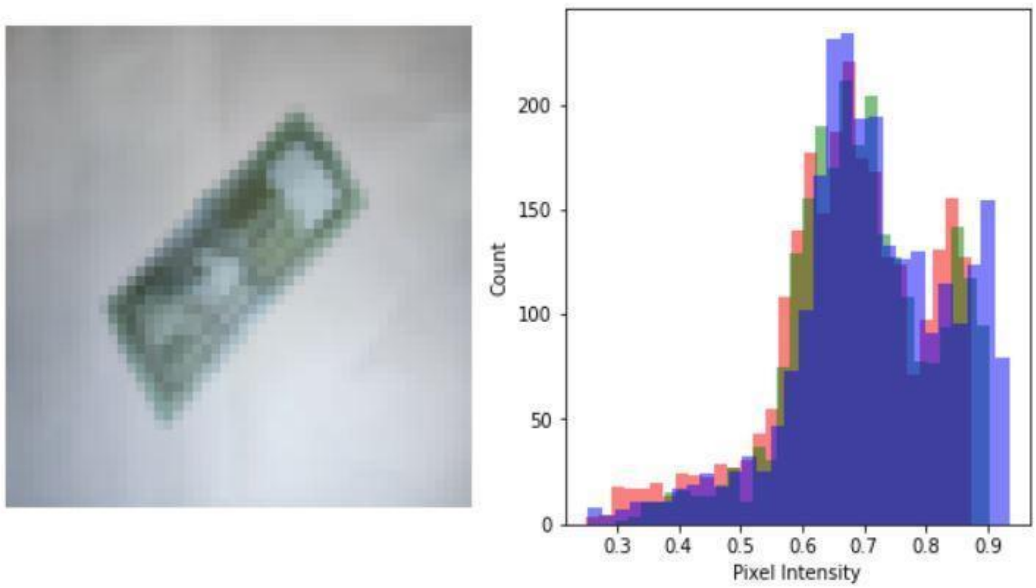

Figure: Pixel intensity histogram

The histogram of an image usually refers to a histogram of the pixel intensity values. A histogram is a graphical representation of a set of data. This histogram is a graph displaying the number of pixels in an image at every exclusive intensity value located in that photo. We can assume an image by really searching its histogram. It's like searching at an x-ray of a bone of a body. The 2nd use of histogram is for brightness purposes. The histograms have big software in photo brightness. Not handiest in brightness, however, histograms also are implemented in adjusting the evaluation of an image.

4.4 Learning curve

Basically A learning curve is a graph illustrating model performance across time or experience. Learning curves are a common machine learning diagnostic tool for algorithms that learn progressively from a training dataset. In the given learning curve figure we can see train and validation accuracy, also we can see train and validation loss.

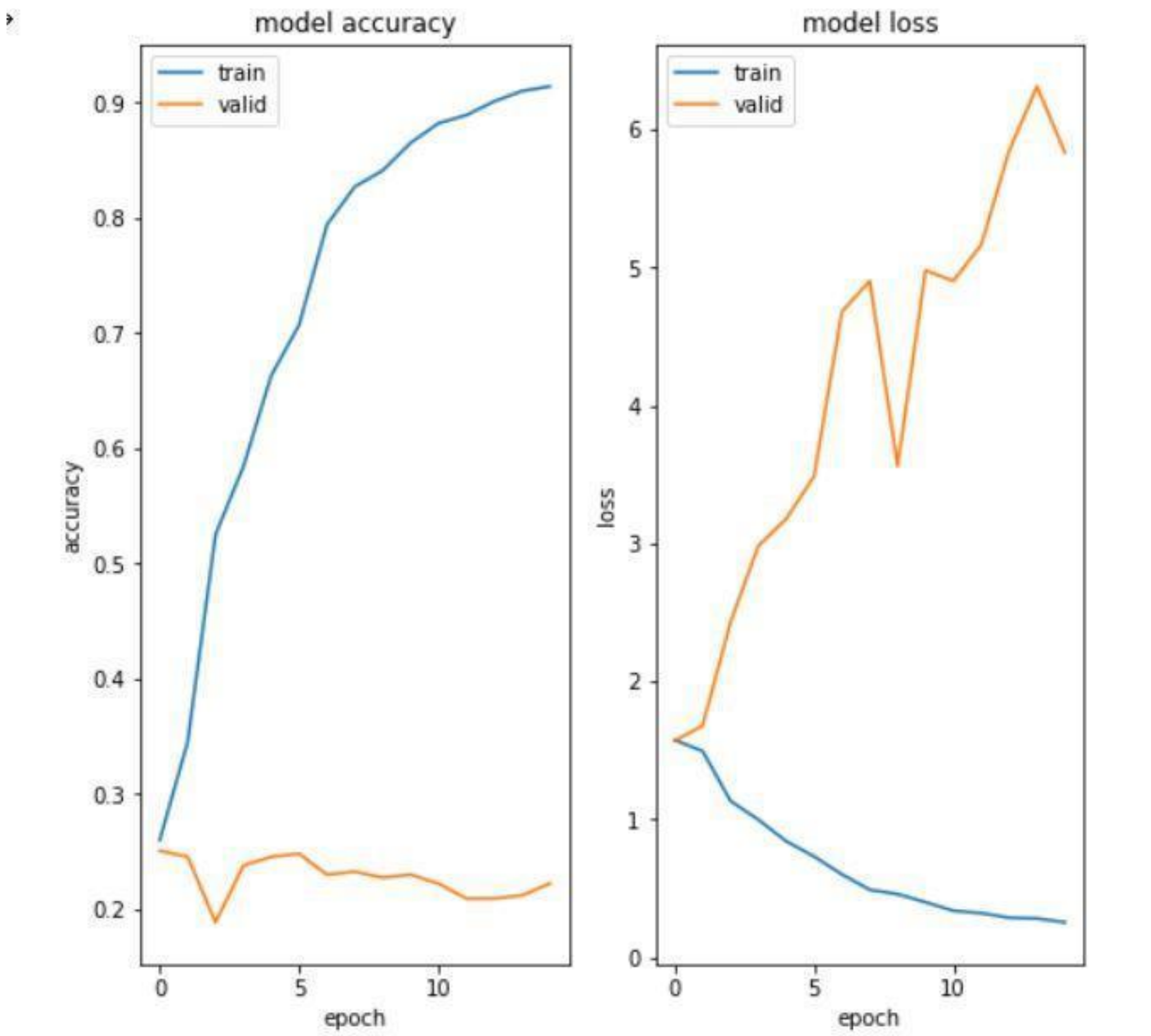

Figure: Learning curve of custom CNN model.

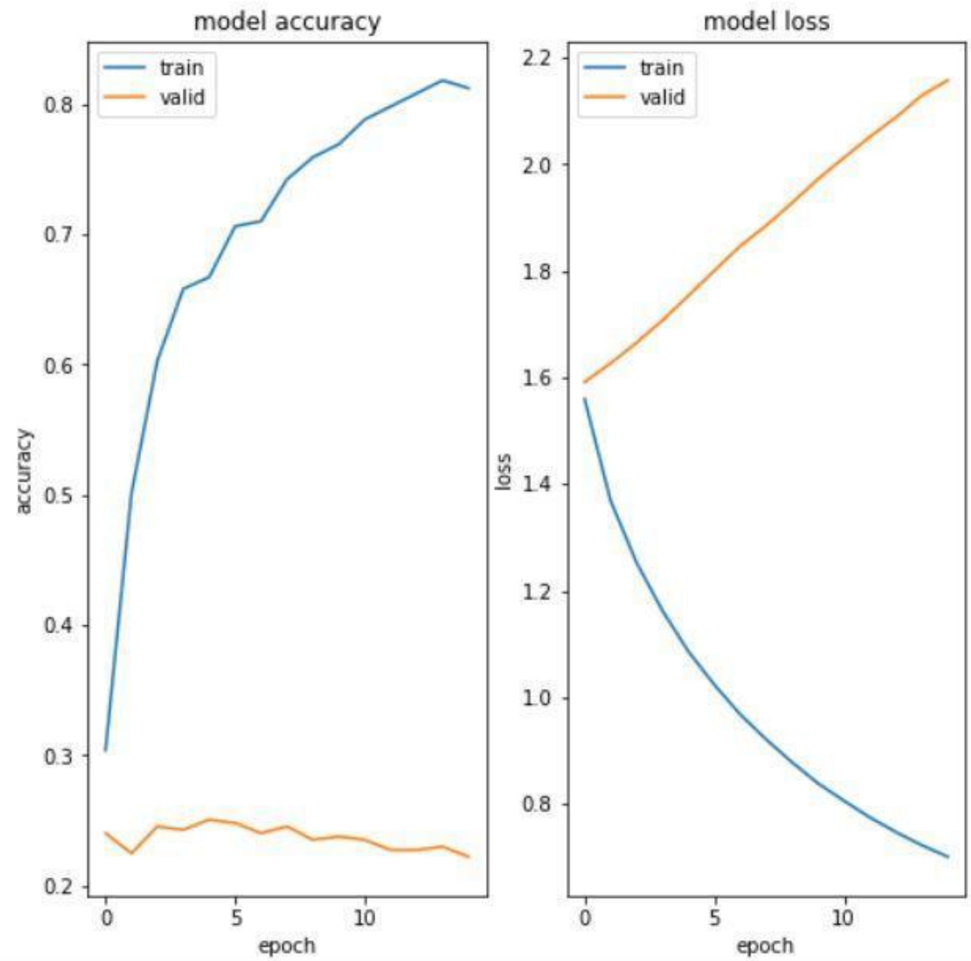

Figure: Learning curve of VGG16 model

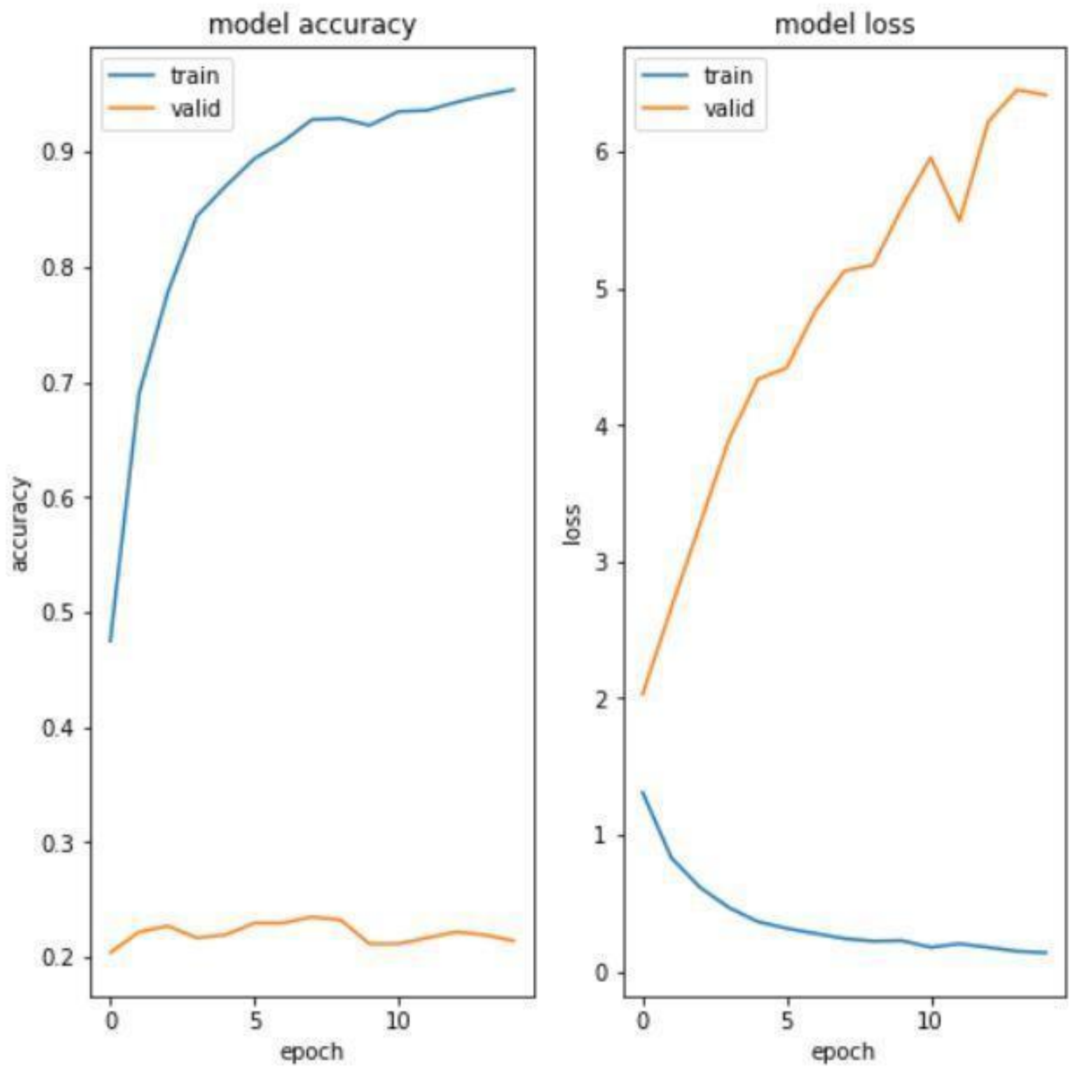

Figure: Learning curve of improved CNN model

CHAPTER 5
CONCLUSION AND FUTURE WORK

5.1 Conclusion.

A money detector for Bangladesh has been developed and tested. A entirely unique Bangladeshi banknote dataset was generated for this purpose. The key motivation for this research is to make the machine clean and user-friendly so that visually impaired people can benefit from it. For the paper currencies that are now available in Bangladesh, we have got successful identity effects. We would like to develop this machine right into a cost-powerful and lightweight smartphone app that can help blind people with everyday transactions. We'll have to check this dataset with different classifiers in the future. Although we've experimented with our system on scanned images of bank notes. A prototype for a Bangladeshi banknote recognition system has been implemented, which is capable of classifying the various denominations of Bangladeshi banknotes. About 3000 images of Bangladeshi banknotes have been collected and arranged in order to train, test, and confirm their denominations. For the identification of banknote denominations from their images, a deep learning-based fully classifier based on the principle of transfer learning has been developed. Deep studying has won great achievement in image-type tasks.

5.2 Future Work

We have collected 3000 raw Data and completed our research. From these data we have been able to identify Bangladesh bank note. We have future plans for this research. We are in the future –

- We will implement our research in web application which is much easy to use for user.
- We will collect more data for our research.
- Our focus is to increase the accuracy of the algorithms.
- We will show the data analysis visually.

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APPENDIX

Research Reflections:

During the time when we were completing our project, it was very difficult for finding the problems and conditions. Firstly, we determined the perfect algorithms among all of the others for getting better results and perfection. Besides, with the help of machine learning and python, all had to take a deep idea about that. Gathering and collecting a huge dataset wasn't as easy as we expected. We were finally able to finish that successfully.

This project is done in combination with the CSE-499 Project/Internship final project