

**BANGLADESHI CURRENCY RECOGNITION AND COUNTERFEIT
DETECTION USING CONVOLUTIONAL NEURAL NETWORKS**

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This Report Presented in Partial Fulfillment of the Requirements for
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APPROVAL

This Thesis titled **Bangladeshi Currency Recognition and Counterfeit Detection Using Convolutional Neural Networks**, submitted by **Saurav Baral**, ID No: **242-25-050** 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 M.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 13-09-2025.

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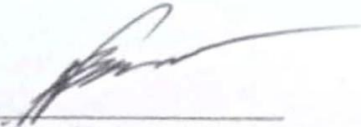
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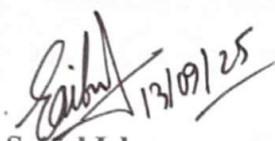


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DECLARATION

I hereby declare that this research has been done by me under the supervision of **Saiful Islam, Assistant Professor, Department of CSE**, Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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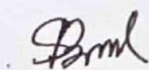


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ABSTRACT

This thesis explores the recognition of Bangladeshi currency and the detection of counterfeit notes using deep learning. The primary objective of the study has been to discover if there is a reliable and time efficient solution where both genuine and fake notes of different denominations are identified.

For this, I have also provided and compared different deep learning models like MobileNet V2, Inception V3, ResNet50, VGG16 and VGG19. Captioning Test Result Table results from test shows MobileNet V2 among the models are the highest. Its accuracy on the dataset was 96.11%. In terms of performance, the accuracy, recall and F 1 -score proved the robustness of such a prediction model. So, in summary, in this particular case we see the model does a good job in classifying real notes and fake notes.

There are also implications for managers based on the results of this research. Some possible applications of such model may include - Application 1: This model could be used to an effort to more readily authenticate notes by individuals, banks, or other institutions operating with other organizations. It could also be used for educational purposes, as it allows for students and researchers to explore the topics of image recognition, and of financial security. Among such advantages are the contribution to the Model for Economic Sustain and assurance for automatic and correct recognition of the counterfeited money, which maintains the materiality of the financial value and elimination of spread of counterfeit money. It promotes the goal of securing the economy and making it more transparent with a little or no human error and optimized performance.

The study showed that deep learning approaches such as MobileNet V2 could be used from a real-world perspective for financial issues. In addition to furnishing an initiative for further studies, this initiative leads to practical user-end tools that would give individuals and institutions access to the state-of-the-art technology for their secure financial transactions and ultimately improved financial stability.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Currency, in its multiple forms, is the backbone of modern economies, an essential medium of exchange, a store of value and a unit of account. Since the beginning of our civilization, from time immemorial, money has played a crucial role for everyone to carry out his/her economic activities conveniently and securely. Aside from its role as a medium of exchange, currency is also a reflection of the economic stability and prosperity of the nation it represents, reflecting the country's financial and governance health. Throughout history, all types of currency have been accepted throughout the world, in the form of notes, coins and even digital money, which allows the use of pertinent currency for a given society. Trust is at the core of the value of money; everyone trusts that the little pieces of paper they're given will be accepted by someone, sometime, somewhere, in exchange for food, lodging or a new car. That trust is the glue that enables economies to run smoothly, and anything that shakes that trust - such as fake money - can lead to disaster. Even in a country like Bangladesh where it is mostly preference-based environment and cash is Supreme, the importance of currency is heightened. But in recent times, advanced counterfeiting methods have emerged that have placed serious threats to the credibility of the national currency, requiring more stringent detection and verification methods guarantee the health of the economy. The challenges of currency recognition and counterfeit detection have never been more important in the modern fast moving global economy, and that is especially true for a country such as Bangladesh, where even today people still rely heavily on cash for day to day transactions in a world that is increasingly moving towards electronic payment methods. With an ever growing population and an immense culture, Bangladesh still primary depends on physical money for majority of its levels of literal transactions. In that situation, it is not only financial sense but an essential part of establishing confidence and stability in the economy to reserve the integrity of the national currency. Throughout history, new, sophisticated methods for counterfeiting have continually been developed which have proven to dramatically challenge old-school methods of currency

authentication, placing business, consumer, and financial institutions at risk. Fake money, previously possible to be recognized just by looking at the note, has become almost identical to a real banknote because of the improvement in printing technology. These fraudulent banknotes have contributed to economic fraud, inflation and lack of public confidence in the financial system, the very linchpin of its sustainability. Despite the various security features implemented by the government of Bangladesh to prevent currency counterfeiting, such as watermarks, security thread and Microtext etc, counterfeiters always find methods to overcome these barriers, is well established that the most advanced and effective methods are needed to verify bank notes. On this background, the application of recent artificial intelligence (AI) and machine learning (ML) approaches, in particular Convolutional Neural Networks (CNNs), as countermeasures for the increasing problem of circulation of counterfeit money has been considered a promising measure. Convolutional Neural Networks (CNNs), which represent one type of deep learning algorithms, have attracted widespread interest in the past years owing to the excellent results they have obtained for the image recognition problems, especially in the cases of complex and high-order input data, for example banknote recognition task. CNNs are particularly good at learning spatial hierarchies of features in images automatically and are very well adapted to tasks such as currency recognition and counterfeit detection where you are trying to tell the difference between genuine and counterfeit banknotes from small differences in the complex patterns and textures. The objective of this study is to investigate application of CNN for developing a strong CNN based reliable and feasible Bangladeshi currency recognition and counterfeit detection system that would provide a technological response to one of the country's most critical problem in its financial ecosystem. The main objective of this study is to develop a CNN model that can identify Bangladeshi Taka notes—regardless of the denomination—and distinguishing them from counterfeit notes with high accuracy. As a national currency, the Bangladeshi Taka has several unique design elements such as intricate patterns, holographic strips, microprints and color-shifting inks that are “very” difficult to duplicate Counterfeiting is the imitation of a currency or financial instrument with the intent to deceive, for economic gain, or to make non-genuine currency items, and is known to be a significant and often lucrative activity. But with improvements in the counterfeiter's art, such counterfeit deterrence measures are being

emulated and so increasingly more advanced means are thus required to distinguish counterfeit money from genuine money. The proposed CNN will be trained on a heterogeneous dataset of the real and forged Taka notes images which are collected in various illumination, angle, and resolution. This will guarantee the models ability to generalize better to practical situations where banknotes are frequently in suboptimal conditions. One of the difficult tasks in training such a model is to model the diversity of possible counterfeits presented by forgers, including low-quality forgeries and higher-level counterfeits trying to imitate as accurately as possible the original banknotes. To address the challenge, the dataset will consider various counterfeit labels of the notes so that the model can differentiate between real and fake currency and, at the same time, between the different grades of counterfeits either. The first stage to develop the system is preprocessing of raw currency note images. This process involves resizing images to a regular resolution, normalizing pixel values in order to reduce variations, and reducing noise which might confuse the learning of useful features by the model. Furthermore, augmenting the dataset by rotating, flipping, cropping the image will be utilized to enlarge the dataset artificially, which can make the model more resistant to real-world variations. The main layer of the CNN model is consisted from several layers of convolution that extract more and more complex characteristics from the images. These layers are able to learn lower-level features such as edges and textures in early layers and higher-level features such as the specific layout and security features evident in the currency notes. The ultimate layers of the network make the actual decision, separating authentic and forged bills according to the features learned. Building such a deep learning model necessitates large amount of data and computing capacity. Hence, various CNN models will be experimented and compared to find the most suitable architecture for the task. The results for each of the architectures VGG16 and Res- Net will be analyzed and compared to define which one best suits the BDT note recognition issue. These models differ from each other in terms of depth, complexity and computational needs; for example, deeper architectures such as ResNet are able to learn complex patterns, but are more computationally demanding and they need more time to be trained. Tuning the hyperparameters will also be very important in maximizing the performance of the model. Hyperparameters, including the learning rate, batch size and the number of epochs will be tuned to ensure the model converges as

efficiently as possible. The model will be tested using cross-validation techniques to ensure that its generalizability by not overfitting on the training data, and that it also works on new, unseen currency notes. I use evaluation metrics (accuracy, precision, recall, F1 score) to ensure the excellent and credible detection of fake notes by my model. One of the main advantages when using CNNs for currency identification and counterfeit detection is the fact that it can real-time validate the banknote. Thereby the system is particularly suitable for implementation in a multitude of environments, including, for example, instead-of Automated Teller Machines (ATMs), point-of-sale (POS) terminals, and mobile payments, where currency authentication needs to be done rapidly and accurately. In such settings, a CNN system can be used to automatically identify counterfeit notes as they are received, or without a user knowing via the exchange of money, thereby providing the user or machine operator with notice of counterfeit currency and for stop use of counterfeit money in routes. Moreover, the scalability of the CNN-based systems can easily be incorporated in financial infrastructures. Bank, treasury and other financial institution cash handling operations can use such systems to enhance the security of their operations and minimize the possibility of introducing counterfeit currency into the money supply. As well as being of practical use in the area of currency validation, this work also has a general applicability for banking houses and police operations. With the introduction of a computer program that can automatically detect counterfeit money, it will be possible to more easily locate, identify, and track false producers and in turn increase the deterrence value of the detection. The system might also lend a hand in criminal investigations, helping to identify forged notes by facilitating tracking of the origins of forged money and thereby putting an end to shady counterfeiting businesses. The merger of currency detection with AI-driven systems represents a major step forward in modernizing and securing financial systems across the globe. Apart from economic aspects, the introduction of such systems would also give rise to ethical considerations concerning transparency, privacy of data, and the effect of automation on labor. CoolDeep CNNs, in common with other deep learning techniques, are not nicknamed to such a polite name. This raises questions about the accountability of the automated systems, particularly as in some cases human judgment would be helpful, for instance, when an alleged counterfeit note is referred for further scrutiny. Furthermore, privacy issues may be relevant if recording of personal data occurs when the currency is

being validated. To this end, interpretable, transparent models need to be developed and guidelines for privacy will need to be laid down. In line with this work, I will make every attempt to ensure that my proposed CNN system is ethical and secure, since there is a fine-line between effective counterfeit detection and privacy preserving and fairness. The research has potential implication beyond Bangladesh, the techniques/ methods developed can be used for currency recognition and counterfeit detection of other country notes. Counterfeit money remains a real thorn for many, so it makes sense that AI-powered security cameras would emerge to do so. This study is a big leap forward for applying machine learning to practical problems, including financial security. Successful implementation of this system will not only uphold the integrity of the Bangladeshi financial system, but also play a role in securing currency operation of other countries of the world.

1.2 Motivation

This research initiative is motivated by the increasing difficulties that Bangladesh has been confronted with in protecting the integrity of its national currency. It is a huge economic and social disruption for a densely populated, low-income country that is dependent on cash transactions to experience counterfeit notes. All of us, from the farmer who purchases seeds, the shopkeeper selling groceries, to the student who pays tuition fees, rely on the integrity of the currency notes we handle. And yet, while counterfeit money also undermines public trust, leads to avoidable losses, and undermines the financial health of the country, there it is. And despite multiple changes in banknote security features by governments, counterfeiters are getting wise and using modern print technology to create near-perfect copies. Old-fashioned human inspection won't cut it anymore, not when even seasoned bankers often can't tell the difference between good fakes and the real thing. With the above pretext, the reason to make technology-driven solution was obvious - as implants the strength of deep learning, i.e. Convolutional Neural Networks (CNNs), to automatically and effectively facilitating the work of money detection and counterfeit distinction. This work is not only driven by academic curiosity but also by the potential social impact that we can achieve in practice. A system that is capable of detecting counterfeit in a reliable manner can protect the general public, strengthen financial institutions, and safeguard the

national economy. More broadly, this work may serve as a model for other countries grappling with the same challenge, showing that technology can be used as a shield against financial crimes.

1.3 Rationale of the Study

The rationale behind this study lies in the urgent need to secure the Bangladeshi Taka (BDT) from counterfeit, which negatively impacts economic expansion and financial stability. The counterfeiters continue to find new ways to replicate the process, even with the advances in watermarks, holograms, security threads, and microtexts. Consequently, a lot of forged money circulates around the market before it is discovered, diminishing the confidence of people in the banking system, as well as the inflation risk.

Machine learning and deep learning, including CNNs, performed very well in recognition tasks of imaging-based in different fields, such as medical imaging, face recognition, or object detection. If checking these models are able to extract complex image features elsewhere, then they may also be used for authenticity checking of currency notes. The motivation of this work is, therefore, to use CNNs for a real-world problem that has both economic and social impact. This research also addresses the lack of Bangladesh specific research as most counterfeit detection systems are designed for foreign currencies such as the US Dollar and the Euro. By using BDT as the niche emphasis, in this paper, the solutions are locally compatible with the local design features, textures, and printing in Bangladeshi banknotes.

1.4 Research Question

This investigation aims to address the following questions:

- How to use CNN most efficiently for recognition of Bangladeshi taka notes?
- How well do CNNs tell the difference between real and fake BDT banknotes, taking into account different lighting conditions, rotation and resolution?
- Which CNN architecture has the best accuracy, precision, recall and F1-score for this problem?
- Is it generalizable to implement the proposed system in practice like ATMs, POS machines, and mobile banking application?

- And beyond Bangladesh, is the approach developed here applicable to other currencies/financial systems that might face similar challenges?

1.4 Expected Outcome

I hope to be able to achieve a strong enough model for it to make real Bangladeshi notes detection. In particular, the system is to:

- Get over 90% accuracy in distinguishing real from fake banknotes.
- Work reliably across various denominations of the BDT.
- Overcome challenges of real-world conditions, including lighting, angle, and note wear-and-tear.
- Be flexible with financial systems like bank, ATM, or mobile system.

I will come up with a trained DL model as well as full framework which can be scaled and applied for the larger use case of Finance in Bangladesh and potentially further.

1.5 Project Management and Finance

The Project management and finance for this thesis are as follows:

- The project would take almost one year, from July 2024 to August 2025.
- The domain and title selection takes one month.
- Literature review and finding an existing study takes one month.
- The dataset is collected over two months.
- The data preprocessing is required one month.
- The experimentation period takes five months.
- The proposed model is defined over one month.



Figure1.1: Study life Cycle

CHAPTER 2

BACKGROUND

In this chapter, the theoretical framework and related work for the Bangladeshi Currency Recognition and Counterfeit Detection are discussed.

The following sub-categories:

- Terminology: The reader is given the necessary background knowledge on Computer Vision, like Machine Learning and Deep Learning.
- Related work: This section compares previous approaches and challenges in the determination of the species and authenticity of medicinal plants in image analyses.
- Comparative Analysis and Summary: Here, this section summarizes and compares the features, performances, and gaps of the method in the literature, as well as discusses the limitations.
- Scope of the Problem: This section includes the research topic and questions of the study describes and elaborates the purpose and usefulness of the developed model.
- Challenges: This section discusses the challenges that were faced during research, and offers suggestions and directions.

2.1 Terminologies

In this section, the necessary background and definitions that would be helpful to present the subject of work are introduced. In this paper, I present Computer Vision and consider Machine Learning and Deep Learning as its sub-disciplines.

2.1.1 Computer Vision

Computer vision is an area of artificial intelligence and computer science that works to enable computers to process the data it obtains from the real world. But it relates to developing algorithms and techniques that allow computers to analyze and understand images or videos. Computer vision applications are generically classified by type of task to which they belong: image recognition, object detection, image segmentation, image classification, among others. Computer Vision mimics the way we (human beings)

perceive the visual world, which is to an extent, let machines see, machines perceive, and make decisions accordingly, all in the visual space. Some of the fields in which this technology is beneficial are hospitals, self-driving cars, security cameras, smart glasses, and factories.

2.1.2 Machine learning

Artificial Intelligence embraces machine learning: generation of models that allow computers to learn to perform specific tasks without being specifically programmed to do so. It is how the programs are made to learn the way of predicting the data by finding the patterns through a number of iterations. For Machine Learning, I take in a large amount of data and let my algorithms learn patterns, see relationship so that it can extrapolate and make predictions on new data were not exposed to.

2.1.3 Deep learning

Deep learning is a subfield of machine learning and is based on an artificial neural network that has multiple layers to learn data representations. It is inspired by the structure of the brain, and has been remarkably successful at tasks such as image and speech recognition, natural language processing, and medical diagnosis.

2.2 Related work

In this section, I describe the present techniques and issues with respect to identification and authentication of Bangladeshi Currency using images.

2.2.1 Traditional methods

Conventional methods used to recognize currency involve feature extraction, such as template matching, color and texture analysis. These approaches use predesigned features, such as serial numbers, holograms, security threads to differentiate genuine notes from fake ones. Though these means have been quite effective, it is becoming more and more difficult to spot forgeries that look very much like real thing. Moreover, conventional approaches are usually time-consuming thus cannot be inspected manually or by a specific instrument.

2.2.2 Recent methods

Recent progression in deep learning has reform the scenario of currency recognition. Many works have been proposed making use of CNN to cope with counterfeit currency. These techniques are based on the extensive training of currency images to the CNN model, so that the network is capable of learning the complex patterns and features that identifies real and forged notes. Deep learning models have several advantages over conventional methods such as better performance, much shorter process time, and the capability of accommodating more complicated design variations of currency.

2.2.3 Comparative Analysis

Over the decades, research of banknote recognition has gradually evolved from image processing to deep learning. The previous systems in Bangladesh applied the traditional image processing methods for making the separation between the forged notes and the valid note such as the image is gray scale, edge detection and their linear classifier, but such systems had been less versatile and unsuccessful against at the high quality forgeries [1] Conventional machine learning models, like SVM and k-NN, introduced more automation while they still depended on hand-designed features and were poor in generalization ability towards noisy real world. Due to the rise of the deep learning, CNN-based methods achieved better performance by automatically learning low-level and high-level features from banknotes images [2]. In the context of Bangladesh, the recent reports from [3] demonstrated that light-weight CNNs with transfer learning can reach more than 98% of accuracy over BDT dataset but their primary concern was note denomination recognition and not counterfeits [3] . More recently, [4] further extended this horizon by implementing a CNN using 50,000+ multiple class data set, embedded in an Android-based application to achieve accuracy of 98.5% and enabled real-time offline recognition [4] . However, datasets such as Bangla Taka have continued to include only clean and authentic bank-note images, with no fake samples [5] and despite the use of real world preprocessing like CLAHE, and YOLO based cropping as in NSTU-BDTAKA, [6] the diversity of counterfeit variations that were captured is stills a problem. Apart from the vision only models [7] expanded a broader standpoint with the help of machine learning, data analytics, and blockchain for counterfeit monitoring, through which system was not based on image

[7]. All in all these two works are symptomatic of a general progress, however, one noticeable void has emerged: Just a handful of these were dedicated for counterfeit detection of Bangladeshi Taka with CNNs on mixed real-life datasets and currency – a gap that this thesis is designed to fill.

2.2.4 Scope of the problem

The issue here is that this work attempts to find an optimal approach for the recognition of the Bangladesh currency and the identification of the fake banknotes by using deep learning models.

The study will look into these aspects of the problem:

- **Data Collection:** The images of genuine and forged notes of Bangladeshi currency notes of all denominations will be collected. Relevant pre-processing techniques will be performed to clean, balance and convert the data into a model-ready format for training and testing.
- **Data Processing:** This work will exploit the CNNs based models and transfer learning methods (MobileNet V2, Inception V3, ResNet50, VGG16, VGG19) in the research work results. The goal will be then to assess their performance regarding accuracy, precision, recall and F1-score, for both denomination recognition and counterfeit detection. New methods to improve feature extraction and classification accuracy will also be investigated.
- **Data Presentation:** The project will determine successful methods of data presentation for currency knowledge and counterfeit detection. One of them is to communicate findings in the form of confusion matrix, classification reports and visualization dashboards for audience analysis including technical and non- technical stakeholders like banks, financial institutions and laymen.

2.2.5 Challenges

There are several challenges in achieving the goal of recognizing and detecting counterfeit Bangladeshi currency images as follows due to the dataset characteristics and the task requirements:

- **Data Quality:** It is a hard task as the extraction of features from the raw image data of banknotes can be patchy, corrupted, low quality and poorly taken under various light and background conditions. In order to produce reliable results, data pre-processing steps, including normalization, augmentation and denoising, are necessary as well as methods to combine and periodically refresh the set with real and generated questionnaire voices.
- **Data Complexity:** The dataset incorporates high-dimensional and heterogeneous image attributes which comes in the form of color variations, textures, watermark details and micro pattern. It is quite challenging handling these complex non-linear features, which needs careful design of CNN architectures, and dimensionality reduction techniques in order to effectively transform and learn this data to enable robust classification and detection.
- **Data dynamics:** Because the counterfeiting designs change through time and new counterfeiting techniques are developed, the dataset is dynamic. The challenge of incrementally updating the model with the new samples, real-time surveillance of recognition cases, and on-line prediction of the spread of forgery is pivotal Research. This demands for developing adaptable techniques that are applicable to streaming or incremental data for lasting performance in real-world scenarios.

CHAPTER 3

RESEARCH METHODOLOGY

This chapter provides brief background of the research work and the process to be adopted in recognition of Bangladeshi currency and detecting counterfeit notes by using CNN.

The following sub-sections:

3.1 Research Subject and Instrumentation: This social project description section presents the study objective as well as the tools/technologies that are intended to be used for the purpose of data collection/analysis. Attention was given only for currency recognition and counterfeit detection for Bangladeshi banknote image datasets. The instrumentation comprises computer vision libraries and python libraries such as Tensor Flow, Keras, OpenCV and deep learning frameworks to build and test CNN models.

3.2 Data Collection Procedure and Dataset Utilized: Data Collection This Section describes the data collection process, which involves collection of genuine and fake Bangladeshi banknote images of various denominations. The structure of the dataset is also introduced, as well as the image preprocessing such as resizing, normalization and augmentation, before the quality and depth balance of the dataset are discussed for CNN models' training and testing.

3.3 Evaluation Matrix and Analysis: This section describes the analysis methods and evaluation measures with which I plan to measure the effectiveness of my models. Accuracy, precision, recall, F1-score and confusion matrix will be used to evaluate the performance of the CNN architecture in denominations recognition and counterfeit detection. Comparison between models (such as MobileNet V2, Inception V3 etc.) and their optimization, research and select the best approach.

3.4 Proposed Methodology or Applied Mechanism: In this section, I present the particular method applied to the study. It uses Convolutional Neural Networks (CNN) and transfer learning techniques for feature extraction from banknote images and classification of true and fake notes. The choice of the proposed technique is motivated by the proven capability of CNN in image recognition and could address complex features like texture, color, watermarking, micro-patterns of currency notes.

3.5 Implementation Requirements: This subsection describes how the proposed approach can be implemented in practice. The use

of excellent computing cluster would help to speed-up the process and avoid the need of stopping early of training on the regular PC. The second reason concerns the system, and the need for clean datasets, preprocessing and model evaluation pipelines. I will then prepare datasets and implement the recognition and detection models gradually, in which both the training, validation, testing and final deployment phase of the recognition and election systems will be presented.

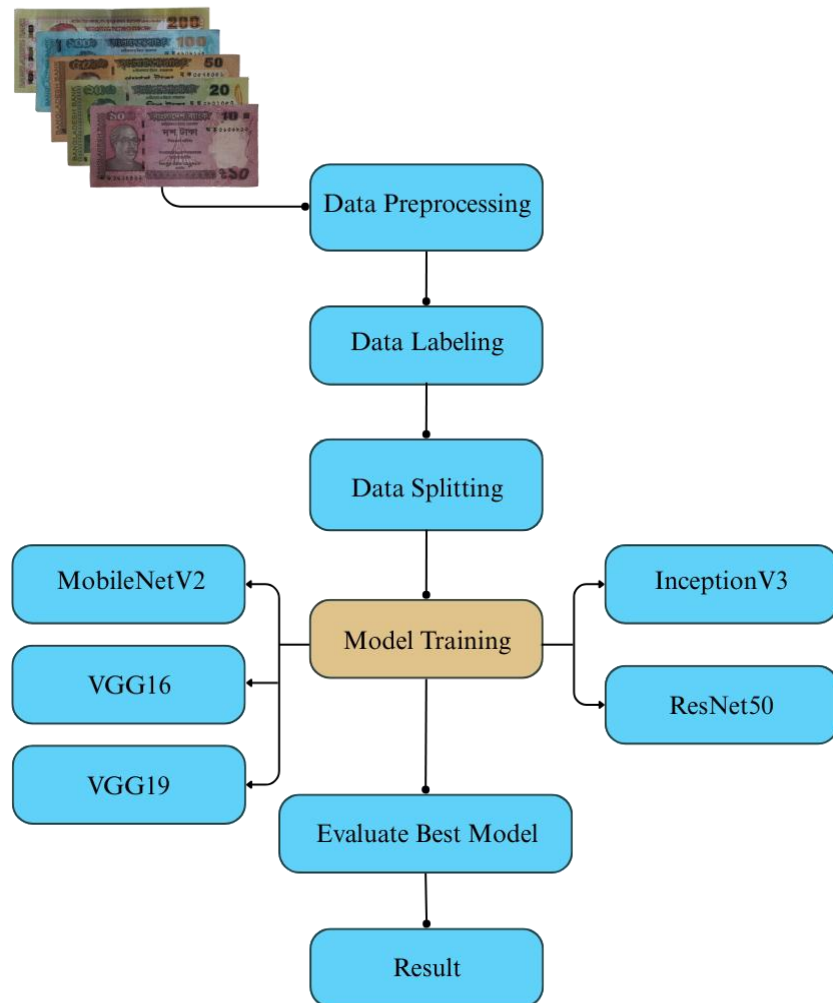


Figure3.1: Model Diagram

3.1 Research Subject and Instrumentation

- Research Subject: The research aim for this work is to analyze forgery notes and to differentiate Bangladeshi notes (of different denominations) using a deep learning

method like lexsd-off model. The objective is to develop an efficient recognition system to discriminate between authentic and counterfeit euro banknote. Circulation of counterfeit note is an alarming economic and social issue in Bangladesh, therefore identification features are the essential point for providing financial security and confidence in the monetary transaction.

- Instrumentation: Some transfer learning is also used The CNN model is the main model applied in this paper. Different pre-trained models such as MobileNet V2, Inception V3, ResNet50, VGG16 and VGG19 are used to recognize the categories of the banknote based on the image features. The training and testing of these models: I employed the printing libraries of Python: TensorFlow 2.0, Keras, and Python running in Google Colab with T4 GPU support, and 2.0 version of TensorFlow, so that it would be exponentially faster to train and test. I used OpenCV and NumPy libraries for preprocessing the images.

3.2 Data Collection Procedure and Dataset Utilized

The dataset to be used in this research was created by collecting both genuine and counterfeit Bangladeshi banknotes from banks and other verified sources. Overall, 2,000 genuine notes and 1,000 counterfeit notes of various denominations, such as Tk 10, Tk 20, Tk 50, Tk 100, and Tk 200, were collected to bring variety. All images were captured using a Canon EOS 250D DSLR camera with an 18-55 mm kit lens (24.1 MP, DIGIC 8 processor). The photographed notes were placed on a plain white background, and with constant white light, these were photographed in order to keep the noise to a minimum and to eliminate any distraction caused by noise. All pictures were identified by two traits, authenticity (genuine or counterfeit) and denomination.

Data augmentation strategies were used in order to make the dataset stronger and enhance model generalization using the original images. Simulations of variation in real life (change of angle, aging, and variations in light) were achieved with methods such as rotation, flipping, zooming, cropping, and manipulating brightness levels. The augmentation procedure increased the sample size to include 2,500 authentic and 2,000 fake images, which brought the total samples up to 4,500. This dataset was subsequently split into

3 parts: 70 percent to training (3,150 images), 20 percent to testing (900 images), and 10 percent to validation (450 images).

There were also challenges in the collection procedure because many of the strong counterfeit samples are hard to find since legal and security regulations limit their locations. In spite of these challenges, the dataset is effective in that it can capture many real-life variants, such as crisp new notes and extremely worn notes. This guarantees that the CNN model, which has been trained, will not only be true in controlled scenarios, but will also be able to be applied to detect counterfeit banknotes in practice.



Label: Genuine



Label: Counterfeit

Sample of Dataset

3.3 Evaluation Matrix and Analysis

- Evaluation Matrix: For the study of the recognition of these models, and for the analysis of the detection of fakes, the following metrics were used.
- Accuracy: It is the ratio of the banknotes that the system helped in tagging the actors to the total amount of samples tested.
- Precision: The number of the banknotes which are properly classified by the system, divided by the total number of tested samples.
- Recall: The proportion of the banknotes of a particular category (genuine/counterfeit) which is of another category that are classified into that category.
- F1 Score: The weighted average of precision and recall, it is a balanced measure between the two.

- Confusion Matrix: It is applied to show the classification process and also spot where the model is unable to distinguish between particular denominations and counterfeit samples.

3.4 Proposed Methodology or Applied Mechanism

Proposed Methodology: My methodology involved several key steps:

- Data Preprocessing: All the images were resized to a fixed size (e.g., 224×224 pixels) and then the pixel values were normalized and preprocessed by data augmentation to increase size of training set. These operations ensured the model will be invariant to number of illuminations, perspective and noise.
- Model Selection: I applied convolutional neural network (CNN) based deep learning models with transfer learning. The pre-trained models in ImageNet (including MobileNetV2, InceptionV3, VGG16, VGG19, ResNet50) were re-trained using my data set. Transfer learning allowed computationally costly feature learning (using ReLU 11 nonlinearities and dropout) from ImageNet7 to greatly improve generalization performance on a small dataset without the need to have many labeled examples.
- Training the Model: All models were trained on the training set for multiple epochs with a given batch size. The cross validation was applied to avoid over-fitting and to validate the stability of the model. I hyperparameter tuned my models quite a bit - adjusting learning rate, optimizer and loss function settings.
- Validation and Testing: The validation set was used to tune the hyper-parameters and to fine-tune the models, whereas the test set was used to report the final evaluation results. Several CNN architecture variants were tested to accommodate for currency classification and counterfeit rejection.

3.5 Implementation Requirements

- Software and frameworks: Python language is widely used not only as a tool for modelling but also for scripting. Keras are deep learning frameworks for building up and training deep learning models.

- Environment for Development: Development and training were carried out in Google Colab and local Jupyter Notebook as there was GPU for computation here.
- Data Preprocessing: Image scaling, normalisation, and augmentation tools were applied to pre-process the dataset and to minimize the raw image-sensitive in the model.
- Parameters for training: I adjusted the hyper-parameters as well as optimized the training:
 - Learning Rate: Tanned to optimize the tradeoff between training time and accuracy.
 - Batch Size: Selected to make the training effective without running out of memory.
 - Epochs: It was determined based on the model converge and no overfitting.
 - Comparison with other methods on LOO evaluation set. Metric: Loss function applied was Categorical cross-entropy.
 - Optimizer: I used Adam Optimizer to update the weights.

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Experimental Setup

I used CNN model to recognize Bangladeshi Currency and Counterfeit notes, compared the algorithms' effectiveness and considered possible improvements. The tests were conducted through Colab with the utilization of Keras, Tensorflow, and Numpy. In the data visualization I used Matplotlib to make plots. The dataset includes 4500 photos. I used 70% of the images for training. For validation, I used 10% of the data and for testing 20% of the data set was used.

Table 4.1: Splitting the dataset for training, validating, and testing

Data Type	Data Point
Training	70%
Validation	10%
Test	20%

4.2 Experimental Results & Analysis

The performance of model was evaluated using some key metrics:

4.2.1 Loss

During the training and validation processes, categorical cross-entropy was paid attention to as the loss. A reduction loss meant that model is gradually improve in terms of recognize the Bangladeshi Currency and Counterfeit notes.

4.2.2 Accuracy

Accuracy of classification computed as the ratio of the number of responded samples to all the samples, offered an overall estimate of the efficiency of the model.

4.2.3 Confusion Matrix

The confusion matrix was used to analyze the behavior of the model to classify and predict the occurrences for each class; this comprised of true positive, true negative, false positive, and false negatives. This matrix gave an indication of some of the possible areas of emphasis and possible difficulties in identifying the Bangladeshi Currency and Counterfeit notes.

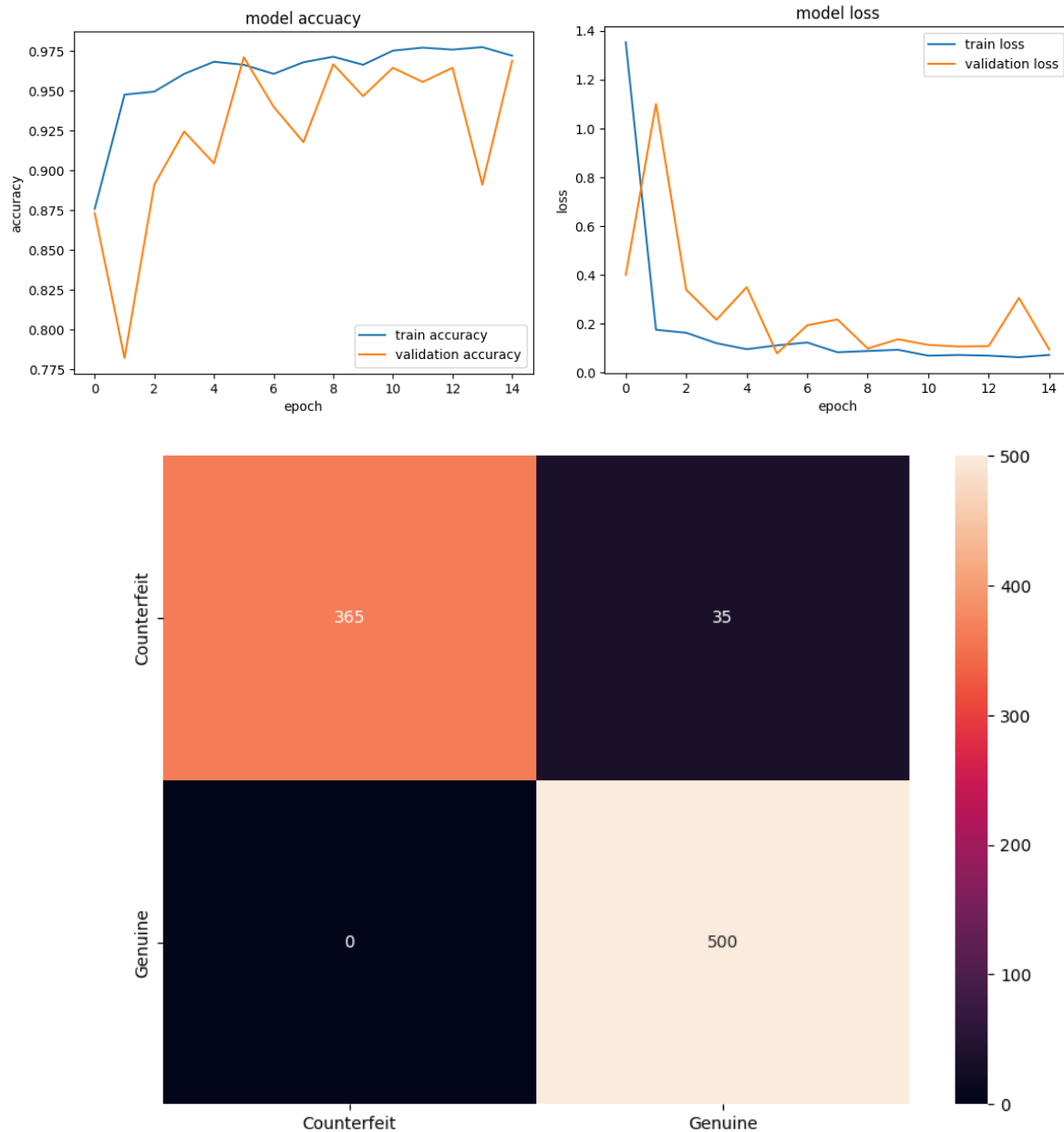


Figure 4.1: Loss and Accuracy, and Confusion Matrix of MobileNet V2

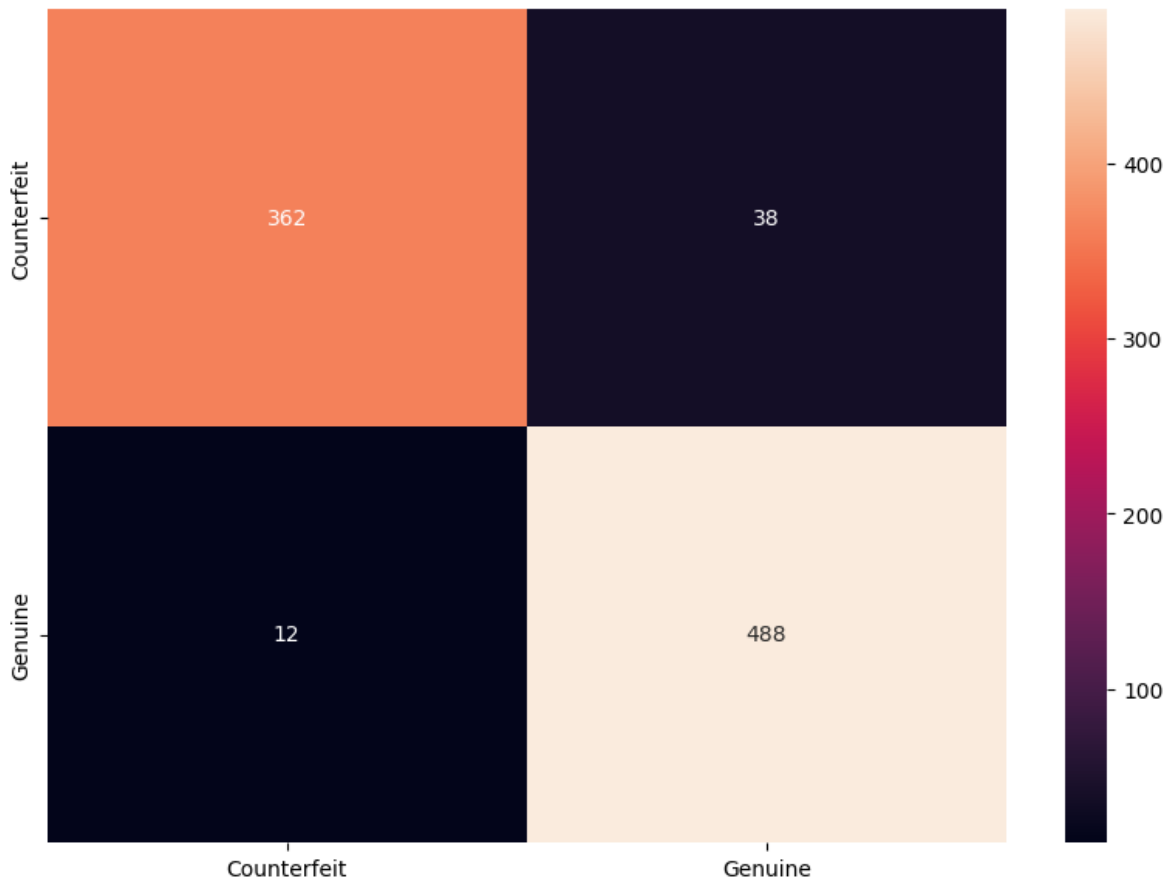
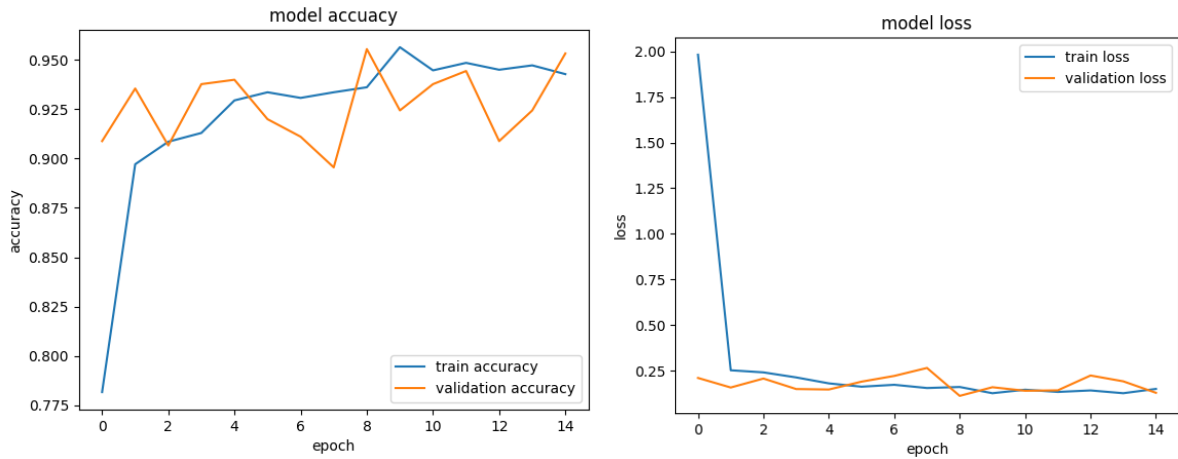


Figure 4.2: Loss and Accuracy, and Confusion Matrix of Inception v3

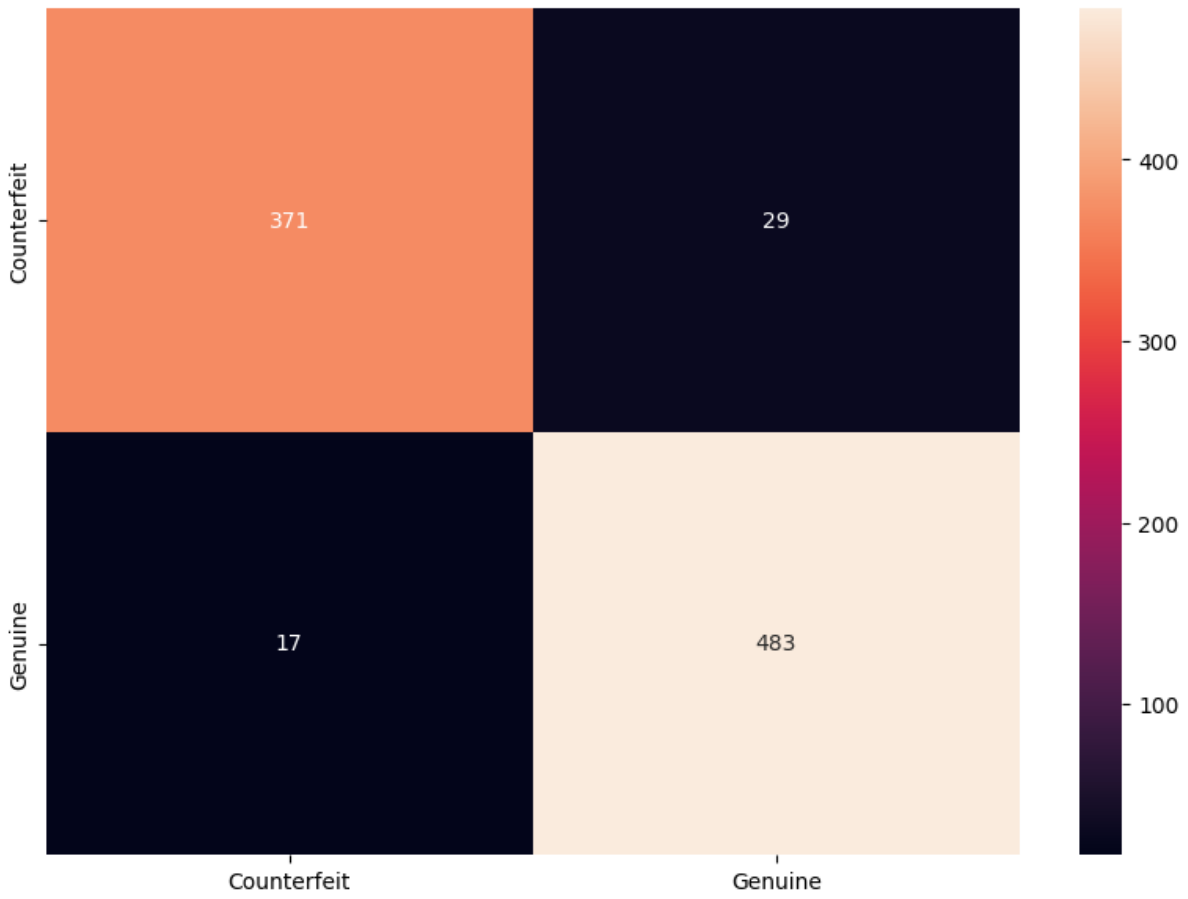
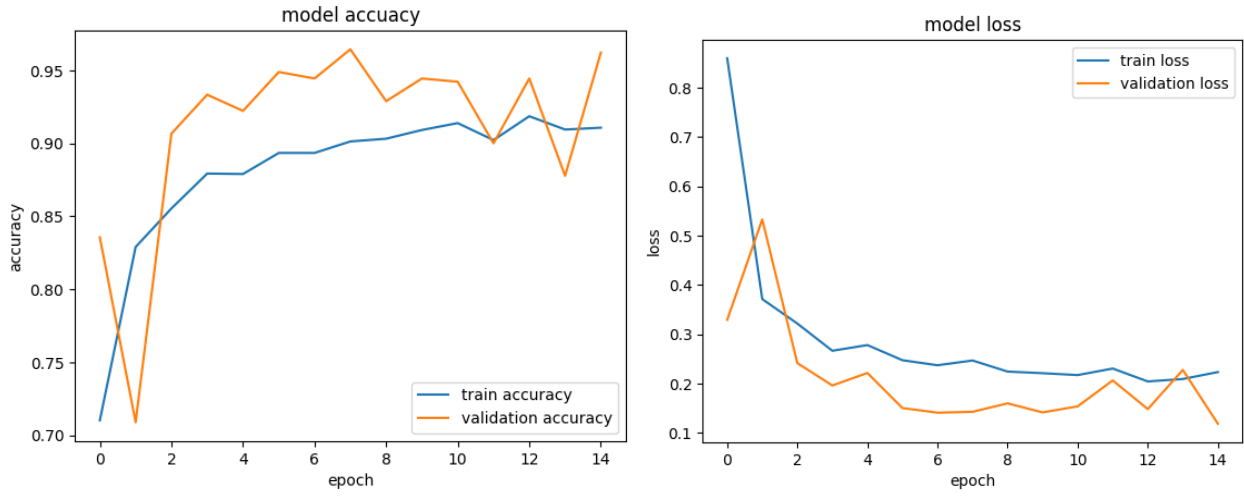


Figure 4.3: Loss and Accuracy, and Confusion Matrix of VGG16

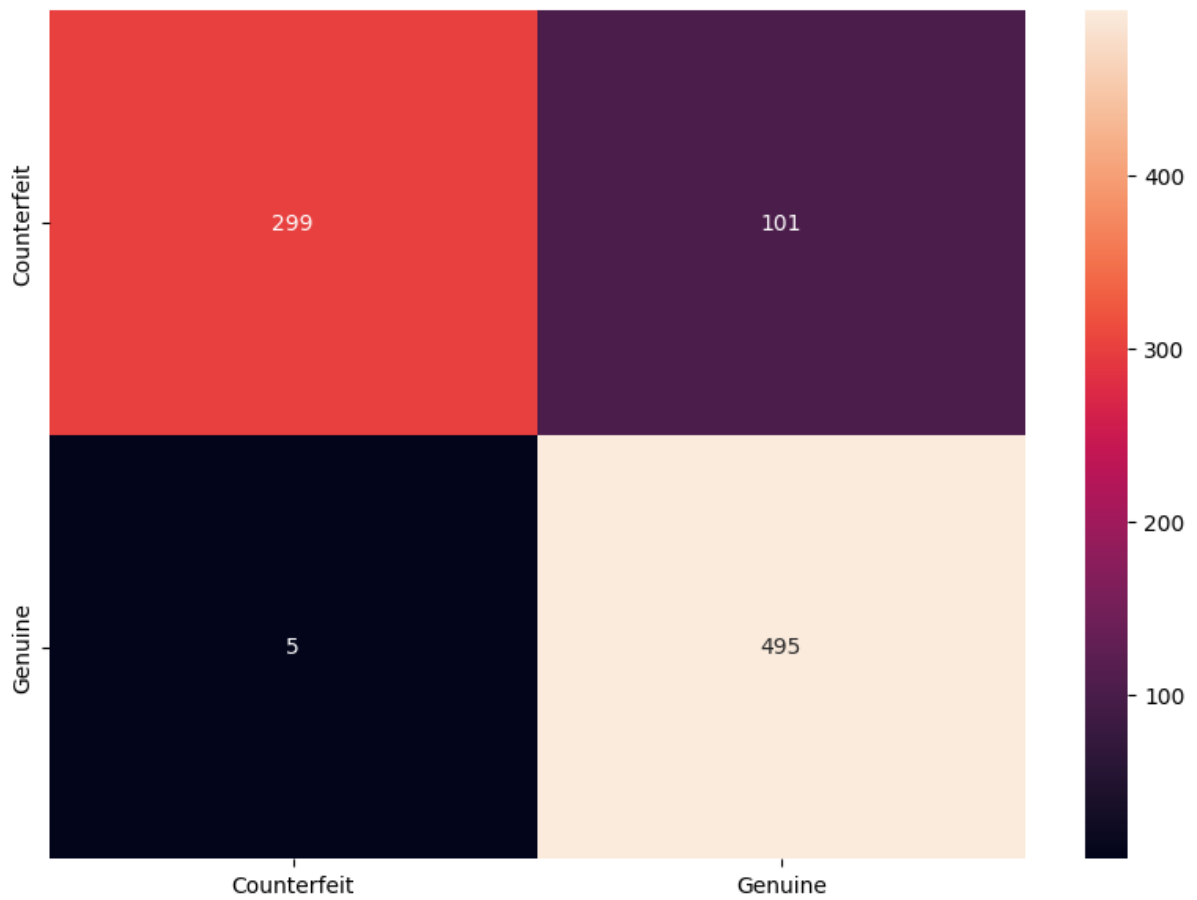
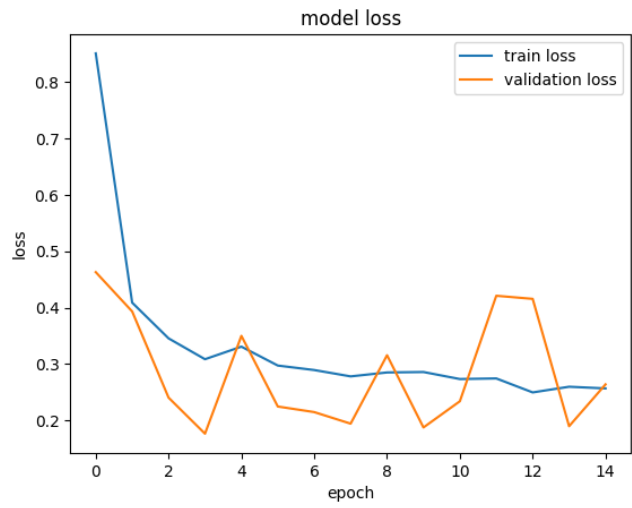
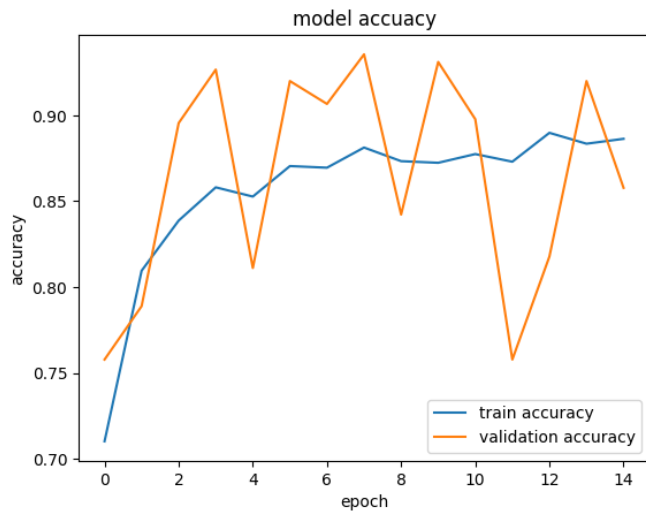


Figure 4.4: Loss and Accuracy, and Confusion Matrix of VGG19

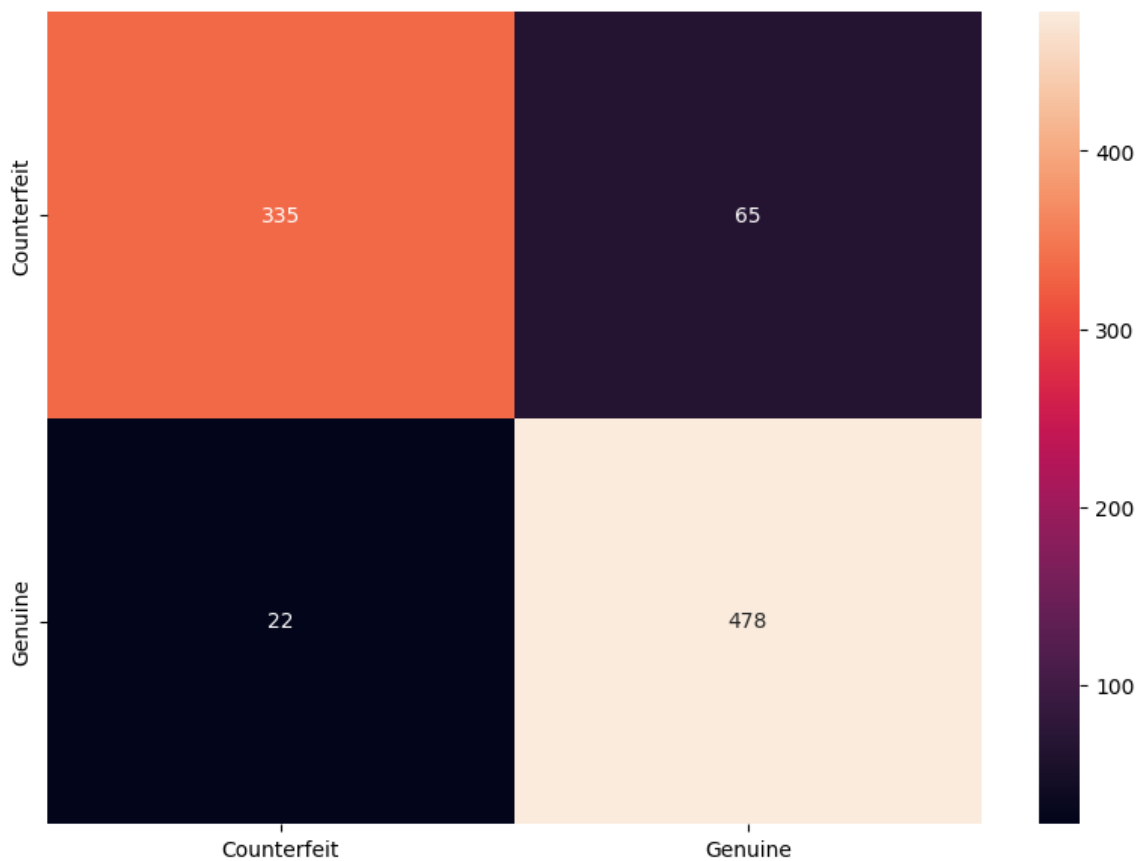
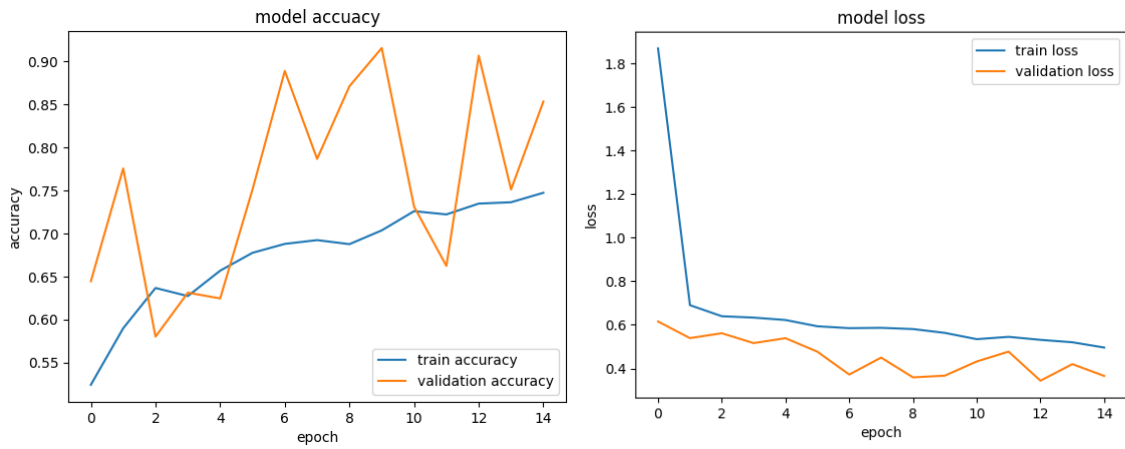


Figure 4.5: Loss and Accuracy, and Confusion Matrix of ResNet50

4.3 Discussion

The results of this experiment are significant as they show that CNNs are very effective for recognizing and discriminating counterfeit from genuine currency of Bangladesh.

I observe that MobileNet V2 obtained the best results with an accuracy of 96.11%, followed by the rest of the models. It may be due to the lightweight yet powerful network design of PPDNet that leverages depthwise separable convolutions and inverted residuals to produce strong feature representations with low computational cost. The higher accuracy of MobileNet V2 demonstrates that it has the good ability to generalize the discrimination between real and counterfeit banknotes even with complex texture, color, visual features, or small features in currency images.

The VGG16 model also achieved comparable performance up to 94.88% accuracy. Although having many parameters, deep convolutional layers in VGG16 was able to learn hierarchical features of the banknotes. This demonstrates that while heavier in compute compared to MobileNet V2, the architecture remains a good choice for image classification tasks with fine-grained structure such as watermark patterns, embedded threads, or print quality differences.

Inception v3 with 94.44% accuracy which is less than VGG16 but it also performs well. Its architecture that concatenates multiple convolutional filter sizes at each layer allows it to model the global and local features of currency notes. Therefore, Inception v3 is very robust on counterfeit detection, especially when the fake pattern variations are more complex.

Meanwhile VGG19 was even less accurate with 88.22%, significantly less accurate than VGG16 and it's deeper! The above performance degradation indicates clumsily deepening the network may not be able to lead to better recognition accuracies. In reality, over-fitting, can readily occur in the deeper network if the dataset is relatively small such as the Bangladeshi currency images. This suggests that the increase of layers in VGG19 might be unnecessary and not provide extra discriminative power. When I tested ResNet50, it achieved an accuracy of 90.33% which is way better than I would have imagined, given the depth of the model. It is evident from this that ResNet50 was able to learn the significance phase transitions very well especially with aid of residual connections that overcomes the vanishing gradient problem. But its performance was a little worse than MobileNet V2, VGG16, and Inception v3. I think it is because ResNet50 is a much deeper model and the network performs well only when you have a large enough dataset. Although

it was only relatively slower than other architectures, the added overhead didn't offer a clear advantage for my task over the simpler, lightweight, and balanced models.

Table 4.2: Proposed Model Summary and Performance by Each Label

Plant Name	Precision	Recall	F1-score	Support
Counterfeit	1.00	0.91	0.95	400
Genuine	0.93	1.00	0.97	500

CHAPTER 5

IMPACT AND SUSTAINABILITY

The chapter thus describes the influence of the research on Bangladeshi currency recognition and fake detection for CNN and its impacts on social, economic and sustainability viewpoints.

It covers these sub-sections:

5.1 Impact on Society: It is evidence that the research can have a positive impact on financial security, fraud and the everyday economic transaction of Bangladeshi people syncing; the average person on a platform.

5.2 Impact on Environment: It makes it evident that perfect detection of counterfeits leads to improvement of economy since of fake note circulation is minimized and also indirectly reduces resources depletion of printing and reprinting of notes.

5.3 Ethical Aspects: Ethical and Societal: Covers on the question of ethical issues like “Who owns the data”, privacy and responsible use of AI for financial systems.

5.4 Sustainability Plan: This section presents the sustainability plan of the research that is the practical continuation of the work, including the maintenance of the methodology and the deep transfer learning model as well as the scalability and accessibility of the developed solutions. The plan guarantees that the system will always be current, easily accessible by the public, and suitable to accommodate technological trends.

5.1 Impact on Society

The research work on identification of medicinal plants using deep transfer learning can have a positive impact on public health and community well-being in various ways:

- **Financial Safety:** Since the presence of fake notes can be highly detrimental to public confidence in currency transactions and banks, the model fortifies this confidence by preventing the circulation of such notes. “This safeguards Bangladeshis’ everyday financial transactions.
- **Banks and Retail Stores:** Counterfeiting detection methods based on this research can be embedded in ATMs, POS machines, and cash counters at both banks and stores, preventing banks and retail stores from losing money to counterfeiting.

- **People Empowerment:** Common man can use the mobile / cost effective tools for detection of the genuineness of his currency, thereby preventing him from being cheated.
- **Educational Value:** Furthermore, this study also has contributions to academia such as computer science, data science, and finance by providing the actual case study of CNN in the finance application.
- **Research Implications:** The baseline model is considered as a foundation structure for the future of financial AI application and future works in fraud detection and financial security.

5.2 Impact on Environment

- **Financial Security:** Fake money hurts financial instruments of any country. Such a system curtails fake notes from being circulated so that the economy gets better grounded, comeback stability in various sectors are seen and public savings are secured.
- **Savings:** Reduces the expense of manual confirmations, as well as re-issuing compromised notes, for the government, banks and other financial companies.
- **Sustained Use of Resources:** The printing of a currency uses paper, ink, and energy. The prevention of circulating counterfeit in turn would suppress the unnecessary consumption of these resources to some extent for environmental protection.

5.3 Ethical Aspects

The research work on Bangladeshi Currency Recognition and Counterfeit Detection Using Convolutional Neural Networks also involves some ethical aspects and challenges:

- **Data Privacy and Ownership:** Even though in the dataset only are notes that contained the sentiment and sentiment on the notes, some of the banknotes includes the official papers so it maybe or could may will absolutely answer to some official/sensitive thing. There are legal and ethical issues to be met by due consideration whether the data is collecting in legal form and the policy of privacy and data ownership also requires security.

- Ethical use of AI: AI should be employed ethically from an application perspective to prevent misuse (e.g., by fraudsters trying to ‘game’ the system). The economic environment needs to be shielded by navigating to the right securities.
- All access: Grant greater access to the system to the banks, the businesses and to the citizens, Strip away the unnecessary costs and share the proceeds more fairly all around.
- Transparency: It is important to be transparent to both developers and researchers and to inform those who use the system, about the functioning of the system, about the limitations of the system and about the exposure in application of the device, to obviate unrealistic expectations.

5.4 Sustainability Plan

The research work on identification of medicinal plants using deep transfer learning also proposes a sustainability plan that involves several strategic actions:

- The Model Ought to Be Latest and Ongoing: The model should always be updated to make it the most current as when the brand new fake emerges.
- Collaboration with Bank and LEA: Formulating operational linkage with Bangladesh Bank, commercial banks and law enforcing agencies, make the tool self sustainable and efficient.
- Community Awareness: Publicist programs for detection system to reduce reliance on forgery vulnerable transactions.
- Scalable: The solution must be scalable to go beyond coins to include mobile apps, banknote counters and retail systems.
- Policy Entrenchment: The system is sustainable over the long term once it is adopted by government and banks.

CHAPTER 6

SUMMARY, CONCLUSION, RECOMMENDATION, AND IMPLICATION FOR FUTURE RESEARCH

6.1 Summary of the Study

In this research work, Bangladeshi Currency Recognition and Counterfeit Detection Using Convolutional Neural Networks, which can be regarded as a complex aspect of artificial intelligence. The first objective was to design a model for Bangladeshi Currency Recognition and Counterfeit Detection from the image of the currency which will help others specifically the people of Bangladesh to identify real and fake banknotes. The results concluded that CNN-related methods can highly accurately detect denominations and fake notes. This highlights how AI-enabled systems can help to secure Bangladesh's financial system.

6.2 Conclusions

- **CNN effectiveness:** The CNNs, with the support of transfer learning, were effective to identify genuine banknote and detect counterfeits with great accuracy.
- **Practical applicability:** The system can be implemented in a real environment such as ATMs, point of sales (POS) devices or mobile applications, thus it is a ready-to-use system for daily basis.
- **Contribution to Monetary Stability:** This security feature helps the public to have more trust in the currency transactions and it contributes to the stability of the economy.

6.3 Recommendation

- **Use in Banks and Other Financial Bodies:** Financial Organizations can use AI-based counterfeit detection in order to supplement the security of their transactions.
- **Community Training:** Awareness sessions to educate the public about the use of AI based verification tools.

- Device Integration: The system would be integrated with ATM, vending machine and retail scanner to allow detection in real time.
- Educational Use: The research model can be used in universities to serve as an example of AI in financial applications.

6.4 Implication for Further Study

- Further data collection; More diverse and larger datasets of counterfeit banknotes for SIL should be gathered, comprising new development types of counterfeit.
- Mobile App Development: Future work can develop mobile apps that are lightweight and can be used on the move for verification.
- Cross-Currency Application: It is also possible to adapt the system to be able to determine the presence of a counterfeit foreign currency.
- Integration with blockchain or IoT: Integration of CNN based detection with blockchain verification or IoT enabled banknote scanner can make the counterfeit note detection more reliable.

APPENDIX

Appendix A: Data Collection

Photographs of genuine and fake Bangladesh banknotes were taken with a Canon EOS 250D DSLR Camera (with 18–55mm KIT Lens, 24.1 MP, DIGIC 8 processor). Standardised light and background conditions were maintained at all times, with controlled lighting and plain white background.

Appendix B: Model Development

CNN-based transfer learning models (MobileNet V2, Inception V3, ResNet50, VGG16, VGG19) were deployed to discriminate denominations and to identify counterfeit notes.

Appendix C: Training Process

- Dataset Preparation: Following this I divided the data into three datasets: training, validation and testing. The discussion above indicates that the testing set was used to train the model, the validation set to calibrate the model and the worked-out model was tested with the test set.
- Model Training: It was trained using high-performance computers. It also showed feeding the model images and tweaking the parameters in an effort to minimize the errors. Training in this case involved a few hours of training and it repeated typing for a few times to get the highest accurate result.

Appendix D: Results

Accuracy: The model worked very well in classifying the Bangladeshi Currency with high accuracy rates. Out of the Bangladeshi Currency from the test images, it was able to correctly identify a large percentage thus making it efficient.

Appendix E: Challenges

- Different Counterfeit Notes: Counterfeit notes are typically not the same quality or texture as authentic notes. as the fake notes doesn't have any standard.
- Restricted Data Availability: There were not enough fake notes available for the study since they were not widely available and, in most cases, not accessible due to security

restrictions. Therefore, the number of images in my database is not as large as one could have desired, and I had to implement a very careful augmentation to extend the size of my database in order to improve generalization.

- **Computational Bound:** Deep learning models such as Inception V3 and ResNet50 require high-GPU resources for training. Due to constraints in computational power, I optimized the training parameters in a way that accuracy and efficiency could both be taken into account.

Appendix F: Future Work

- **Dataset Enlargement:** A bigger and broader data set of existing and New emerging counterfeit pattern of notes should be added in the library.
- **Field Testing:** The model can be implemented in the banking machines (ATMs, POS terminals and currency counting machines) for performance monitoring in real time.
- **Mobile App Development:** When ready the proposed tool can also be available as an Android/iOS app, making it possible for the common citizens to verify the notes on the fly.
- **Cross-Currency Application:** The proposed framework can be generalized to facilitate counterfeit currency detection of other countries making it beneficial for international research.

Appendix G: Additional Visualizations

Complementary visualizations were also proposed to help validate the experimental results.

- **Samples:** Some samples of Bangladeshi banknotes (both genuine and counterfeit) in various denominations.
- **Confusion Matrices:** Interpretation of the results for banknotes, describing the extent to which the model identified each denomination/depreciating banknote.
- **Accuracy Graphs:** Training and validation accuracy graphs per epoch, showing when the model is beginning to converge.
- **Loss Curves:** Charts showing a decrease in the loss with time, both for training and validation sets, indicating learning was happening as desired.

- Model Comparison Charts: Bar graphs comparison of Accuracy, Precision, Recall, and F1-Score between CNN architectures (MobileNet V2, Inception V3, ResNet50, VGG16, VGG19).

Appendix H: Code Repository Information

All Python scripts, model training codes and code for the pre-processing pipelines are available on GitHub in a private repository during the thesis period and could be made public after.

Appendix I: Contact Information

For any questions or further information, please contact:

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Institution: Daffodil International University

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CURRENCY RECOGNITION AND COUNTERFEIT

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