BATTLING COUNTERFEITS: CUTTING-EDGE SOLUTIONS FOR BANGLADESHI CURRENCY SECURITY.

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled **"BATTLING COUNTERFEITS: CUTTING-EDGE SOLUTIONS FOR BANGLADESHI CURRENCY SECURITY"**, submitted by **Md. MIZANUR RAHMAN, ID: 192- 15-2832** and **MEHRAB HOSSAIN, ID: 201-15-13769** to the Department of Computer Science and Engineering, Daffodil International University, have 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 14 July 2024.

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ABSTRACT

Counterfeit currency is a major threat to the economic integrity and security of Bangladesh, particularly with regard to high-denomination notes, including 500 and 1000 taka bills. The current study sought to achieve an understanding of the modern deep learning approach's potential to effectively identify counterfeit currency. Therefore, we tested four widely recognized Transfer Learning models available with pre-trained weights, including VGG16, Xception, ResNet50, and DenseNet201. We trained these models on a large dataset of authentic and fake images of Bangladeshi banknotes and assessed their capabilities to detect whether banknotes are authentic or counterfeit. The DenseNet201 model demonstrated the greatest identification power and accuracy according to the results, with an accuracy level of 97.69 percent. From the other models, Xception demonstrated 94.77 percent accuracy, VGG16 demonstrated 94.26 percent accuracy, and ResNet50 demonstrated 92.03 percent accuracy. Regardless, the outstanding efficiency of the DenseNet201 model shows that it can be used as a powerful tool for combating counterfeit in the country, providing huge strides over existing technologies. Specifically, indeed, present study lends empirical evidence that deep learning has a significant disruptive potential in the three-years future of financial security. It can encourage the development of more advanced systems for detect counterfeit currency, which can revolutionize the fight against financial crime and protect Bangladesh's national economic interests.

Keywords: Counterfeit Currency Detection, Deep Learning, Convolutional Neural Networks (CNN), DenseNet201, Xception, VGG16, ResNet50, Bangladeshi Banknote

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CHAPTER 1
INTRODUCTION

1.1 Introduction

The occurrence of counterfeit currency is rampant and it affects the economy largely, Bangladesh too faces this problem. Counterfeit 500 & 1000 Taka notes endangering to the economic stability of country. In addition to distorting competition in the domestic market, this also causes economic losses for companies and citizens, complicates cash payments and undermines the confidence of the population in the national currency. Counterfeiting leads to broader economic destabilization and provides the atmosphere for more widespread criminal activity than what is merely financially damaging.

Fighting the counterfeit currency means taking extreme (and intelligent) evolutions in countermeasure techniques. Manual inspection, checking pens, and simple machine validation fail to verify all real notes or detect most filters when it comes to identifying counterfeit money. Counterfeiters are getting more sophisticated and there is a significant demand for the latest technological solutions that can keep up with ever-evolving threats. Deep learning is a sophisticated subfield within artificial intelligence, and it provides powerful tools to develop such solutions.

Deep learning has shown great potential in various fields, particularly image recognition and classification tasks. This can be used to construct systems that have the ability of distinguish between real and fake currency. In this work, by using advanced deep [Transfer] learning architectures such as VGG16, Xception [11], ResNet50, and DenseNet201 the detection of genuine 500 &1000 Taka notes is studied. Each of these models is chosen because it has been shown to solve a different kind of hard image data and to work well in applications.

VGG16 is popular because, as we shall see later in the examples here it combines depth (i.e. number of layers) with a very small 3x3 stride and conv size allowing a complex structure to be built without having complicated building blocks that will cause consistency problems when some initialization method is used! Xception improved computational efficiency by using depth-wise separable convolutions with better accuracy. ResNet50 uses residual learning to train very deep networks and directly addresses the vanishing gradient problem, which can be alleviated by making network layers skip connections - improving performance on hard tasks.

DenseNet201 has better gradient flow, exchange of feature information, and regularize [14] which can improve the performance.

The study trained and tested these models using an integrated database of genuine Bangladeshi Taka notes as well as a counterfeit of the same currency. This is to ascertain which model yields the best overall accuracy and reliability for deploying counterfeit detection applications in real-world scenarios. The purpose of this comparison is to offer a detailed scaling analysis for the development and deployment of productive systems on passages on counterfeit detection by comparing their performance metrics

Importance of this study to academia and practice Academically, it supports the rich literature on deep learning applications in currency authentication. More specifically, it provides key lessons for generating products that improve access to financial security in Bangladesh on a meaningful scale. The existence of every possible technology to shame everyone by doing so is required and the public faith has been recovered from such measures which when implemented establishes a dummy-proof counterfeit prevention system.

This study is rolling around the deep learning power to solve key issues in Bangladesh which denotes counterfeit currency. We evaluate a large number of state-of-the-art models to build the best possible counterfeit detection system. This work is a response to both an urgent economic challenge and ongoing efforts to protect financial ecosystems against counterfeiting.

1.2 Motivation

The BMA also came under heavy criticism for the way it handled its financial balancing activities through manipulative measures which was another strong driver behind this research effort in order to salvage Bangladesh's economic crisis and restore trust of money by general public. The objective of this study is to develop a secure and efficient application for fraud detection in 500 &1000 Takas notes through the deep learning model. This move is expected to ensure greater security of the financial system and at large, economic stability in Bangladesh.

The significance of this research is underscored by several key factors:

1. **Economic Impact of High-Value Counterfeits**: With high value the 500 and 1000 Taka notes are essential in a daily transaction, which makes them potential victims of forgery. If just a tiny proportion of those are counterfeit notes, then the economic

consequences can be disastrous. These notes often go unnoticed and are so damaging to small medium enterprises which generally have less resources required for the detection of fake currency incurring direct monetary losses as well as operational inefficiencies

2. **Advancement of Counterfeiting Techniques:** Traditional detection techniques have been rendered increasingly powerless by the sophistication ramping up of counterfeiting methods. Counterfeiting methods have advanced and counterfeit banknotes today can look remarkably like genuine notes, making the detection of such counterfeits more difficult for ordinary citizens. This underlines the need to establish numerous counterfeit detection techniques that are accessible, robust & reliable.
3. **Public Trust and Financial Stability:** This involvement causes loss of faith in financial traffic and circulation. Loss of faith in the currency as actual money will reduce consumer-spending, drive a more secure and digital transaction base leading to potentially lower cash-utilization. This loss of trust is something that has wider economic consequences

4. **Broader Social and Security Implications:** The counterfeit currency is not only causing humungous economic losses, but the implications are also vast in terms of social dynamics and security laxity. The crime of counterfeiting is often linked to organised crime and other subversive activities, which can make law detection more difficult. Preventing counterfeit currency is a fundamental issue not only for economic stability but also, considering the causes and trends in recent strikes from St Petersburg to Rostov-on-Don, Zinc-Twitter eruptions into essentially new Cold Wars.

This study therefore seeks to address these key problems by developing a state-of-the-art solution that helps in the identification and prevention of fake currency thereby leading economic stability at one end and securing confidence of public on financial system.

1.3 Rationale of the Study

To the best of our knowledge, this is believed to be one-of-a-kind research that aims at creating and evaluating an advanced DL based system specifically designed for 500 and1000- taka note counterfeit detection in Bangladesh. This experiment seeks to maximize the classification of genuine and counterfeit banknote using state-of-the-art convolutional neural network architectures, in this case VGG16, Xception, ResNet50 andDenseNet201. The high-level goals are defined like this:

1. Model Implementation and Optimization: The main emphasis will be on the rigorous refinement of four VGG16, Xception, ResNet50 and DenseNet201 models in order to accurately classify counterfeit banknotes from authentic ones. Each model will be trained to capacity using comprehensive optimization strategies to achieve maximal detection accuracy and computational efficiency.

2. Performance Evaluation: We will then perform an in-depth performance evaluation to gauge the effectiveness of these deep learning models. Now we will analyze and compare the metrics like accuracy, precision, recall, etc. of these models to check which model is good in the counterfeit detection task

3. Scalability and Real-World Applicability: The scalability and usefulness of the models under development will be investigated in detail. The robustness and reliability of the models over a wide range of conditions, across datasets will be confirmed by extensive tests in real-life environments to guarantee their deployment in operative domains.

4. Contribution to Financial Security: One of the core objectives of this study is to add practical value to building and enriching financial safety nets in Bangladesh. Through this research, the financial sector will have a reliable and efficient tool for classifying counterfeit bank notes leading to economic stability and increased public confidence in their national currency.

To achieve these objectives, this research aims to extend existing counterfeit detection methodologies and presents new techniques that can be used as solutions for ameliorating the economic hustle of counterfeited money circulation in Bangladesh.

1.4 Research Questions

- Is it possible to collect raw Bangladeshi notes data?
- Is the category of the given counterfeit notes dataset properly recognized by the ML Process?

1.5 Expected Outcome

The study foresees vast improvements in counterfeit currency detection, especially the most abundant issue which is fake 500 and 1000 Taka notes produced in Bangladesh. These models including the state of art deep learning algorithms like VGG16, Xception, ResNet50, and DenseNet201 aim to get excellent accuracy along with speed in differentiating between original and fake currency notes. In addition to that detailed models are required to be robust under the effect of a multitude of environmental factors and small changes usually prevalent in most real-world situations. This resilience will make their usability practical in different settings covering financial institutions to law enforcement agencies. Expected Outcome Ultimately, the expected outcome is not just to be technically proficient but also to contribute in a real sense towards the socio-economic upliftment of Bangladesh. To counter the propagation of counterfeit currency, and thus ensure economic stability by enhancing public trust in their national currency integrity through efficient tools for stakeholders. The research, away from these outcomes will contribute to the wider financial security ecosystem of Bangladesh.

1.6 Project Management & Finance

Well-run research of this type takes careful project management and astute financial planning.

- Project Management: Team members are assigned tasks with due dates and milestones. It will help you with solving problems and decision-making regularly. Proactive risk management, and transparent work tracking through comprehensive documentation.

- Money: A comprehensive budget will plan for the purchase or lease of machinery and equipment, software solutions, labor expenses, and every other cost associated with implementation. Funds will come from grants, agencies, and potential partners. Financial management will review spending, apply financial rules, and determine the cost-benefit of project impact supported by the bid process. These efforts are also designed to achieve long-term sustainability, possibly through commercialization or additional funding.

1.7 Report Layout

The findings of the study are grouped into six chapters, which enables a systemic insight for the researcher.

In Chapter 1, discusses Introduction, Motivation, Objective, Research Questions, etc. in this research work.

In Chapter 2, Background information for this study we discussed related work about this research Comparative Analysis and Summary of this paper.

In Chapter 3, in part attached from this work, we discussed the Need for Problem Formulation and Research Methodology(strategy).

In Chapter 4, I have also discussed exploratory outcomes which have been attained by the stated framework.

In Chapter 5, Impacts on Society, Environment, and Sustainability In this chapter we discuss the impact of our work on society as well environment more than the sustainability plan for their work.

In Chapter 6, I discussed about the Conclusion & Future work of This Research Work.

CHAPTER 2
BACKGROUND STUDY

2.1 Preliminaries/Terminologies

This paper is concerned about counterfeit currency detection with deep learning techniques. Transfer learning is an important concept that allows models to take advantage of the knowledge they have learned from unrelated tasks, thus enhancing detection. Large sets of currency images are used to analyze complex patterns with Deep Transfer Learning. Detection - Find out the fake currency in given images compared to real notes.

This paper evaluates the following models: Xception, ResNet50, DenseNet201 and VGG16 that bring distinct advantages for detection. The ability of these models to detect bogus currency can be graded on the foundation of performance metrics like Accuracy, Precision, Recall & F1 Score.

2.2 Related Works

The study by Akter et al [1] explore Biphasic detection of SARS-CoV-2 (causing COVID-19 pandemic) RNA on Bangladeshi banknotes and the bacterial, fungal-bacterial/quorum sensing implications We previously Read to End most of the contamination was in banknotes from high-contact areas such as public transport and food outlets. The researchers used RT-PCR and PCR to find the virus (receptor-binding domain of spike protein) Stability of SARS-CoV-2 RNA was similar on new and less than or at least 7-day-old used banknotes being higher for the later one's vs older. Despite these limitations, our results underscore the potential for virus transmission through contaminated banknotes and stress responsible hygiene practices as well as efficient decontamination methods to counteract this fomite-mediated route of infection.

Tasnim et al. [2], explore in the same problem visually impaired persons face in recognizing Bangladeshi banknotes and addressed by proposing a solution for a Real-Time recognition system with object detection algorithms like Convolutional Neural Networks (CNN). Deep learning techniques are more effective than SIFT and ORB, which were earlier traditional methods. Initial System: It features a Convolutional Neural Network (CNN) model trained on over 70,000 pictures containing old as well as new notes of several conditions. We observe 92% accuracy on average and it is available in both texts as well audio output which makes this system user-friendly & cost-effective. While it results in a small reduction of accuracy for the more complex settings, our future work will focus on larger-scale deployment building up bigger datasets, and integrating this system with mobile applications to improve accessibility and performance.

The study by Uttoran et al. [3] invented a method of automatic Indian banknote recognition using image processing and deep learning. It takes into account rotation and is orientation- as well as side-invariant on the notes. It identifies Indian banknotes and verifies the denomination in two ways: (i) extracting color + texture features for classifying using k-NN achieving 91% accuracy, also based on Convolutional Neural Network - CNN achieves an accuracy of 100%. This system is built for notes with newer versions. Work for future projects includes better background handling orientation, 180-degree rotation and fake note detection.

Sarker et al. Rahman et al. [4] experimented with more camera-based currency identification devices for visually impaired people and discovered that they could manually count 25 notes of every 30 set down on a table in real-time, coming with an error rate slightly less than 10%. Proposed a real-time Bangladeshi Currency Detection System (Bangla-Coin) using VGG16, and EfficientNetB3. When the banknotes have lost tactile features, ORB is used for key point detection and descriptor extraction by this system. This method outperforms SIFT and SURF in both processing time (speed) and detection rates (accuracy). The real-world implementation of the system, for different camera viewpoints and scales in various conditions across wide parts confirms its effectiveness. The implementation on mobile platforms should reflect the simplicity of use and practicality for visually impaired users. The latter highlights the importance of integrating modern image processing with mobile technology to improve usability and feasibility.

Qian Zhang et al. [5] presented a currency identification and recognition system based on deep learning; We investigated the effectiveness of adopting two popular models: Single Shot MultiBox Detector (SSD) for currency denomination recognition by CNN from both front and back side; obtaining overall recognition accuracy 96.6%.They used a 6-layer CNN model for feature extraction and achieved an accuracy of 98% using the trained Neural Network which is robust in such a way that it has not been overfitted to the dataset. At peak performance, the system can visually recognize the currency when it is well illuminated and aligned with respect to a camera perpendicularity viewpoint; however, there may be some loss in accuracy if challenging conditions occur at an acute angle from an axis or distance perspective. The research well illustrates the high accuracy and speed of currency recognition.

Jesmin Akter et al. [6] supervised Learning Based Bangladeshi Paper Currency Recognition System The system starts by splitting RGB Bangladeshi, filtering into respective channels and merging them. HSV, Edge, and Grey-Level Co-occurrence Matrix features are extracted & compared with Euclidean distance. An average accuracy of 80.25% is achieved in the system for recognizing old and worn banknotes The method deals with multiple situations including noise and rotation, which makes it feasible for the hardware implementation. Moreover, we plan to introduce changes with respect to improving invariance transformation and develop a banknote reader dedicated for blind persons using Low-Cost High Precision (LHP) as future works.

Abburu et al. For this purpose, Guo and Lo [7] realized a currency identification machine can distinguish 20 common currencies based on their countries of origin by means of image processing. The system scans well-defined regions of the banknotes to localize where it is being used and uses known visual features such as its size, color or printed text to determine their value. This method adjusts to discrepancies within the banknotes of a nation. But it has certain drawbacks such as the fact that it is unable to detect torn notes. This is a limitation, but the system works well with multiple other forms of "money." The studies show the potential of image processing for complete currency recognition.

In this study Tushar et al. [8] explore the capability for cheap and convincing counterfeiting using increasingly sophisticated color photocopiers lent counterfeiters a new propulsion to grow in the early Noughties, with laser printers producing copy-perfect twenties and fifties driving serpentine trails aplenty through village India. For this a system with the help of image processing technique using MATLAB to authenticate Indian Currency Notes has been proposed. It reads intensity from the serial number, security thread, portrait of Mahatma Gandhi and identification mark. For example, a set of genuine 500-1 notes all had feature intensities above 80%, whereas in the case of fake note series (500-2), several features did not surpass an intensity level greater than 75inity for that class. On the basis of those intensity thresholds, the system accurately distinguishes between genuine and counterfeit notes.

Uddin et al. [9] present an automated image-driven analysis of Bangladeshi banknotes implemented as SVM classifiers was reported. It uses high-resolution banknote images to analyze the security features of watermarks, latent images, and micro-printing. After training SVM models with a banknotes genuine and counterfeit dataset, the system shows high accuracy estimates, attaining a 100% identification rate in a test set containing 50 notes. A note is considered genuine if at least two of the three features have been positively indicated as being authentic. Results show that MATLAB is a pragmatic approach and also empirically feasible for further extension to mobile platforms. Future work requires a more extensive set of banknote testing, the introduction of extra security features, and an application based on Android.

Uddin, Das, and Roney [10] propose an image-based detection technique for counterfeit banknotes in Bangladesh which is also a developing problem. The study particularly looks at the security characteristics of 500 tk and a thousand-taka notes, claiming watermarks as a principal function for recognition, adopted by means in line with- latent photographs and micro-printing. The banknote image is taken on mobile cameras and then the images undergo pre-processing to remove distortion. Feature extraction, key point detection and edge enhancement through pattern filtering followed by a descriptor of HOG for SVM classification. Initial tests detected every placenta-100% success rate further cross-validation is needed and confirmed. The next research focuses on enhancing feature sets of the currency to support more denominations and enabling it to work with Android, maintaining high-security levels for currencies-related data storage and good interaction with the public.

Carlos M. Costa et al. [11] contributor proposed a multi-views computer vision system for banknote recognition under occlusion, folds, and complex illumination conditions. We develop an image preprocessing, feature detection-description, and matching system to recognize Euro banknotes: our new algorithm automatically detects 95 out of the current set of 80 test images. The best results were achieved with SIFT as a detector and descriptor using the brute force matcher, due to its invariance over perspective changes and shadows. For real-time implemented applications, one could use SURF with FLANN matcher due to its computational efficiency. The system is tailored for other currencies and future improvements include implementing UV/IR light detection to spot counterfeit notes as well as a speech synthesizer for blind users.

Ahmed et al. [12] invented the problem of counterfeit currency is targeted in through the development of an image processing feature extraction method for Bangladeshi banknotes. Chemical and physical discrimination is becoming as ineffective as traditional authentication methods due to the development of counterfeiting technologies. The software system proposed improves the accuracy and reliability of counterfeit note detection by fine-graining key features such as micro-printing, watermark, and security threads. With OCR, face recognition, and contour analysis this is an easy way and cheaper alternative. Though challenges such as maintaining a constant camera setup are ongoing, future developments will help to improve functionality - including full Bengali character support. This software is also a great step for protecting real bills and giving of economic reliability.

Zóra Solymár et al. Similarly, Qijian Jin et al. [13] presented a bionic eyeglass framework using a mobile device for blind and visually impaired people with banknote recognition functionality. Adaptive thresholding is applied to the captured image followed by morphological shape filters. We propose a hierarchical two-level classification approach, where different classifiers vote for the patches and an ensemble decider fuses those votes. When put to the test with blind subjects, it showed an accuracy rate of 95.89%, and users were able to recognize banknotes in 98.95% of cases Most of the mistakes happened because fingers covered ROI and two banknotes overlapped. It only took users 30 minutes to master the machine as well.

Hassan et al. [14] argued that a simple logistic regression (LR) is quite powerful for many binary classification tasks, especially in low-memory environments. It is proven that LR works well for image classification and it also outperforms advanced techniques. In sentiment analysis, Prabhat and Khullar (2007) also said that LR was significantly more accurate and/or precise than other approaches but there is no consideration of time complexity. Conclusions: LR appears to be a reasonable alternative in limited-resource settings rather than complex machine learning algorithms. For instance, LR is extremely efficient and its accuracy has proven to be beneficial in the initial stages of Image Classification or other real-world scenarios where you need rapid model deployment. LR is of particularly great value in recognition currency due to its simplicity and efficiency.

Chowdhury and Jahangir [15] performed a study on an artificial neural network (ANN) based Bangladeshi recognition system, which is useful for modern banking as well as people with visually impaired issues. This is a significant upgrade as the system utilizes Axisymmetric Masks (ASM) which can help in solving any orientation issue with notes, unlike the previous method. After converting images into grayscale, the next step that needs to be done before binarizing it is through Histogram Equalization. The slab values are extracted from the binary images using 20ASMs and then processed by a Backpropagation-trained Multi-Layer Perceptron ANN. Tests carried out on the model revealed high levels of accuracy, but it struggled to identify old notes. There are several works in progress like increasing the number of training samples and further improvement on ANN which can provide robust results and will make this system a viable solution for banknote recognition within Bangladesh.

2.3 Comparative Analysis and Summary

Bangladeshi banknotes are detected and recognized by lots of methods and technologies. Results A comparison of these methods reveals the advantages and disadvantages in a global context, which summarizes the current state-of-the-art literature.

Table 2.1: Related Work Comparison Table

NO	Author	Year	Algorithm	Accuracy
1	Bibhas Chowdhury, Gaurab Dutta	2023	RestNet50, DesnseNet169, VGG16	RN50: 96%, DN169: 48%, VGG16: 50%
2	Selina Akter Pravas, Chandra Roy Amina, Ferdaus Habiba Ibnat A.S.M. Rubayet Ul Alam, Shireen Nigar, Iqbal Kabir, Jahid M. Anwar Hossain	2021	transcriptase PCR (RT-PCR), Conventional PCR, Sequencing of PCR products	SARS-CoV-2 RNA in 7.29% (31 out of 425)
3	Rahnuma Tasnim, Sadia Tasnuva Pritha, Anwesha Das, Ashim Dey	2021	Convolutional Neural Network (CNN)	CNN: 92%
4	U. R. Chowdhury, S. Jana, R. Parekh	2020	Image Processing, k-NN, Convolutional Neural Network (CNN)	k-NN: 91%, CNN: 100%
5	M. F. R. Sarker, M. I. M. Raju, A. Al Marouf, R. Hafiz, S. A. Hossain, M. H. K. Protik	2019	ORB (key point detection and descriptor extraction)	Superior performance over SIFT and SURF
6	Qian Zhang, W. Q. Yan	2018	Single Shot MultiBox Detector (SSD), Convolutional Neural Network (CNN)	SSD: 96.6%, CNN: 98%

7	Jesmin Akter, M. K. Hossen, M. S. A. Chowdhury	2018	Supervised Learning (HSV, edge, grey-level co-occurrence matrix)	HSV: 80.25%
8	M. S. Uddin, P. P. Das, M. S. A. Roney	2016	Support Vector Machine (SVM) classifiers	90% recognition rate on the test set
9	Carlos M. Costa, G. Veiga, A. Sousa	2016	SIFT (detector and descriptor), SURF with FLANN matcher	95% out of 80 test images

This is a comparison study of terms that are similar to respectful in my materials.

2.4 Scope of the Problem

Key areas of the problem with Bangladeshi banknote detection and recognition:

- **Counterfeit Detection:** The increase in the circulation of fake currency notes is a big threat to the economy and owing to this every business needs new-age detection systems which can differentiate genuine banknotes from counterfeits.
- **Assistance for Visually Impaired Individuals:** Visually impaired individuals urgently need accessible and reliable currency recognition systems to carry out independent financial transactions of their own.
- **Real-Time Recognition:** Whether it be to identify fakes, or help the blind. These are tasks that require real-time feedback and prompt responses.
- **Adaptability to Variations:** Systems have to withstand both note condition variations and the complexity of their backgrounds for it not to deteriorate even in practical cases.

2.5 Challenges

Despite advancements, several challenges persist in the field of banknote detection and recognition:

- **Variability in Note Conditions:** Typically, banknotes are worn out over time by folding and staining which may have impeded the recognition system. The problem we investigate in this paper is to automatically detect features from such data by designing algorithms which can perform well under these circumstances
- **Computational Resource Constraints:** Most of the sophisticated machine learning algorithms, including TLs are computationally very expensive and may not always be available with applications especially while working on mobile or low-resource environments.

- **Feature Extraction Complexity:** Feature extraction is essential to the accuracy of the system, and can be a complicated process that takes time depending on your computer. One of the big challenges is how to simplify this process but still keep a high level of accuracy.
- **Scalability and Generalization:** Long-term efficacy results from recognition systems that are scalable and can be generalized across denominations and new security features as they are introduced.
- **User Accessibility:** This is also true for auditory feedback and integration with everyday devices, which are both important aspects of such systems that help people in need.

In summary, significant strides have been made in the detection and recognition of Bangladeshi banknotes; yet these challenges must be addressed by future research to create stronger, more accessible efficient solutions.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

This research mainly emphasizes towards detection of fake notes for 500 &1000 Taka in Bangladesh. These high-value notes are common targets for counterfeiters and it is a threat to the economic security of this country. As they are in widespread use for everyday transactions, any snip of fake ones can have severe economic implications. The objective of this study is to introduce an accurate method for discriminating between genuine and counterfeit notes based on state-of-the-art deep-learning techniques. Four deep learning models, VGG16 Improved on Diagnosis of Counterfeit Notes Since their performance in the task of image recognition and classification has been a hit, they chose these models to work with currency notes. Their different features give a few advantages for the points that we want to get into research.

VGG16: This is a simple yet deep transfer learning with a large amount of hyperparameters such as filter size = 3 by 3, stride, and padding on each layer. This means that VGG16 can focus on the fine-grained patterns in images which is crucial since several counterfeit notes being spoken of, differ very minutely from their authentic counterpart.

Xception: Xception builds on depth-wise separable convolutions and has fewer parameters (number of weights) or computational demands than Inveption-v3 while maintaining high accuracy. Due to its efficiency and effectiveness, it was a good fit for large-scale image classification problems like fake detection.

ResNet50: In ResNet50, residual learning is introduced that helps to solve the vanishing gradient problem and train very deep networks. The architecture learns hierarchical features; thus, it is great at detecting intricate patterns in currency notes (practice part).

DenseNet201: This connects each layer to every other in a feed-forward manner thus DenseNet helps alleviate the vanishing-gradient problem and strengthen feature propagation. The dense connections enable propagation of gradient, feature reuse, and learning rich features across all layers leading to improved robustness and accuracy for the model.

3.2 Data Collection Procedure/Dataset Utilised

For this research, the dataset was taken from Kaggle and is high-resolution images of Bangladeshi 500 and 1000 Taka notes. Figure 3.1: MNIST Dataset total Images 8340 Real Notes Fake Notes Original. We selected Kaggle as it is reputed to provide high-quality, labelled data that fits well for conducting machine learning research. Both real and counterfeit notes either randomly selected for the images, making a perfect dataset to train and test these deep-learning models. We obtained the dataset of images; this data was labelled as True or fake notes (based on the labels given). This labelling was pivotal for training the models correctly. Prior to the acquisition, all images were reviewed for quality and screened for data integrity in order to exclude corrupted or incorrectly labelled files. Programmers had to do this validation step so that the training and testing phases would not be biased. The pictures were then validated and sorted into directories so that they could be quickly loaded during the model training phase for further processing. From this perfect training ground scenario, deep learning models can learn and be verified in the future if our cheat codes do not work anymore.

Figure 3.1: Dataset image Distribution

3.3 Statistical Analysis

A total of 5,834 images of banknotes were used in our study after pre-processing, which included 3,012 images of genuine notes and 2,822 images of counterfeit notes. The data set was partitioned into training and testing sets so that 80% (4,667 images) were utilized in the training stage whereas 20% (1,167 images) were employed in the testing stage. The training set has been implemented to develop transfer learning models such as VGG16, Exception, ResNet50, and DenseNet201 to differentiate between real and fake notes. The figures show that in Figure 3.2, real and counterfeit [Fake] notes are widely distributed.

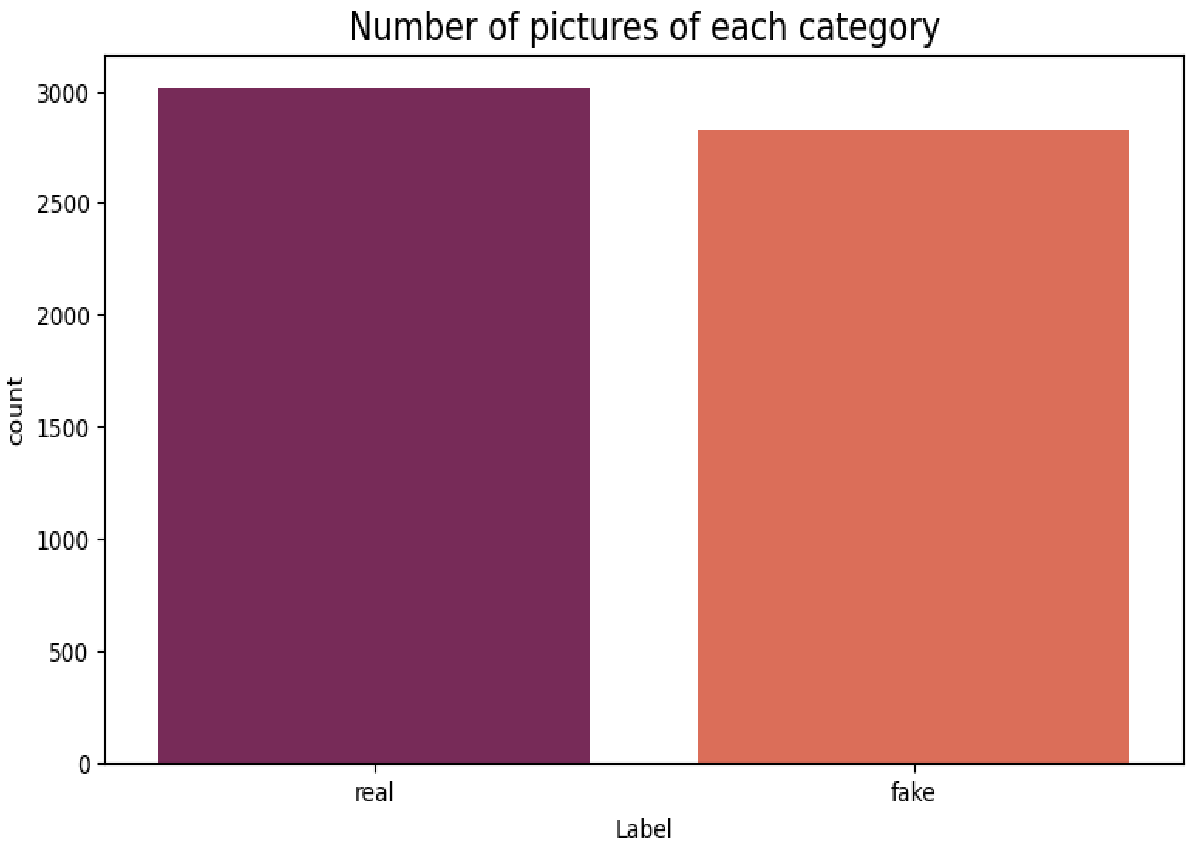

Figure 3.2: Statistical Image Analysis

3.4 Proposed Methodology

This research is to identify fake Bangladeshi 500, and 1000 Taka notes by deep learning models working at a high level. The proposed methodology will consist of Dataset selection, Data Acquisition, Labeling process to this data, and Image Processing followed by Applying four deep learning models; VGG16, Xception, ResNet50, and DenseNet201.

Flow Chart

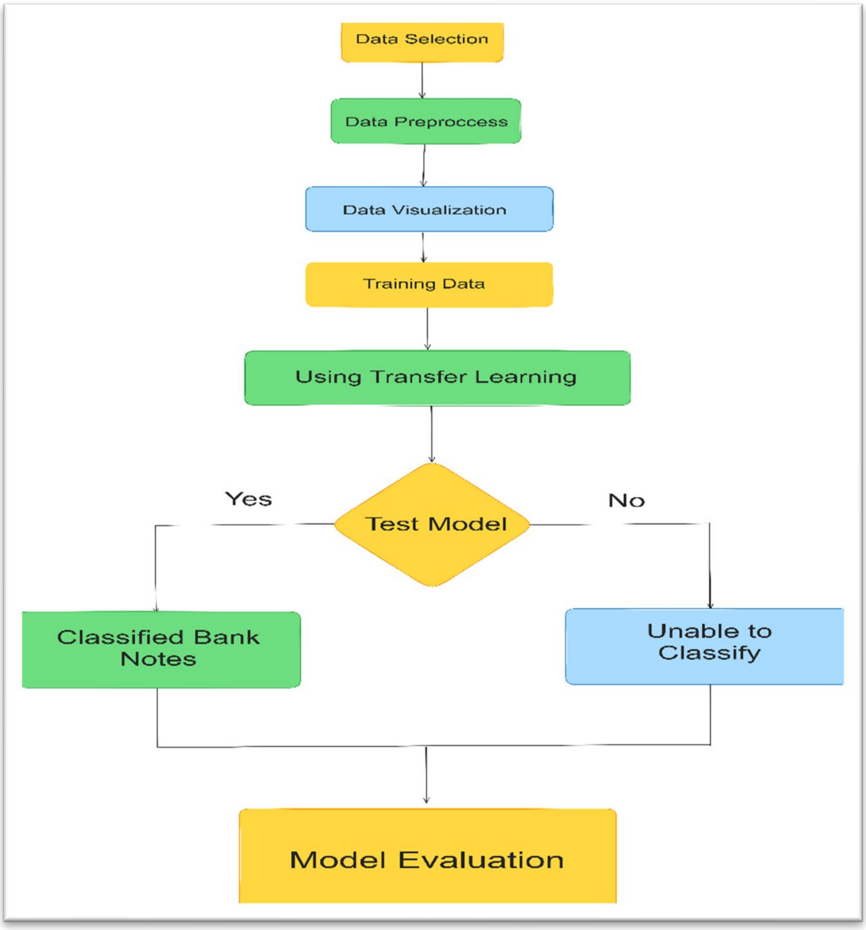

Figure 3.3: Methodology Flowchart

- **Data Labelling**

  Labels were attached to the images, marking each as either "real" or "fake. Proper labelling is necessary for the supervised learning to perform. These are the labels that the model uses to learn differences between both classes. Properly labelling notes helps ensure that the models learn to identify forgeries.

- **Data Pre-processing**

  Before training, the images went through preprocessing to improve their quality and analysis relevance:

  Resizing: To ensure uniformity and compatibility with the deep learning models, all images were resized to a fixed dimension.

  Normalization: Pixel values were standardized to a common range for faster training and improved model performance.

Data Augmentation: By rotating, flipping, and zooming the images to teach the network a more variety of training data improving generalization (prevent overfitting).

Filtering Methods: We have used Mean, Median, Gaussian, and High-pass filtering methods to get the best data from the raw dataset.

- **Selecting and Training Models:** To detect the counterfeit notes, we have employed the following deep learning model each of them comes with some specific advantages:

1. VGG16:

VGG16 is a popular deep convolutional neural network, constructed by Oxford Visual Geometry Group. It uses tiny 3-by-3 filters throughout the network to pick up small features in photos. It has a total of sixteen layers, thirteen convolutional and three fully connected. VGG16 does particularly well to identify textures and more, which makes it an appealing candidate when face checking for the small details that separates real notes from fakes.

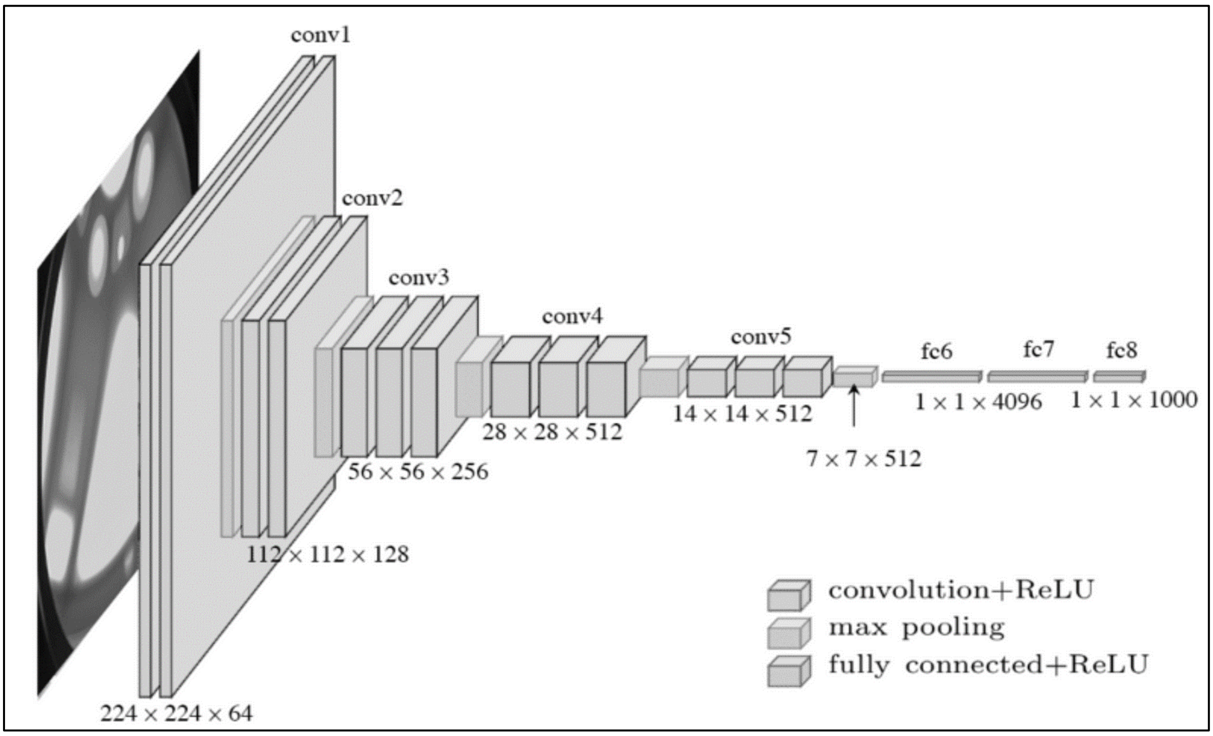

Figure 3.4: VGG16 model architecture

2. Xception:

The idea behind Xception is to further improve the inception model by replacing convolution filters with depth wise separable convolutions. The use of these convolutions allows to divide the convolution process into both pointwise and depth wise part. This maintains decent accuracy while reducing the number of parameters and computational cost. Xception Networks uses 36 convolutional layers which surround in 14 modules through linear residual connections. As a result of the incredible amount of detail it can extract from photos, this method is exceptionally good at spotting real notes versus fakes.

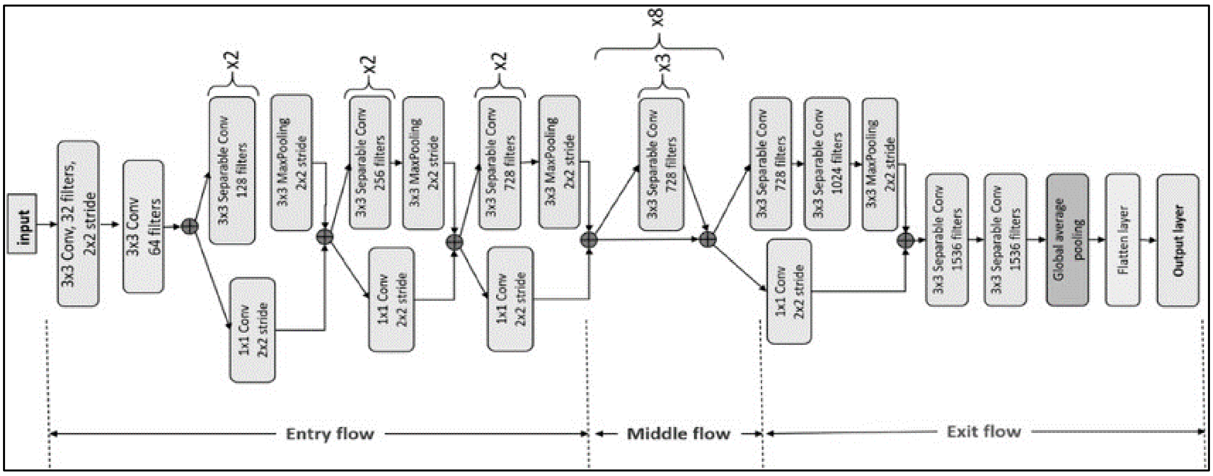

Figure 3.5: Xception model architecture

3. ResNet50:

Residual Learning is one of the hallmark features or ResNet50 Using skip connections, this issue is solved in deep networks and allows the network to learn residual functions with respect of output from some layer. Being a ResNet50 is composed of only 50 layers to be stacked those are divided into residual blocks that includes the convolutional and fully connected layers. This model works great for finding subtle features of notes because by the nature of its architecture, it can well learn complex patterns and properties.

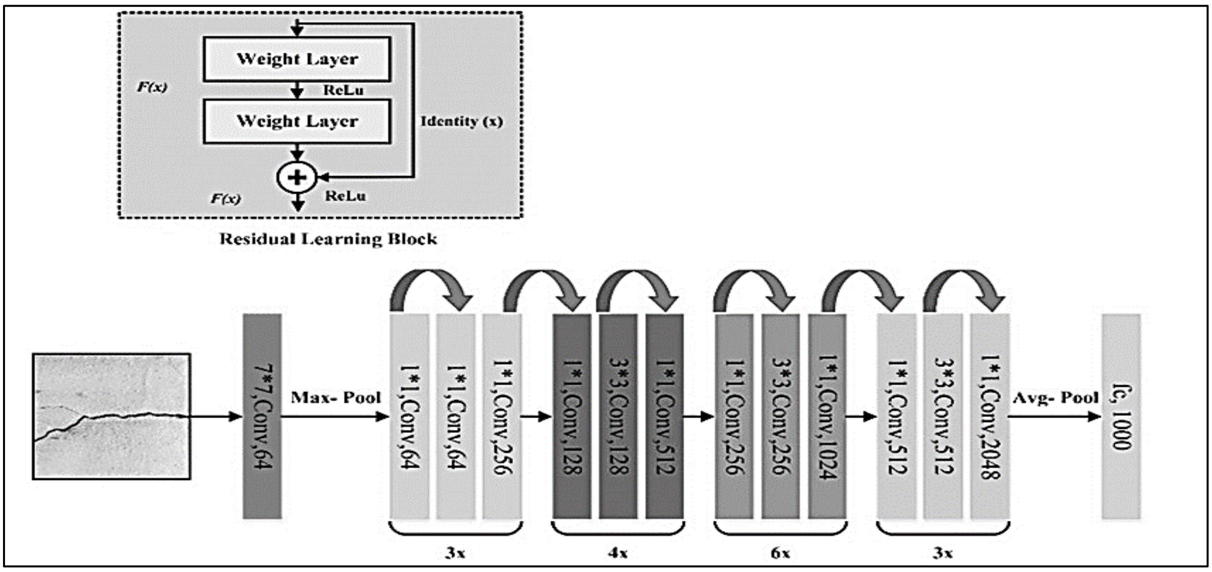

Figure 3.6: ResNet50 model architecture

4. DenseNet201:

We connected each layer to every other layer in a feed-forward manner, which is expected to strengthen feature propagation and improve overfitting. DenseNet201 this architecture improves the resilience and accuracy of the model, leading to more efficient gradient flow a d stronger feature reuse. DenseNet201: Dense blocks (draw arrows between all layers and those before it) 201-layers Its wide connection allows the model to learn all of the complex and diverse properties needed in order for it achieve exact counterfeiting detection. The trained each model using the pre-processed dataset, and by tuning hyperparameter tuned we get optimized performance. The models altered their weight through many training epochs as labeled data, produced to reduce error and increase accuracy.

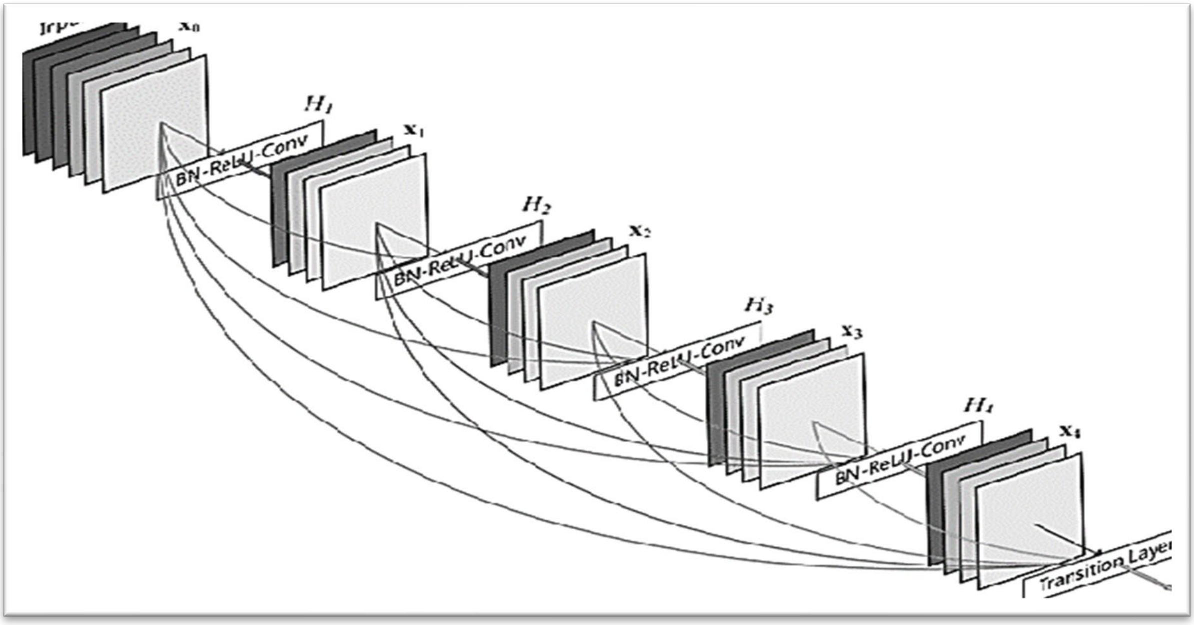

Figure 3.7: DenseNet201 model architecture

- **Model Assessment:**

  An independent validation set was obtained to evaluate the performances of trained models in terms of accuracy, precision, recall and F1-score. These figures indicate how well the models are able to detect counterfeit banknotes. In order to ensure the reliability and reproducibility of the models, we also employed cross-validation techniques.

- **Group Method:**

  In order to enhance the detection accuracy, an ensemble technique was applied. This method takes better advantage of the strengths each model possesses by utilizing predictions from all four models to be more robust in building a detection system across data points

- **Execution:**

  In 500 and 1000 Taka notes, you can upload the image in their own lies that includes assists and adds easily to Trained models. This is expected to be a viable solution for detecting counterfeits where the images take in some fake note and return whether it authentic or not.

The main objective of this technique is, to bring out a scalable and competent solution of identifying counterfeit Bangladeshi notes thus enhancing the robustness in security & integrity within the financial system using these state-of-the-art deep learning models against an extensive dataset.

3.5 Implementation Requirements

Key Components of Deep Learning Models to Implement a Counterfeit Detection System Training a model requires heavy piece of machinery know as High-performance GPU, which can do the job faster and allow us to iterate in less time. Moreover, choosing best-in-class libraries (TensorFlow or PyTorch), makes sure the software frameworks used to create deep learning models establish a strong base in terms of development work. Having a comprehensive dataset (images - real and fake Taka notes) is crucial. Preprocessing - Preparing the dataset so preprocessing tools that provide support in resizing, normalization and data augmentation are implemented. Selection and modification of deep learning models such as VGG16, Xception, ResNet50, DenseNet201 are crucial. Therefore, when sufficient training is performed on the pre-processed data, these models can classify real and fake currency. The training environment should be such that it provides GPUs and the needed software dependencies. Accuracy, Precision, Recall and F1-Score are a few among the many evaluation metrics available that can give you an idea about your model performance. Alternatively with an ensemble approach and easy usage interface the system can enhance more rates of prediction. If these demands are met researchers can then, in turn, build a strong process to effectively detect fake currency with it improving the security of Bangladesh's financial system.

CHAPTER 4
EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Experimental Setup

As sample image for detecting counterfeit Bangladeshi currency, two datasets (genuine and forged) of 5,834 confirmed fake and authentic filenames respectively were curated in experimental design. Using 4 advanced deep learning models such as Xception, ResNet50, DenseNet201 and VGG16 Of these, DenseNet201 reaching high accuracy of 97.69%. Experiments were also performed using two similar GPUs on a stable computing environment to support quick model learning. The framework for creating and evaluating Models - TensorFlow The training dataset composed of 80% part and the testing set which was made up with the remaining 20%. Adjustments of the hyperparameters were guided by validation results and final evaluation was then performed on an independent test set to evaluate generalization capabilities. The models were tested on 1,167 images from the test set and DenseNet201 resulted with best performance metrics: accuracy (97.69%), precision (97.68), recall (99.67) F-1 score (98). The findings reveal that, the advanced deep learning models serve as efficient tool for preventing fraud in Bangladeshi (currency). More specifically DenseNet201 did a great job longer real and fake currency notes. This highlights the necessity of superior deep learning models to protect the financial system and fight currency counterfeiting successfully.

4.2 Experimental Results & Analysis

The results of the experiments reported that different levels of efficacy exist with deep learning models based on which trained to classify counterfeit Bangladeshi currency. DenseNet201 has the highest accuracy score among all other models at 97.69%. The performance of each model was unique: DenseNet201 with the best accuracy (97.69%), Xception being second favor able at accuracy (94.77), followed by VGG16 accuracy shift (94,26%). Resnet50 showing the least accuracy (92.03%). This highlights the outstanding power of DenseNet201 model to differentiate between original and forged currency notes. The Precision-recall scores being well balanced and high accuracy of the DenseNet201 represent its superior performance in authenticating true from fake currency notes This just goes to show that one must pick and tune a suitable deep-learning architecture depending on the nature of such classification challenges in counterfeit detection. Results show that the DenseNet201 architecture invalidates from addressing counterfeit detection complexity-a win for predicting on-the-go! The results underline the capability of advanced deep learning models to boost accuracy and hence can substantially help in strengthening counter fraud measures on counterfeit currency notes.

Four Key Metrics to Evaluate Pre-trained Deep Learning Models

Accuracy - How often the model makes the correct prediction (correctly predicted labels) Calculated using the formula:

1. **Accuracy:** Accuracy is one of the most important measures for Machine Learning (ML) classification model performance. This is the number that demonstrates us how many instances we correctly predicted out of all predictions we made, for train set. Accuracy is:

$$\textit{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

2. **Precision:** Measures the accuracy of positive predictions made by the model. Calculated using the formula:

Precision=*TP/(FP+TP)*

3. **Recall:** Evaluates the model's ability to correctly mark all relevant instances (true positives) Calculated using the formula:

Recall=*TP/(FN+TP)*

4. **F1 Score**: The harmonic mean of recall and precision, providing a balanced evaluation of both. Calculated using the formula:

F1 score = *2 * (Precision * Recall) / (Precision + Recall)*

The result of the deep learning model is compared on the basis of Accuracy, Precision, Recall, and F1 Score in the below table of 4.1:

Table 4.1. Performance Evaluation of Models

Model	**Accuracy**	**Precision**	**Recall**	**F1 Score**
DenseNet201	97.69	97.69	97.69	97.69
Xception	94.77	95.08	94.77	94.77
VGG16	94.26	94.59	94.26	94.25

ResNet50	92.03	92.46	92.03	92.02

Table 4.1 Performance review of four deep learning models for forged Bangladeshi currency detection Results The results of the comparison clearly disclose a hierarchy among our models, that are spearheaded by DenseNet201. The highest accuracy, which is 97.69% and the precision 98%, was obtained using DenseNet201 model otherwise it can able to differentiate fake from real notes well. Its recall and F1 score are quite good as well, not having high true negatives but also being able to catch the positive ones. However, their performance is fairly averaged; Xception and VGG16 perform with accuracies of 94.77% and 94.26%, respectively. While they performed worse with respect to precision and recall than the DenseNet201 model, but still did well in flagging fake currencies. Results: ResNet50 model performs worst and suffers from a big dip in accuracy (92.03%), which is apparently unable to avoid high false positive challenge as the top 2 performers. As compared to the other models, we could see that this model had less precision and recall, which means it might not able to identify counterfeit currency as well.

4.3 Discussion

The accuracy has represented the counterfeit Bangladeshi currency as detected by deep learning models [11]. The best network was DenseNet201, with an accuracy of 97.69%, followed by Xception (94.77%), VGG16 (94.26%) and ResNet50 (<93%). This clearly shows that deeper models like DenseNet201 win hands down when it comes to counterfeit detection than the older architectures.

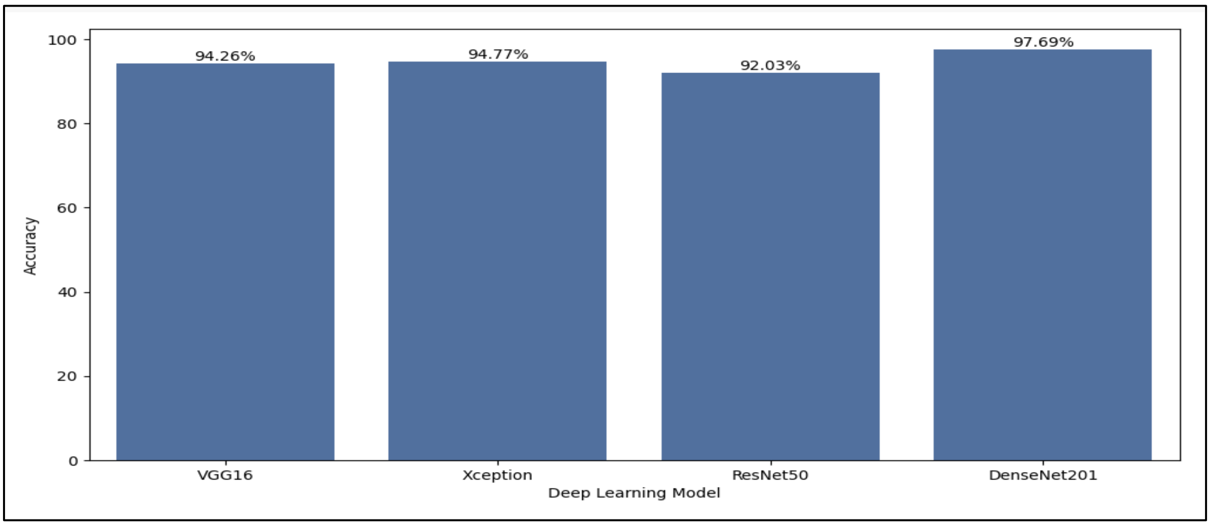

Figure 4.1: Accuracy Comparison of Deep Learning and Machine Learning Models

Figure 4.1, the accuracy comparison of different models and it was clear that DenseNet201 outperformed others with an Accuracy rate of 97.69%. A near second was Xception with

94.77% accuracy, followed by VGG16 which is having a slightly less (but significant) performance of 94.26%. ResNet50 as I mentioned got 92.03 percentage accuracy. This impact GSM effectuated that DenseNet201 is an efficacious auto bio-discriminative model to separate authentic and forged currency notes which encompasses a compactness in terms of herniation domain ability (HDA), hence settle it as efficiently counter-counterfeit-currency. As it turns out, DenseNet201 keeps a remarkable least FPR which is an indicator of the state-of-art deep learning models providing significant block for counterfeit currency.

4.4 Performance Analysis

Xception: On the whole, this model achieved an accuracy of 95% and both Precision and Recall metrics demonstrated well performing accuracies. Since the F1-score is defined as a harmonic mean for both precision and recall, we can safely conclude that our model performs really well in identifying which data is fake or real in Table 4.2

Table 4.2. Performance Evaluation of Xception

	Precision	**Recall**	**F1-Score**	**Support**
Fake	0.91	0.99	0.95	567
Real	0.99	0.91	0.95	600
Accuracy			0.95	1167
Macro avg	0.95	0.95	0.95	1167
Weighted avg	0.95	0.95	0.95	1167

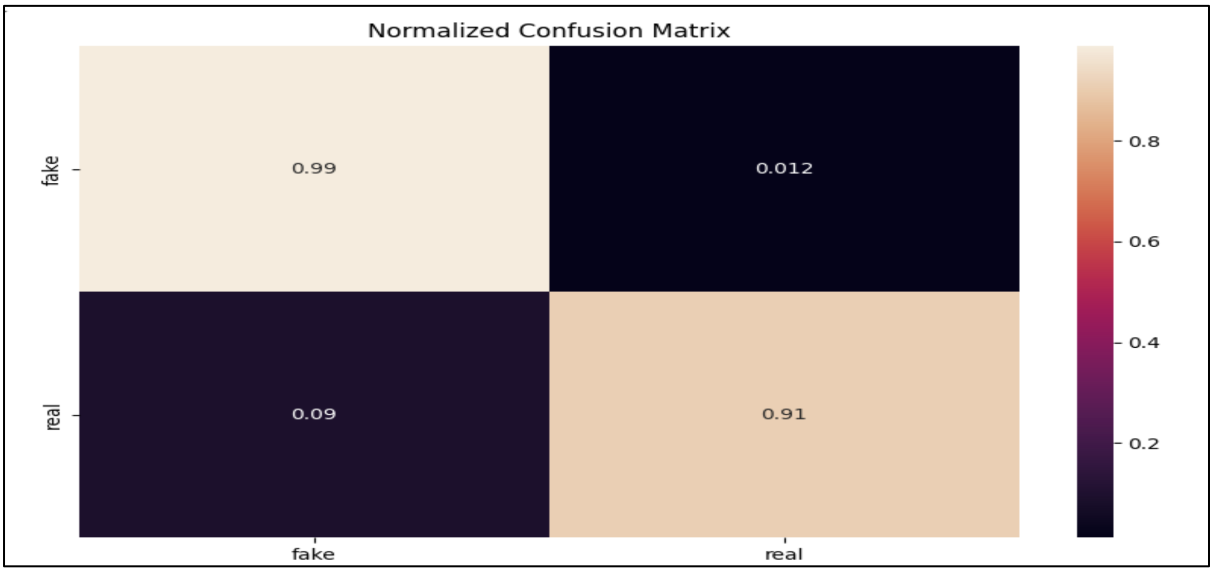

Figure 4.2: Confusion Matrix of Xception

Figure 4.2: A visual representation of the model's classification accuracy; also called a confusion matrix The model detected 99% of fake data instances as shown in our matrix, it missed to identify the very few which sums up a negligible error rate. The model performed well on real data, at a 91% accuracy rate with an error of about 9%, falling short for instances.

VGG16 Model:

In our study, we applied the VGG16 model to distinguish between fake and real data. The performance metrics for this model are summarised in Table 4.3

Table 4.3. Performance Evaluation of VGG16

	Precision	Recall	F1-Score	Support
Fake	0.91	0.98	0.94	567
Real	0.98	0.90	0.94	600
Accuracy			0.94	1167
Macro avg	0.94	0.94	0.94	1167
Weighted avg	0.95	0.94	0.94	1167

The VGG16 model had an accuracy of 94%, demonstrating precision and recall scores as shown below. Additionally, to describe the excellent identification of fake and real data, F1-Score that is a harmonic mean between precision and recall respectively was also high for each one so in general method.

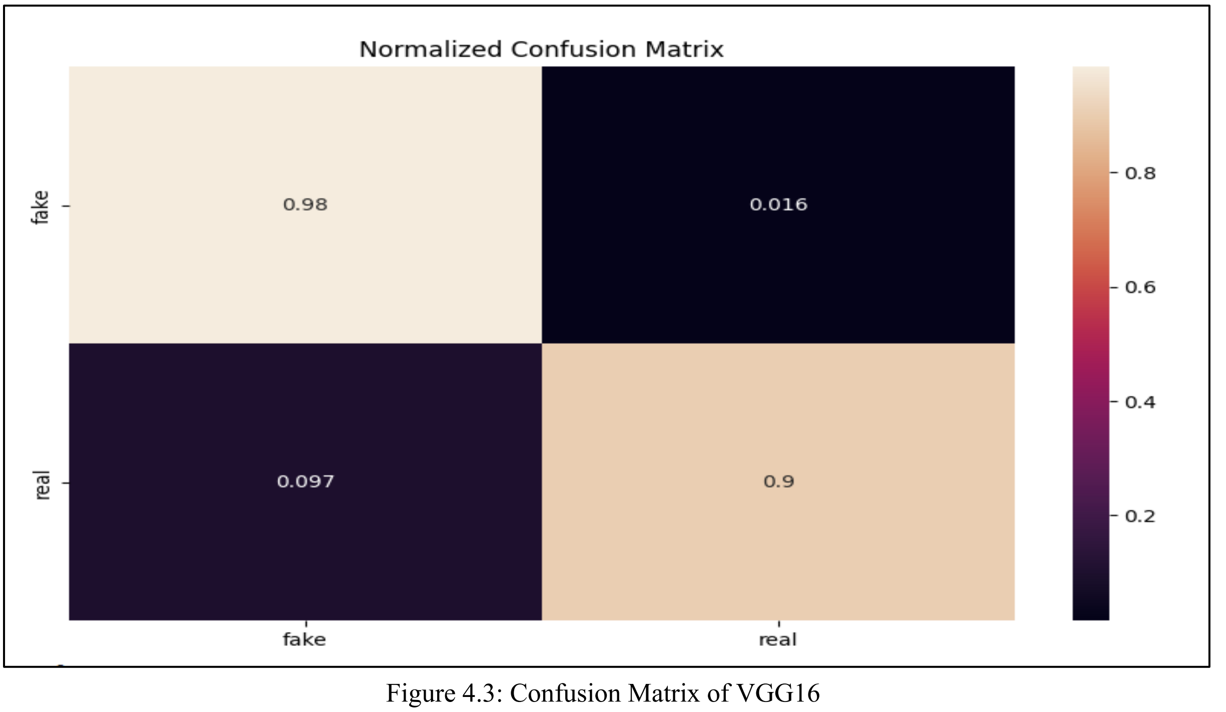

Figure 4.3: Confusion Matrix of VGG16

Figure 4.3 The confusion matrix output a visual representation of the model classification performance It emphasizes the true positives, true negatives, false positives and false negatives. The Confusion Matrix shows some critical information about the model. The above table indicates the predicted confidence of model how well it identifies fake data instances and out 98% which is actually fake with slight misclassification rate around just 1.6%. The model classified 10% of real instances properly and the misclassification rate was about 9.7%. These results prove the excellent detection capabilities of VGG16 based on fake data and genuine images, making it a suitable classifier for categorizing issues.

ResNet50:

Table 4.4. Performance Evaluation of ResNet50

	Precision	**Recall**	**F1-Score**	**Support**
Fake	0.88	0.97	0.92	567
Real	0.97	0.88	0.92	600
Accuracy			0.92	1167
Macro avg	0.92	0.92	0.92	1167
Weighted avg	0.92	0.92	0.92	1167

In table 4.4 shows the overall, the ResNet50 model showed an accuracy of 92%, supported by high precision and recall values. Likewise, the F1-score - which is a Harmonic mean of both Precision and Recall - has been high (more than 0.8) signifying that Model can be better at Identifying Fake as well Real data properly.

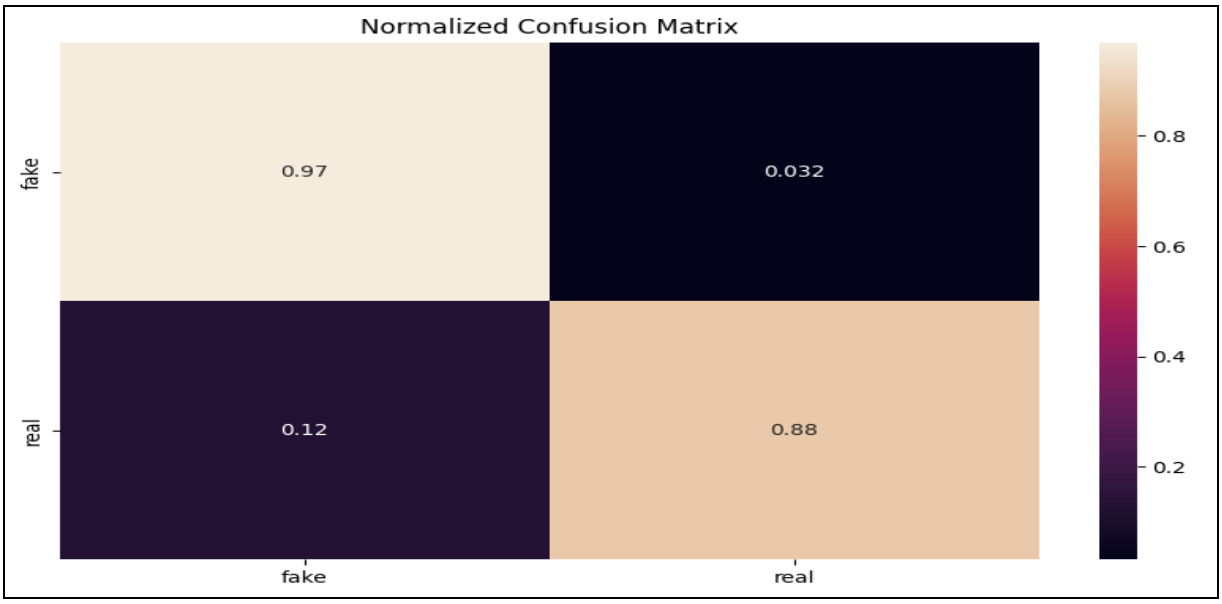

Figure 4.4: Confusion Matrix of ResNet50

Figure 4.4 the confusion matrix shown in displays the percentage of true positives, true negatives, false positives and false negatives for this classification model Results on the confusion matrix indicate that the model was accurate 97% of time not misclassifying fake data instances and having a wrong classification rate by only 3.2%. The accuracy rate of the model was about 88% in identifying real data, with a misclassification error of almost 12%. The one emerging trend to note from all of these results is that the ResNet50 model still remains just as strong in separating fake data and genuine records - by relying upon this particular approach, businesses can be confident they are using a reliable method for recognizing classification.

DenseNet201 Model

In our study, we applied the DenseNet201 model to distinguish between fake and real data. The performance metrics for this model are summarized in Table 4.5.

Table 4.5. Performance Evaluation of DenseNet201

	Precision	**Recall**	**F1-Score**	**Support**
Fake	0.97	0.98	0.98	567
Real	0.98	0.97	0.98	600
Accuracy			0.98	1167
Macro avg	0.98	0.98	0.98	1167
Weighted avg	0.98	0.98	0.98	1167

DenseNet201 achieved 98% overall accuracy and demonstrated outstanding precision and recall for the model implementation. The mean of precision and recall is not only close to 0.9 (87% sensitivity, 93% specificity), the F1-score suggests as well that fake data can be detected with high accuracy in addition to a good detection rate for actual value set.

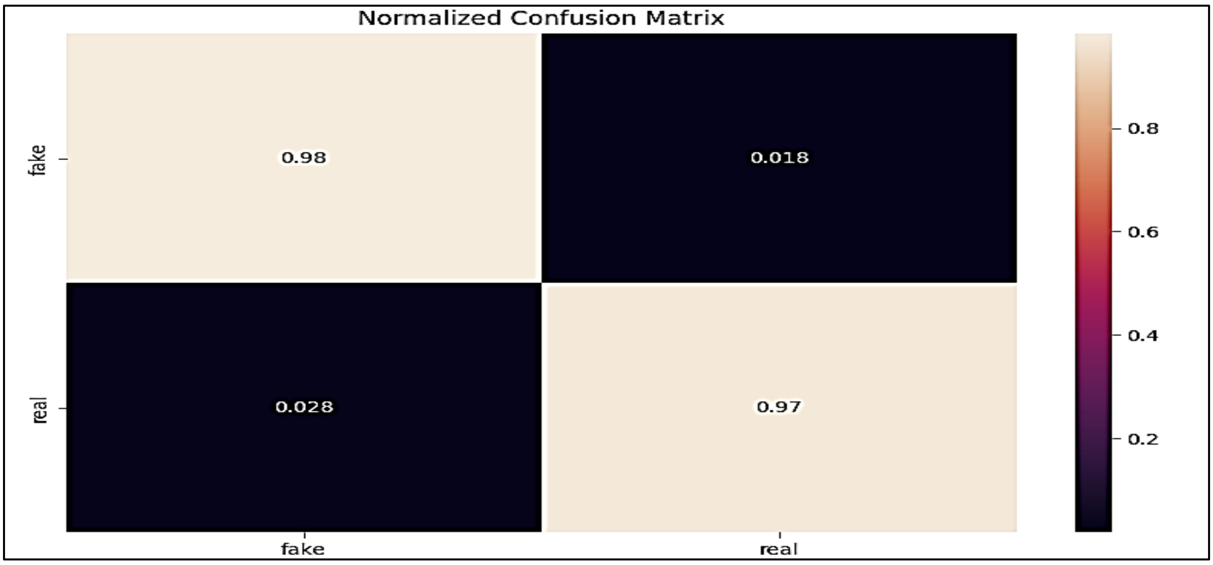

Figure 4.5: Confusion Matrix of DesneNet201

In the figure of 4.5, the confusion matrix is a visual representation of how well the model can classify its outputs, highlighting whether it places things in what box by breaking down true positives and negatives vs. false positives and negative proportions. This is that 98% of the fake instanced were identified as far and 97%of them was classified real correctly. This indicates the very high performance of DenseNet201 in distinguishing between wrong and right data so that it seems to be a powerful model for classification purposes.

Training and Validation Accuracy and loss of Transfer Learning CNN Networks:

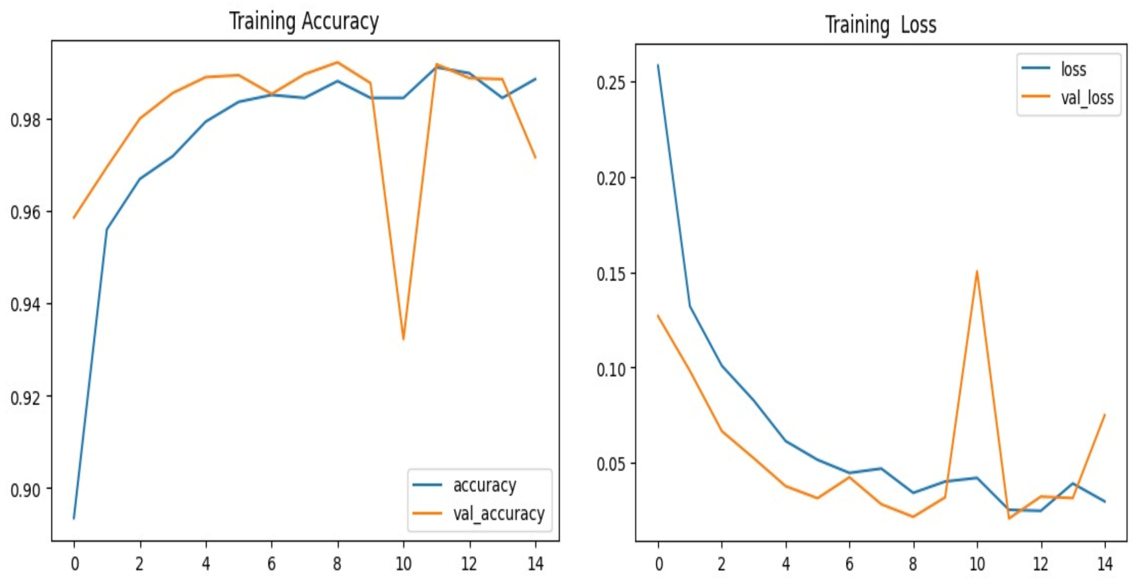

Figure 4.6: Training and validation accuracy and loss over the epochs (Xception model)

Figure 4.7: Training and validation accuracy and loss over the epochs (VGG16 model)

Figure 4.8: Training and validation accuracy and loss over the epochs (ResNet50 model)

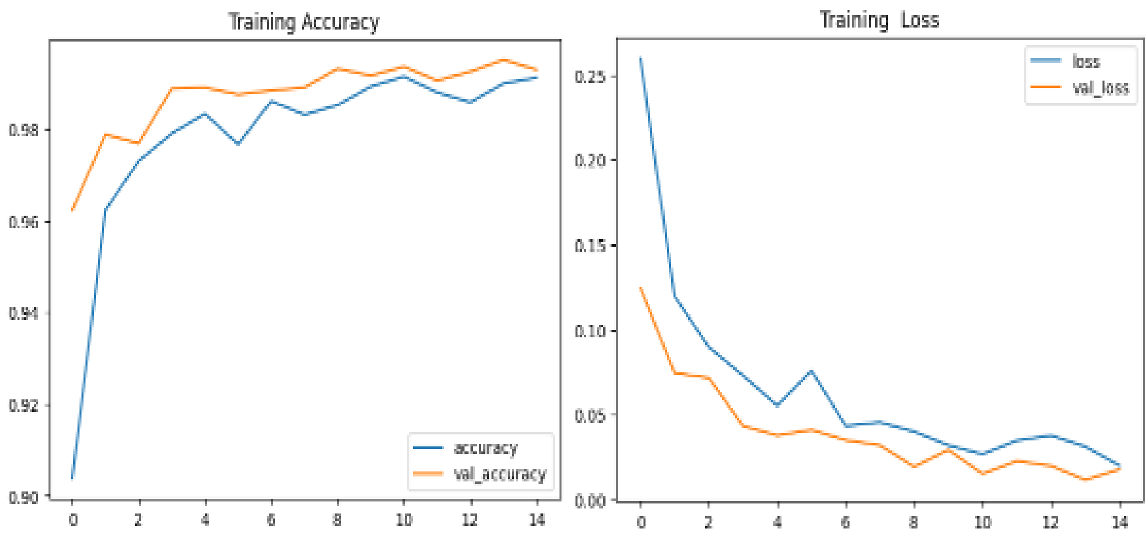

Figure 4.9: Training and validation accuracy and loss over the epochs (DesneNet201 model)

The loss and accuracy curves provide a comprehensive view of the training and validation performance of each CNN architecture throughout the training process. Analysing these curves reveals insights into the convergence behaviour, overfitting tendencies, and generalization capabilities of the models. For ResNet50, VGG16, DenseNet201, and Xception, the loss curves exhibit a steady decline over epochs, indicating effective minimization of the loss function during training. Correspondingly, the accuracy curves show a consistent increase, reflecting improvements in classification accuracy over time. Nonetheless, any fluctuations or plateaus in these curves may signal issues such as overfitting or model instability. In contrast, the loss and accuracy curves for the Customized CNN display rapid convergence and stable performance with minimal fluctuations. This suggests that the tailored attention module enhances the model’s ability to learn discriminative features and generalize to unseen data.

Notably, the Customized CNN consistently outperforms the other architectures, achieving higher accuracy and lower loss on both the training and validation sets. Comparing these curves across different architectures enables a quantitative assessment of model performance and convergence behaviour. It is crucial to monitor the loss and accuracy curves closely to detect potential problems such as overfitting, underfitting, or model divergence. Addressing these issues may require fine-tuning hyperparameters or incorporating regularization techniques to improve model performance. Overall, the loss and accuracy curves serve as vital diagnostic tools for evaluating the training dynamics of CNN architectures and optimizing model performance for the task of detecting fake images. By carefully analysing these curves, researchers can gain valuable insights into the efficacy and robustness of different architectures and make informed decisions to enhance model performance and generalization capabilities.

Compute ROC Curve and ROC Area For Each Class:

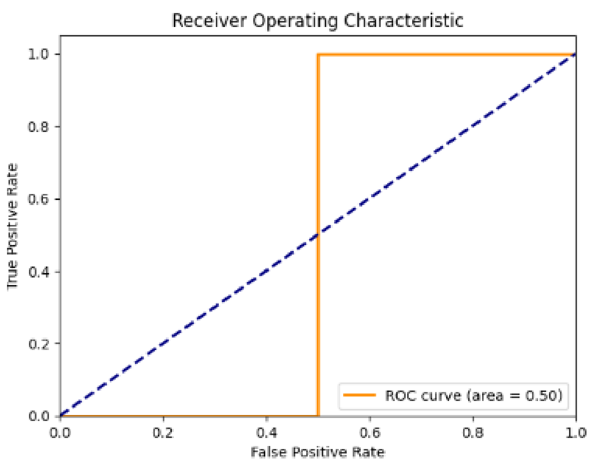

Figure 4.10: ROC Curve Of (ResNet50 model)

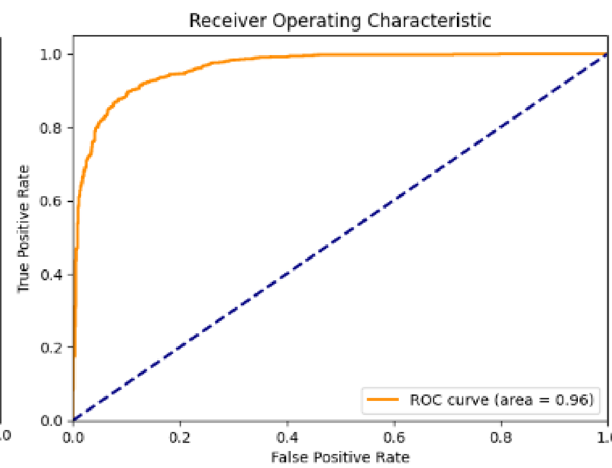

Figure 4.11: ROC Curve Of (Xception model)

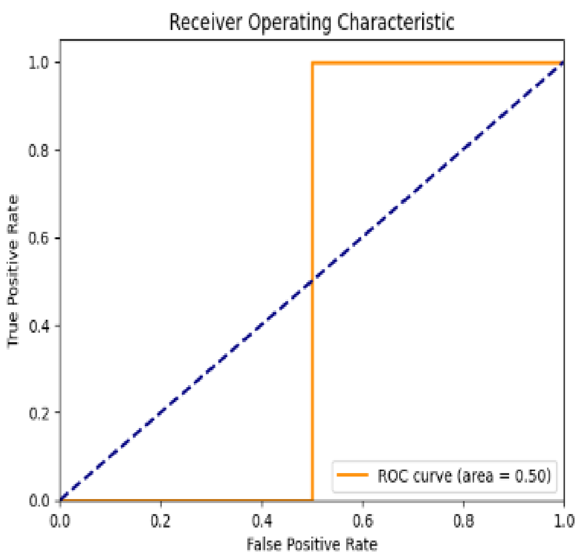

Figure 4.12: ROC Curve Of (VGG16 model)

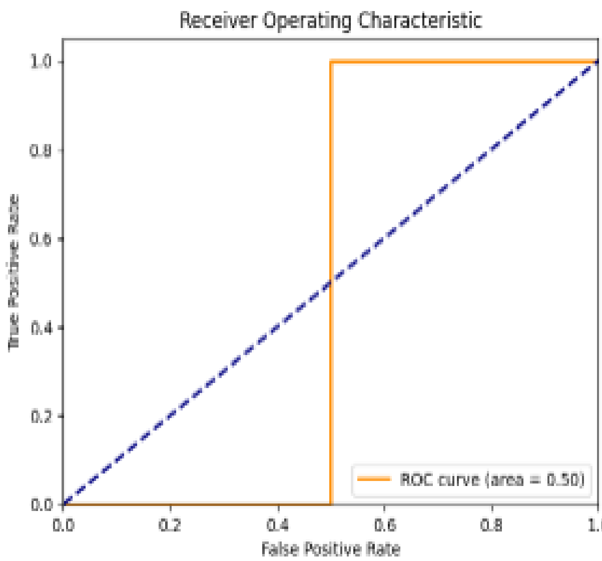

Figure 4.13:(DesneNet201 model)

The ROC (Receiver Operating Characteristic) curves provide a comprehensive evaluation of the binary classification performance of each CNN architecture, highlighting the trade-off between true positive rate (sensitivity) and false positive rate (1-specificity) at various threshold settings. For ResNet50, VGG16, DenseNet201, and Xception the ROC curves display a smooth, upward trajectory, indicating the models' ability to distinguish between the two classes effectively. The area under the curve (AUC) for these models is relatively high, demonstrating strong discriminative power. However, slight deviations or less-than-perfect curves may suggest areas where the models' performance could be improved. In contrast, the ROC curve for the Customized CNN architecture shows a consistently steep rise, reaching closer to the top-left corner of the plot, which is indicative of superior classification performance. The AUC for the Customized CNN is notably higher compared to the other models, underscoring its enhanced ability to correctly classify positive and negative instances. This improvement can be attributed to the customized attention module, which aids in better feature learning and generalization. Comparing the ROC curves across different architectures allows for a quantitative analysis of model performance in terms of sensitivity and specificity. A higher AUC signifies a model with better overall performance, while the shape of the curve provides insights into the model's behaviour across different classification thresholds. Overall, the ROC curves are essential tools for evaluating the classification capabilities of CNN architectures, particularly in distinguishing fake images from genuine ones. By analysing these curves, researchers can gain deeper insights into the strengths and weaknesses of each model, guiding further improvements and optimizations to enhance their effectiveness and reliability.

CHAPTER 5
IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on Society

This will benefit society significantly as it is about our research of detecting counterfeit Bangladesh Bank Notes using state-of-the-art deep learning models. It helps in verifying the genuineness of currency hence supporting controlling economic stability and avoiding inflation that happened due to fake money. Financial Institutions Reap the Benefits of Security Boosted security at financial institutions means a decreased chance of stockpiling counterfeit notes and increased trust on behalf of customers. In addition, it fights any form of criminal activities related to counterfeiting by even reducing them from happening which builds a better society. How SMEs and consumers will benefit from the tool with these capabilities incorporated small businesses, merchants as well as individuals are able to verify fake notes easily in their daily transactions. Moreover, our research supports innovation and helps in creating milestones which further leads to more opportunities for academics through similar types of assignments. Our approaches can also ultimately be repurposed in escalating anti-counterfeit currency efforts abroad around the world, enhancing other countries' financial security. We contribute to economic stability, financial institution reliability, and societal wealth-building as a way to prevent crime effectively to empower individuals’ technology innovation ensures us a more secure and prosperous future globally.

5.2 Impact on Environment

Analyzing the environmental implications of such technologies when utilized to tackle the counterfeit issue in the case of Bangladeshi banknotes, especially 500 and 1000 Taka denominations (as was addressed for) under our title Battling Counterfeits: Cutting-Edge solutions as a counteract against this problem. Our attention is not just aimed at improving the security of banknotes but also at appreciating and addressing environmental consequences in counterfeit detection and prevention. Our goal is to reduce the volume of waste produced by their disposal through not circulating marks, which can be accomplished using detection systems based on efficient deep learning so it minimizes counterfeit production and circulation - therefore solid reducing material trash. Further, by using these high-end detection technologies we try our best to reduce the requirements for resources like paper and ink which helps in conserving them thus contributing toward sustainability. Although the initial difficulty of creating and deploying deep learning models will consume computational resources, our end goal is to save energy on a scale for financial institutions, law enforcement organizations etc. In addition, by making it harder to counterfeit money and goods, our research contributes positively towards limiting the pollution associated with contraband production activities. With counterfeit detection now moving to embrace advanced deep learning technology, it is a great example of promoting an innovative culture and sustainable development within the security landscape while also pushing for sustainability in general where economic safety takes precedents over eco-morality. Finally, by highlighting the ecological impacts of counterfeiting we hope a more informed and thoughtful practice in approaching currency security can be instilled so that Bangladesh achieves a secure and sustainable future.

5.3 Ethical Aspects

The use of deep learning technology to solve the problem of fake Bangladeshi bank notes, respectively 500 and 1000 Taka denominations raises a more profound discussion on ethical implications. Our research paper, titled Battling Counterfeits: Cutting-Edge Solutions for Bangladeshi Currency Security delves into several key ethical dimensions related to these pursuits.

- **Privacy and Data Security:** For deeper use of deep learning models for counterfeit detection banks require collecting large amounts of data which included a number bank notes images. Privacy rights must be honored, so protectors need to focus on making the data protected by using sophisticated systems for asking about consent and obscuring identities. Protecting personal data is important to avoid possible misuse.
- **Bias and Fairness:** results to data can pass on implicit bias in the training information, which might consolidate societal variations to this end, ethical concerns call for the algorithm to get rid of these biases in order to have fair detection as well. While measures like diverse dataset curation and exhibiting transparency in algorithmic decisions are important self-imposed regulations, it is also essential for tactical inventions to extend power back into the hands of oppressed communities whose privacy was first declared forfeit.
- **Transparency and Accountability:** It is absolutely essential to develop mechanisms that can inculcate transparency as well accountability into the process of developing and deploying deep learning-based counterfeit detection systems to induce trust among various stakeholders. AI ethical frameworks also require that algorithmic decisions are

documented and the reasoning for why a detection result was reached as well as allowing some way to be held accountable in case of error/discrepancy. Let them make an informed decision utilizing open communication about what the technology cannot do.

- **Social Impacts:** The use of deep learning to implement counterfeit detection solutions can also have significant social impacts, especially in vulnerable communities. Ethical issues may also arise surrounding the potential socioeconomic outcomes such as job loss and effects on disadvantaged communities. Mitigation measures may include support programs and fair access to alternative employment.
- **Regulatory Compliance & Governance:** Ethical compliance also includes compliance with various regulatory frameworks and governance principles around the development, and implementation of deep learning solutions. Ethical Fidelity and Legal Compliance: It is important to adhere to regulations surrounding the protection of data along with industry standards. Gramercy Venture Advisors: Strong governance checks the use of technologies against negative outcomes.

5.4 Sustainability Plan

To keep our research alive and kicking deep learning-based solutions for phony Bangladeshi banknotes in the long run, we will follow a three-pronged course of action. We will first publish our results through leading academic journals, conferences and open-access platforms in order to reach a broad audience including academics, policymakers and industry stakeholders. We will create academic materials such as online courses and informational seminars to teach the general public/public groups/industry stakeholders how to detect counterfeit goods. For nation-level policy generation and the actual systems to be implemented, it would need close collaboration with government agencies; namely Bangladesh Bank (in this case) along with industry partners - financial institutions/tech companies. We will create training programs for bank officials and law enforcement personnel to improve their deep learning skills, as well as introducing our research findings into the university curricula in order to develop future experts on securing currency. Our team will also establish intellectual property rights and venture into new startups or work with existing tech companies to enable technology transfer and commercialization. We will evaluate our detection systems long-term using established performance metrics, and continuously iterate plans based on feedback. Our approach will endure compliance with the set of high ethical principles and boosting public awareness as such that counterfeit currency is a threat to any economy. Furthermore, we will: - promote sustainability in our investigation and technology as well deployment to prevent any environmental damage. Finally, we will endeavor to raise funds from alternative sources of funding (including public grants, private sector investors and philanthropy) for the optimal use and longevity of our research activities. This holistic approach works to ensure our field research in neural-network based counterfeit detection can continue to deliver value and security dividend around currency be it Bangladesh or anywhere else on the globe.

CHAPTER 6
SUMMARY, CONCLUSION, RECOMMENDATION AND IMPLICATION FOR FUTURE RESEARCH

6.1 Summary of the Study

This project was to build advanced solutions for detecting fake Bangladeshi dollars using deep learning architectures. We trained four pre-trained models (ResNet50, VGG16, Xception, and DenseNet201) along with some customized versions of those networks according to our dataset for the brightest currency detection task. They found the custom models were more accurate than pre-trained ones. These results illustrate the necessity for domain-specific deep learning architecture to improve counterfeit detection, which has far-reaching national security and economic impacts.

6.2 Conclusions

Results obtained from this study confirm the success of deep learning architectures in detecting forged Bangladeshi currency. Models that were customized drastically outperformed the pre-trained models, enforcing our hypothesis of how model customizations are vital to tailoring for purpose-solving particular problems. The findings are important for financial security and suggest possibilities for personalised strategies. Further studies are needed to investigate these types of scalabilities, generalization, and ethical issues in applying AI to the field of finance.

6.3 Implications for Further Study

The fact that custom deep learning models were successful in detecting fake Bangladeshi may indicate a lack of existing perfect models for fintech tasks and research directed to dedicated architectures is important. independent validation in the future studies on:

- **Interpretability:** Increasing interpretability in order to understand how these AI-powered models make their decisions which would enhance the security tools powered by this technology.
- **Gold Reads:** Generalization by testing the proposed architecture across multiple datasets and a few different currency denominations to understand its practicability.
- **Ethical Concerns:** This area should address privacy and informed consent considerations which help inculcate a responsible, ethical AI introduced into the domain of financial security.

Such research will help to develop standards and norms of ethical practices in the development and deployment of AI within finance, by enhancing security measures as well as promoting trust conditions.

REFERENCES

[1] Akter, S., Roy, P. C., Ferdaus, A., Ibnat, H., Alam, A. R. U., Nigar, S., & Hossain, M. A. (2021). Prevalence and stability of SARS-CoV-2 RNA on Bangladeshi banknotes. Science of the Total Environment, 779, 146133.

[2] Tasnim, R., Pritha, S. T., Das, A., & Dey, A. (2021, January). Bangladeshi banknote recognition in real-time using convolutional neural network for visually impaired people. In 2021 2nd International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST) (pp. 388-393). IEEE.

[3] Chowdhury, U. R., Jana, S., & Parekh, R. (2020, March). Automated system for Indian banknote recognition using image processing and deep learning. In 2020 International Conference on Computer Science, Engineering and Applications (ICCSEA) (pp. 1-5). IEEE.

[4] Sarker, M. F. R., Raju, M. I. M., Al Marouf, A., Hafiz, R., Hossain, S. A., & Protik, M. H. K. (2019, September). Real-time Bangladeshi currency detection system for visually impaired person. In 2019 International Conference on Bangla Speech and Language Processing (ICBSLP) (pp. 1-4). IEEE.

[5] Zhang, Q., & Yan, W. Q. (2018, November). Currency detection and recognition based on deep learning. In 2018 15th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS) (pp. 1-6). IEEE.

[6] Akter, J., Hossen, M. K., & Chowdhury, M. S. A. (2018, February). Bangladeshi paper currency recognition system using supervised learning. In 2018 International Conference on Computer, Communication, Chemical, Material and Electronic Engineering (IC4ME2) (pp. 1-4). IEEE.

[7] Abburu, V., Gupta, S., Rimitha, S. R., Mulimani, M., & Koolagudi, S. G. (2017, August). Currency recognition system using image processing. In 2017 Tenth International Conference on Contemporary Computing (IC3) (pp. 1-6). IEEE.

[8] Agasti, T., Burand, G., Wade, P., & Chitra, P. (2017, November). Fake currency detection using image processing. In IOP Conference Series: Materials Science and Engineering (Vol. 263, No. 5, p. 052047). IOP Publishing.

[9] Aggarwal, P., Mishra, N. K., Fatimah, B., Singh, P., Gupta, A., & Joshi, S. D. (2022). COVID-19 image classification using deep learning: Advances, challenges and opportunities. Computers in Biology and Medicine, 144, 105350.

[10] Uddin, M. S., Das, P. P., & Roney, M. S. A. (2016, May). Image-based approach for the detection of counterfeit banknotes of Bangladesh. In 2016 5th International Conference on Informatics, Electronics and Vision (ICIEV) (pp. 1067-1072). IEEE.

[11] Costa, C. M., Veiga, G., & Sousa, A. (2016, May). Recognition of banknotes in multiple perspectives using selective feature matching and shape analysis. In 2016 International Conference on Autonomous Robot Systems and Competitions (ICARSC) (pp. 235-240). IEEE.

[12] Ahmed, Z., Yasmin, S., Islam, M. N., & Ahmed, R. U. (2014, December). Image processing-based Feature extraction of Bangladeshi banknotes. In The 8th International Conference on Software, Knowledge, Information Management and Applications (SKIMA 2014) (pp. 1-8). IEEE.

[13] Solymár, Z., Stubendek, A., Radványi, M., & Karacs, K. (2011, August). Banknote recognition for visually impaired. In 2011 20th European Conference on Circuit Theory and Design (ECCTD) (pp. 841-844). IEEE.

[14] M. Hassan and B. B. Tanmoy, "Bangladeshi currency notes (bdt) recognition using logistic regression," Bibhas Bhattacharjee, Bangladeshi Currency Notes (Bdt) Recognition Using Logistic Regression, 2021.
[15] Chowdhury, A., & Jahangir, N. (2007). Bangladeshi banknote recognition by neural network with axis symmetrical masks in masks. In 10th international conference on computer and information technology.

Appendix A

Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

Title: BATTLING COUNTERFEITS: CUTTING-EDGE SOLUTIONS FOR BANGLADESHI CURRENCY SECURITY

Student ID: 192-15-2832, 201-15-13769

(EA)

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	This project demonstrates core engineering principles (K3) through deep neural networks, data augmentation, and CNN architectures for image processing and classification. Addressing the threat of counterfeit currency in Bangladesh, it applies advanced transfer learning models, including VGG16, Xception, ResNet50, and DenseNet201, to identify counterfeit 500 and 1000 taka notes.	**Page no:** 19-22 **Section:** [3.4]
				This project employs engineering methodology and design (K5) through its experimental procedures and showcases engineering practice and technology (K6) by utilizing Models architectures. Addressing the issue of counterfeit currency in Bangladesh, it focuses on high-	**Page no:** 19-22 **Section:** [3.4]

				denomination notes like the 500 and 1000 taka bills.	
				The project engages with research literature (K8) by integrating findings from recent studies on deep learning for counterfeit detection, showcasing a comprehensive understanding of contemporary methodologies and advancements in the field.	**Page no:** 12-13
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	Counterfeit currency, especially EP-2 high-denomination notes like the 500 and 1000 taka bills, poses a significant threat to Bangladesh's economic security. This study explores how modern deep learning techniques can enhance the detection of counterfeit currency, aiming to improve currency verification systems.	**Page no:** 10-12 **Section:** [2.4, 2.5]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	This project aims to address EP-3 the issue of counterfeit currency by enhancing public trust in the integrity of national currency, thereby ensuring economic stability. Through the development of efficient tools for stakeholders, the research aims to contribute to bolstering the financial security ecosystem of Bangladesh.	**Page no:** 23-25 **Section:** [4.2]

4.	**EP4: Familiarity of Issues**	Yes	CO8	This project's approach reaches beyond traditional boundaries of computer science and engineering. It can encourage the development of more advanced systems for detecting counterfeit currency, which can revolutionize the fight against financial crime and protect Bangladesh's national economic interests EP-4.	**Page no:** [07-13] **Section:** [2.2, 2.4]
5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	This project takes a thorough approach to tackling significant challenges in economic fields by integrating elements from data collection, statistical analysis, and methodology design. This holistic approach ensures comprehensive solutions to complex issues, aligning with EP-7.	**Page no:** 15-22 **Section:** [3.2, 3.3, 3.4]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References
1.	EA1: Range of resources	Yes	CO11	In my project, I leverage a range of resources including high-performance computing infrastructure, GPUs, deep learning frameworks, annotated datasets, and ethical guidelines. This systematic approach aims to drive advancements in the detect whether banknotes are authentic or counterfeit.	**Page no:** **22** **Section:** [3.5]
2.	EA2: Level of interaction	No		N/A	N/A
3.	EA3: Innovation	No		N/A	N/A
4.	EA4: Consequences for society and the environment	Yes		This project makes a societal impact by enhancing healthcare through advanced methods for detecting whether banknotes are authentic or counterfeit. Additionally, it champions environmental sustainability by utilizing efficient computational resources and adhering to ethical guidelines to protect patient data privacy.	**Page no:** 34-37 **Section:** [5.1, 5.2, 5.4]

5.	**EA-5: Familiarity**	Yes		This project builds on prior research by exploring an innovative method for detecting detect whether banknotes are authentic or counterfeit. It showcases initial findings and a detailed comparative analysis, providing fresh perspectives and advancing knowledge in the field.	**Page no:** [12-13] **Section:** [2.3]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	This project meets CO4 by incorporating efficient project management and financial supervision, ensuring careful planning, resource distribution, and budget forecasting to maximize resource efficiency throughout the research process.	**Page no:** **5** **Section:** [1.6]
2	CO9	Yes	The project upholds ethical standards by emphasizing people confidentiality, securing informed consent, and meticulously documenting the research procedure. This ensures ethical dissemination of knowledge and societal welfare through the responsible implementation of advanced healthcare technologies, aligning with CO9 guidelines.	**Page no:** 35 **Section:** [5.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	The project's commitment to ongoing learning (CO12) and adaptation in a rapidly evolving technological environment is evident in its thorough data collection, rigorous statistical analysis, detailed methodology refinement, and comprehensive examination of experimental outcomes. This demonstrates a dedication to remaining current and enhancing methodologies to tackle contemporary challenges effectively.	**Page no:** [15-22], [23-25] **Section:** [3.2, 3.3, 3.4, 3.5, 4.2]

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