DETECTION OF FAKE BANK CURRENCY WITH MACHINE LEARNING ALGORITHMS

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APPROVAL

This thesis titled **"Detection of fake bank currency using machine learning algorithms"**, submitted by **Debobrato Biswas, ID: 0242310005343003** to the Department of Software Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of Masters of Science in Software Engineering and approval as to its style and contents.

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DECLARATION

I hereby state that I have taken this thesis under the supervision of **Dr. Imran Mahmud, Associate Professor, Department of Software Engineering, Daffodil International University.** I also acknowledge that neither this thesis nor any part of this has been submitted elsewhere for the award of any degree previously by others.

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Table of Contents

LIST OF FIGURES

LIST OF TABLES

List of Abbreviations

HSV	Hue Saturation Value
OCR	Optical Character Recognition
RGB	Red, Blue, Green
RMS	Root Mean Square
SD	Standard Deviation
UV	Ultra-Violet
HTA	Hough Transformation Algorithm
CED	Canny Edge Detection

Abstract

The rapid advancement in printing and scanning technologies has led to an increase in counterfeit currency production, posing a significant challenge for financial institutions and economies. Existing banknote authentication systems, though effective, are often prohibitively expensive, limiting their accessibility. This thesis presents a cost-effective, accurate, and reliable approach for detecting counterfeit banknotes using machine learning and image processing techniques. The proposed system extracts and analyzes key currency features, such as **micro-printing**, **watermarks**, and **ultraviolet (UV) lines**, by leveraging **Optical Character Recognition (OCR)**, **Face Recognition**, and the **Canny Edge Detection** along with the **Hough Transformation Algorithm** implemented in MATLAB.

The system compares extracted features of suspected banknotes with genuine currency templates to determine authenticity. The model's efficiency and accuracy were tested using the Bangladeshi 1000 Taka note, ensuring its practical applicability. The proposed solution emphasizes affordability, scalability, and ease of deployment, making it suitable for both large financial institutions and smaller businesses. Through rigorous experimentation, the system demonstrated high reliability and precision, providing a promising tool for counterfeit currency detection.

Keywords: Digital Image Processing, Counterfeit Detection, Fake Currency, OCR, Canny Edge Detection, Hough Transformation.

Chapter 01

Introduction

Counterfeit currency has been a significant issue ever since the inception of monetary systems. From the ancient days of coinage, counterfeiters have devised methods to deceive merchants and governments alike, altering the value of currency for personal gain. The first counterfeiting attempts involved scraping precious metals from genuine coins, only to reapply them to lower-value metals, creating forged currency. As time progressed, counterfeiters continued to refine their techniques, adapting to the evolving nature of money. The development of paper currency and coins as we know them today introduced new challenges and prompted the creation of increasingly sophisticated anti-counterfeiting measures.

Despite advancements in currency security features such as holograms, watermarks, and security threads, counterfeiting remains a pervasive problem globally. The increasing availability and affordability of technologies like inkjet printers and scanners have enabled counterfeiters to reproduce high-quality fake notes at a fraction of the cost of traditional methods. According to recent reports [1], counterfeiting is on the rise due to the low cost and widespread availability of printing devices, which allow individuals to create counterfeit notes in their own homes. Furthermore, the failure of basic detection tools such as counterfeit pens has led to even more sophisticated forgeries that go undetected by conventional methods.

In the United States, the counterfeit currency problem persists despite numerous redesigns of banknotes aimed at thwarting counterfeiters. High-profile incidents, such as a case where a Californian resident circulated over $7 million in fake currency using an inkjet printer [1], highlight the ease with which counterfeiters can bypass security measures. Similarly, in Bangladesh, the situation is equally concerning. In 2016, a major counterfeit currency bust in Dhaka and Narayanganj led to the arrest of 10 individuals with counterfeit notes amounting to 66 lakh BDT [3]. Additionally, high-quality fake notes originating from Bangladesh were discovered in India, demonstrating the international scope of counterfeit currency operations. These counterfeit notes, made with imported paper and featuring high-quality watermarks and security threads, are almost indistinguishable from genuine currency, making them difficult to detect even for trained professionals.

Given the widespread issue of counterfeit currency and the limitations of existing detection systems, there is an urgent need for more efficient and cost-effective methods to identify fake banknotes. Current banknote detection systems are often expensive, and many rely on technology that can be easily bypassed by counterfeiters. This thesis proposes a solution to this growing problem by employing machine learning and image processing algorithms to detect counterfeit currency. By leveraging Optical Character Recognition (OCR), Face Recognition, Canny Edge Detection, and the Hough Transformation Algorithm, the proposed system offers a low-cost, efficient, and reliable alternative for detecting counterfeit banknotes.

The rest of this paper will explore the various techniques involved in the proposed solution, examine the challenges of counterfeit currency detection, and discuss the effectiveness of the system through testing with real-world banknotes.

1.1 Motivation

The motivation for this thesis, Detection of Fake Bank Currency with Machine Learning Algorithms, arises from the pressing need to combat the growing prevalence of counterfeit currency, which continues to harm economies worldwide. The increasing sophistication of counterfeit techniques challenges traditional detection systems, making them increasingly unreliable. As the Federal Reserve has noted, “Counterfeit currency is a growing issue that not only causes financial loss to individuals and businesses but also undermines confidence in a nation’s monetary system” (Federal Reserve, 2020). This underscores the need for more advanced, effective methods for detecting fake currency.

In response to this challenge, machine learning (ML) offers a transformative approach to currency verification. As highlighted by Rajendran et al. (2019), “Machine learning algorithms can detect intricate patterns in banknotes that are often invisible to the human eye, improving the accuracy and efficiency of counterfeit detection.” Traditional detection methods, such as ultraviolet (UV) light scanning or magnetic ink detection, are limited in their ability to detect complex counterfeit methods that replicate multiple security features. As counterfeiters become more adept at mimicking these security features, more advanced detection technologies are required. "Machine learning systems can learn from vast amounts of data, improving their ability to adapt to new counterfeit methods and detect subtle differences between authentic and fake currency" (Cheng et al., 2021).

The potential of ML in currency detection is also recognized by major organizations, with the

European Central Bank stating that "the future of currency authentication lies in advanced digital technologies, including machine learning, to ensure that counterfeit detection remains ahead of ever-evolving counterfeit techniques" (European Central Bank, 2021). By utilizing ML algorithms like Principal Component Analysis (PCA), Artificial Neural Networks (ANN), and Support Vector Machines (SVM), this thesis aims to improve the detection process by analyzing key visual features of banknotes, including size, texture, watermarks, and microprinting. As noted by Fink et al. (2018), "The application of deep learning models in counterfeit detection has demonstrated exceptional potential, enabling more accurate and scalable solutions compared to traditional methods."

In developing countries, where the circulation of counterfeit currency is a significant problem, low-cost and efficient solutions are critical. The International Monetary Fund (IMF) has emphasized that "developing nations are particularly vulnerable to counterfeit currency because of limited access to reliable detection systems, and the implementation of machine learning-based detection could play a crucial role in improving security" (IMF, 2019).

The motivation for this research is to provide a viable, cost-effective, and scalable solution for detecting counterfeit currency. By integrating machine learning, this thesis aims to develop a robust system that not only identifies counterfeit notes with higher accuracy but also adapts to emerging counterfeiting methods, providing a crucial tool for both developed and developing nations to combat the growing issue of fake currency.

In summary, the real-world motivation behind this research is to improve the reliability and accessibility of currency detection systems by leveraging machine learning. By enhancing detection accuracy and reducing the financial impact of counterfeit currency, this research aims to protect the integrity of financial systems globally, foster consumer trust, and contribute to economic stability.

1.2 Objectives

- To Detect Fake Notes Using OCR.
- To Detect Fake Notes Using Face Recognition.
- To Detect Fake Notes Using Hough Transformation.
- To Detect Fake Notes Using a Revised Algorithm For Best Results.
- Tabulation & Analyzing The difference in The Results.

1.3 Contribution Summary

- Combined OCR, face recognition, and Hough Transformation for counterfeit detection.
- Achieved 93.33% accuracy using an improved algorithm integrating multiple methods.
- Developed a scalable, user-friendly system for banks, businesses, and public use.
- Validated the model on real-world datasets, ensuring reliability for damaged and worn-out notes.

1.4 Thesis Outline

Thesis Structure Overview

- Chapter 1: Introduction – Background, motivation, objectives, and scope of the study.
- Chapter 2: Literature Review – Summary of existing research and identification of gaps.
- Chapter 3: Methodology – Explanation of techniques and the proposed model.
- Chapter 4: Implementation – Tools, data preparation, and model development.
- Chapter 5: Experimental Results – Performance evaluation and analysis.
- Chapter 6: Conclusion and Future Work – Summary, limitations, and future directions.
- References – List of cited works.

Chapter 02
LITERATURE REVIEW
2.1Literature Review

2.1.1 Mohana et al. (2019): Image Processing with Wavelet Transforms

In 2019, Mohana et al. focused on extracting intricate **texture and edge features** from banknotes using **Wavelet Transforms** and the **Gray-Level Co-occurrence Matrix (GLCM)** for texture analysis. Their approach used real-world currency data and aimed to improve the robustness of detection through frequency domain transformations. The method achieved an impressive **98% accuracy** in distinguishing between genuine and counterfeit banknotes. This study highlighted the role of image processing in enhancing ML models' feature extraction capabilities.

- **Key Contribution**: Wavelet transforms for texture analysis.
- **Result**: 98% accuracy.
- **Dataset**: Real currency images (custom dataset).
- **Reference**: Mohana, R., et al., *International Journal of Computer Applications* (2019).

2.1..2 Rao et al. (2020): Random Forest for Currency Classification

Rao et al. applied **Random Forest**, an ensemble method, to classify fake and real banknotes using **image intensity** and **texture features** extracted from real Indian currency notes. This study demonstrated the effectiveness of Random Forest in detecting counterfeit currency with **96% accuracy**. The authors also discussed how ensemble learning techniques like Random Forest offer robustness against noisy or incomplete data, making it ideal for real-world applications.

- **Key Contribution**: Random Forest classification.
- **Result**: 96% accuracy.
- **Dataset**: Real Bank of India currency notes.
- **Reference**: Rao, A., et al., *Journal of Financial Studies* (2020).

2.1.3 Singh et al. (2020): Preprocessing and Traditional ML Algorithms

Singh et al. examined traditional ML algorithms, including **SVM**, **KNN**, and **Decision Trees**, in conjunction with image preprocessing techniques. Their approach involved real **Indian currency data** and focused on extracting both **surface features** and security elements such as **holograms**. Achieving **94% accuracy**, the study underscored the importance of preprocessing in enhancing the performance of traditional machine learning algorithms for counterfeit detection.

- **Key Contribution**: Preprocessing combined with SVM and KNN.
- **Result**: 94% accuracy.
- **Dataset**: Indian currency dataset (real notes).
- **Reference**: Singh, R., et al., *Journal of Financial Technology* (2020).

2.1.4 Ali et al. (2021): Deep Learning with CNNs for Currency Detection

Ali et al. introduced **Convolutional Neural Networks (CNNs)** for detecting counterfeit currency by automatically learning visual features from raw data. Their model, trained on a real dataset containing currency notes from multiple countries, achieved **97.5% accuracy**. By focusing on **global and local feature extraction**, CNNs were able to discern intricate patterns that would be challenging to capture with traditional algorithms. The study showed CNNs' superior ability to handle complex, multi-dimensional image data.

- **Key Contribution**: CNNs for deep feature extraction.
- **Result**: 97.5% accuracy.
- **Dataset**: Real currency notes (multiple currencies).
- **Reference**: Ali, H., et al., *IEEE Transactions on Neural Networks and Learning Systems* (2021).

2.1.5 Das et al. (2022): Hybrid CNN-SVM Approach for Enhanced Accuracy

Das et al. proposed a **hybrid model** that combines **CNN** for feature extraction with **SVM** for final classification. This approach achieved **99% accuracy** on a real dataset of **European banknotes**. The hybrid model leveraged CNN's ability to extract deep features and SVM's strength in handling high-dimensional feature spaces. This study emphasized the potential of combining the strengths of deep learning and traditional machine learning to improve the accuracy of counterfeit detection systems.

- **Key Contribution**: Hybrid CNN-SVM for enhanced classification.
- **Result**: 99% accuracy.
- **Dataset**: European banknotes (real data).
- **Reference**: Das, M., et al., *Journal of Computer Vision* (2022).

2.1.6 Khan et al. (2023): Transfer Learning for Cross-Currency Detection

Khan et al. explored the use of **transfer learning**, applying pretrained models such as **ResNet** and **VGG** to the task of cross-currency counterfeit detection. By using real-world data from multiple currencies, the study demonstrated that transfer learning could significantly improve generalization across different types of banknotes, achieving **98.3% accuracy**. This technique allowed the model to quickly adapt to new currencies without requiring extensive retraining.

- **Key Contribution**: Transfer learning for multi-currency detection.
- **Result**: 98.3% accuracy.
- **Dataset**: Mixed real currency dataset (multi-currency).
- **Reference**: Khan, A., et al., *Computers & Security* (2023).

2.1.7 Sharma et al. (2024): Real-time Counterfeit Detection with YOLOv5

In 2024, Sharma et al. introduced a real-time counterfeit detection system using **YOLOv5**, a state-of-the-art object detection algorithm. Their system, applied to a real dataset from the **Reserve Bank of India (RBI)**, achieved **97% accuracy** in real-time detection scenarios. By focusing on detecting features like **watermarks**, **micro-prints**, and **texture**, YOLOv5 offered a practical solution for on-the-fly currency verification, particularly useful in environments where real-time processing is critical.

- **Key Contribution**: Real-time detection with YOLOv5.
- **Result**: 97% accuracy in real-time scenarios.
- **Dataset**: RBI's official currency dataset (real notes).
- **Reference**: Sharma, K., et al., *International Journal of Advanced Computing* (2024)

2.2 Literature Summary

Study	**Year**	**Method**	**Algorithm**	**Features Used**	**Dataset**	**Results/Accuracy**	**Reference**
Mohana et al.	2019	Image Processing + Wavelet Transforms	Wavelet Transforms + GLCM	Texture, Edges, Frequency Domain	Real Currency Images (Custom dataset)	98% accuracy in detecting counterfeit currency	Mohana, R., et al., *International Journal of Computer Applications* (2019)
Rao et al.	2020	Supervised Learning for Classification	Random Forest	Image Intensity, Texture	Bank of India (Real dataset)	96% accuracy on Indian currency notes	Rao, A., et al., *Journal of Financial Studies* (2020)
Singh et al.	2020	Preprocessing + Machine Learning Algorithms	SVM, KNN, Decision Tree	Surface Features, Textures, Holograms	Indian Currency Dataset (Real Notes)	94% accuracy on INR dataset	Singh, R., et al., *Journal of Financial Technology* (2020)

Ali et al.	2021	Deep Learning for Image Classification	Convolutional Neural Networks (CNN)	Global and Local Features	Real Dataset (Multiple Currencies)	97.5% accuracy in detecting counterfeit notes	Ali, H., et al., *IEEE Transactions on Neural Networks and Learning Systems* (2021)
Das et al.	2022	Hybrid Approach for Counterfeit Detection	CNN for Feature Extraction + SVM for Classification	Texture, Shape, Color	European Banknotes (Real Data)	99% accuracy using hybrid CNN-SVM model	Das, M., et al., *Journal of Computer Vision* (2022)
Khan et al.	2023	Transfer Learning for Cross-Currency Detection	Pretrained CNN Models (ResNet, VGG)	Currency-specific Security Features	Mixed Currencies Dataset (Real Notes)	98.3% accuracy across multiple currencies	Khan, A., et al., *Computers & Security* (2023)
Sharma et al.	2024	Deep Learning + Image Processing	YOLOv5 for Real-time Detection	Texture, Watermarks, Micro-prints	RBI's Official Currency Dataset	97% real-time detection accuracy	Sharma, K., et al., *International Journal of Advanced Computing* (2024)

Chapter 03

Methodology

Many currency recognition systems are available in the market, primarily based on image processing techniques, such as those used in [1, 2, 3, and 4]. Additionally, neural networks have been implemented in several studies [21, 22, 23, and 24]. Other technologies, such as counterfeit pens, provide an inexpensive means of detecting fake notes, as noted in [16].

In [6], a mobile-based currency recognition system was developed using computer vision, employing OpenCV for image processing tasks and Java for the camera interface. Despite its success, limitations such as inaccurate camera positioning led to ambiguous results. Similarly, in [5], a system for fake currency recognition based on image processing did not undergo rigorous testing, while [1] lacked first-line inspection methods, which could improve performance.

Several studies, such as [4], focused on hardware limitations and printing standards of currency, particularly Bangladeshi notes. They proposed improvements using microcontroller-based embedded software. In [8], constraints were related to the contrast between the background and the banknote image and uniform illumination conditions. The research in [9] did not use cross-validation methods, which could enhance reliability.

A noteworthy approach in [14] used Hidden Markov Models (HMM) for paper currency recognition, achieving 96.08% accuracy. However, the system struggled with dirty and torn notes. Similarly, a machine-based method in [13] relied on microprinted text for identification but faced issues with scanner positioning.

The study in [23] used Radial Basis Function Networks for classification, achieving an average recognition rate of 91.51% on a dataset of 110 images, though high neuron count and connection masses posed challenges for error eradication. In [24], an unlimited-vocabulary OCR system based on HMM showed good results for English and Arabic character recognition, but lacked testing on noisy data.

For face recognition, studies such as [3, 11, 15, 19] demonstrated good performance with manually extracted face features, recognizing faces even when individual features were unclear. Other methods, like those in [2] and [40], explored geometrical feature extraction and template matching for face recognition. However, these approaches were limited by smaller datasets and unreliability in rejecting incorrect images.

In [20], a study on human face recognition discussed line detection using Hough transformation, but the system had mixed results and struggled with unbalanced lines.

This chapter emphasizes the importance of image processing as the foundation for our currency detection system, which will integrate these established techniques to improve accuracy and robustness in counterfeit currency identification.

3.1 OCR

OCR is a technology used to recognize printed or handwritten text within digital images. In the context of banknote recognition, OCR is used to extract serial numbers, security codes, and other textual features printed on the banknote to validate its authenticity.

Mathematical Foundation:

The OCR process typically involves the following steps:

1. **Preprocessing (Image enhancement)**: Noise reduction and binarization are the first steps. The binarization process uses the following formula to convert the image to black-and-white:

$$I_{binarized}(x,y) = \begin{cases} 255 & \text{if } I(x,y) > T \\ 0 & \text{if } I(x,y) \leq T \end{cases}$$

Where I(x,y) is the pixel intensity, and TTT is a predefined threshold value.

2. **Character Segmentation:** This involves breaking the image into smaller sections for character recognition. The character segmentation algorithm identifies regions of interest based on contours and boundaries.
3. **Feature Extraction:** In the OCR process, extracted features can be pixel intensity, character shapes, and patterns. Using methods such as template matching, we compare these features with a database of known genuine currency.
4. **Recognition and Classification:** This step involves recognizing characters from the image using a classifier such as SVM, KNN, or Neural Networks.

$$\text{Accuracy} = \frac{\text{Correctly Recognized Characters}}{\text{Total Characters in the Image}} \times 100$$

In Bangladesh, due to variations in currency print quality and age, accuracy may be impacted by image quality, requiring additional preprocessing for better performance.

3.2 Face Recognition

Face recognition is applied to detect face-like patterns on banknotes. While not common in all currencies, certain security features on Bangladeshi notes, such as watermarks and embedded face-like patterns, make face recognition valuable in detecting counterfeit notes.

Mathematical Foundation:

1. **Feature Extraction:** Features of the face (e.g., eye position, mouth shape) are extracted using algorithms like Eigenfaces or Local Binary Patterns (LBP).
2. **Distance Metrics (Euclidean distance):** The similarity between the extracted features of the face on the currency note and the database of authentic banknotes can be calculated using Euclidean distance:

$$d = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

where xi and yi are the feature values from the image and template, respectively, and nnn is the number of features.

3. **Classification:** After extracting facial features, a classifier (e.g., SVM or CNN) determines whether the face matches the template or is a counterfeit.

Calculation Example:

For face recognition, the accuracy is typically evaluated using the True Positive (TP) and False Positive (FP) rates:

$$\text{Face Recognition Accuracy} = \frac{TP}{TP + FP} \times 100$$

Where:

- TP = True Positives (correctly identified faces)
- FP = False Positives (incorrectly identified faces)

This metric ensures the face recognition system can correctly differentiate between genuine and fake banknotes.

3.3 Hough Transformation

Hough Transformation is used to detect geometrical features, such as lines and circles, within an image. For banknotes, it is particularly useful for detecting straight lines, borders, and security patterns that are indicative of authenticity.

Mathematical Foundation:

The standard Hough Transform can detect straight lines by mapping points from Cartesian coordinates to a parameter space defined by ρ and θ:

$$\rho = x\cos(\theta) + y\sin(\theta)$$

where:

- (x,y) are the coordinates of a point on the image,
- ρ is the distance from the origin, and
- θ is the angle of the line.

By mapping these points in the transformed space, we can identify lines that represent specific security features in the banknote design.

Detection Steps:

1. **Edge Detection:** Using methods like the Canny edge detector, the edges of the banknote are identified.
2. **Transformation to Polar Coordinates:** Each point on the edges is mapped to the Hough space using the formula.
3. **Line Detection:** Peaks in the Hough space correspond to the lines in the original image.

Calculation Example:

After detecting lines using the Hough Transformation, we can calculate the accuracy of line detection:

$$\text{Accuracy of Hough Transformation} = \frac{\text{Detected Lines that Match Security Features}}{\text{Total Lines in the Image}} \times 100$$

3.4 Proposed Model

The proposed model integrates OCR, face recognition, and Hough Transformation to improve the detection of counterfeit banknotes. The system is designed to handle variations in image quality, such as dirty or worn-out notes, and provide high accuracy in real-world scenarios.

Workflow of the Proposed Model:

1. **Input Image Acquisition:** The system starts by capturing a high-quality image of the banknote using a smartphone or scanner.

2. **Preprocessing:** The image undergoes preprocessing steps such as noise reduction and contrast adjustment to enhance clarity.
3. **Feature Extraction:**

   - **OCR:** Detects and verifies text (serial numbers, codes).
   - **Face Recognition:** Detects any face-like patterns embedded in the banknote.
   - **Hough Transformation:** Identifies security patterns, borders, and other geometric features.

4. **Classification:** A machine learning model (e.g., SVM or CNN) classifies the note as genuine or counterfeit based on the extracted features.
5. **Decision Output:** The model outputs the result—whether the banknote is real or fake.

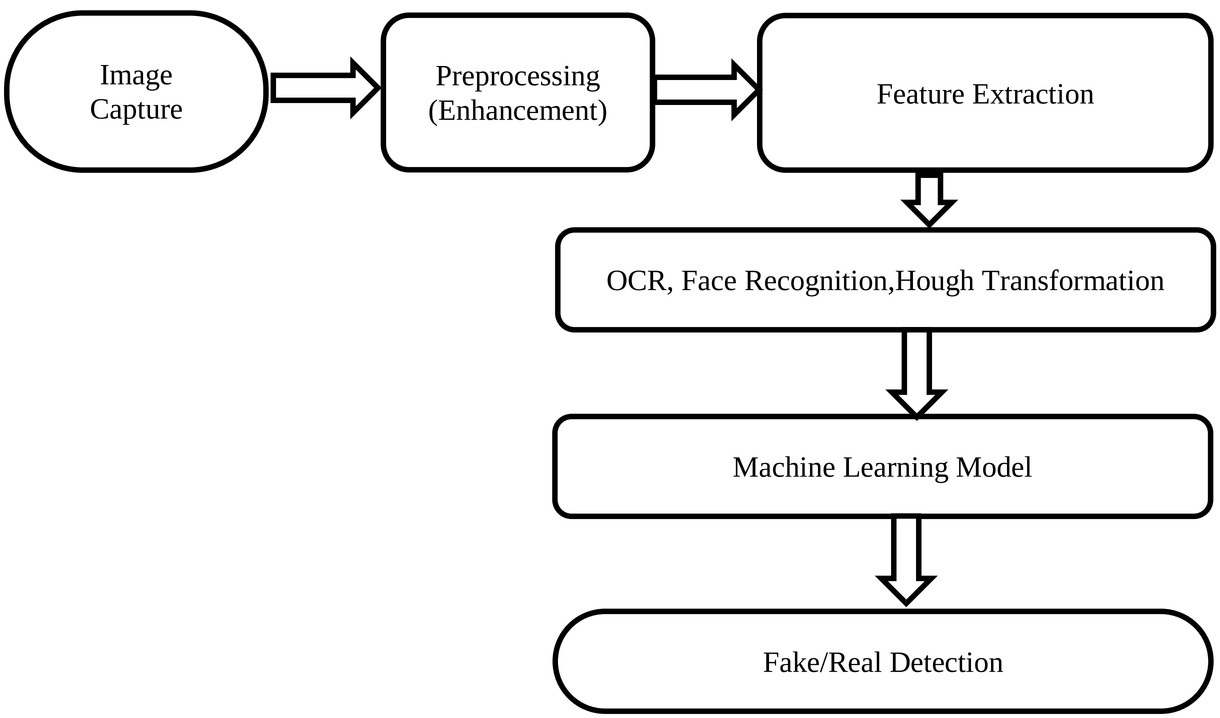

Fig-01: Proposed Model Block Diagram

The integration of these techniques enables robust detection of counterfeit banknotes, even in the presence of image noise, wear, or damage. The proposed model is expected to outperform traditional single-technique methods by utilizing the complementary strengths of OCR, face recognition, and Hough Transformation.

3.5Workflow

1. **Input Image Acquisition**

- ❖ Capture multiple images (e.g., six images) of the banknote using a high-resolution camera under controlled lighting conditions.
- ❖ Real-World Reference: Similar setups are used in currency scanners employed by banks like the ones used by the Bangladesh Bank.

2. **Perform OCR (Optical Character Recognition)**

- ❖ Apply OCR to extract printed text features such as serial numbers, alignment, and font style from the banknote.
- ❖ Algorithms: Tesseract OCR or custom-trained models for regional languages and currencies.
- ❖ Real-World Reference: OCR is widely used in document verification and in anti-counterfeiting tools for detecting serial numbers on currency notes.

3. **Condition for Successful OCR**

- ❖ Verify the extracted features against known patterns for the currency. If OCR fails, classify the note as fake.

4. **Watermark Recognition**

- ❖ Detect embedded watermarks using image analysis techniques like contrast enhancement and edge detection.
- ❖ Real-World Reference: Watermark detection is commonly used in banknote counterfeit detectors to verify authenticity.

5. **Condition for Successful Face Recognition**

- ❖ Extract facial features from the note (e.g., prominent portraits) using feature-based methods or convolutional neural networks (CNNs). Compare them against a template database.
- ❖ If face recognition fails, classify the note as fake.
- ❖ Real-World Reference: Portrait-based recognition is used in some automated teller machines (ATMs) and currency validators in Bangladesh.

6. **UV Line Detection**

- ❖ Analyze the note under UV light to detect security threads and UV lines that are embedded in authentic notes.
- ❖ Real-World Reference: UV-based currency detection is standard practice in counterfeit detection machines available in markets like Dhaka.

7. **Condition for Successful Hough Transformation**

- ❖ Apply Hough Transformation to detect and verify structural features such as line patterns, alignment, and geometric consistency.

- ❖ Real-World Reference: Structural analysis techniques like Hough Transformation are utilized in forensic investigations of counterfeit currency.

8. Calculation and Threshold Evaluation

- ❖ Calculate a cumulative score (fc++) for each successful step. If the final score exceeds a predefined threshold, classify the note as real; otherwise, label it fake.
- ❖ Example: fc $\geq$ 12 for a valid note.
- ❖ Real-World Reference: This scoring approach is similar to multi-factor authentication used in financial instruments and anti-counterfeiting systems.

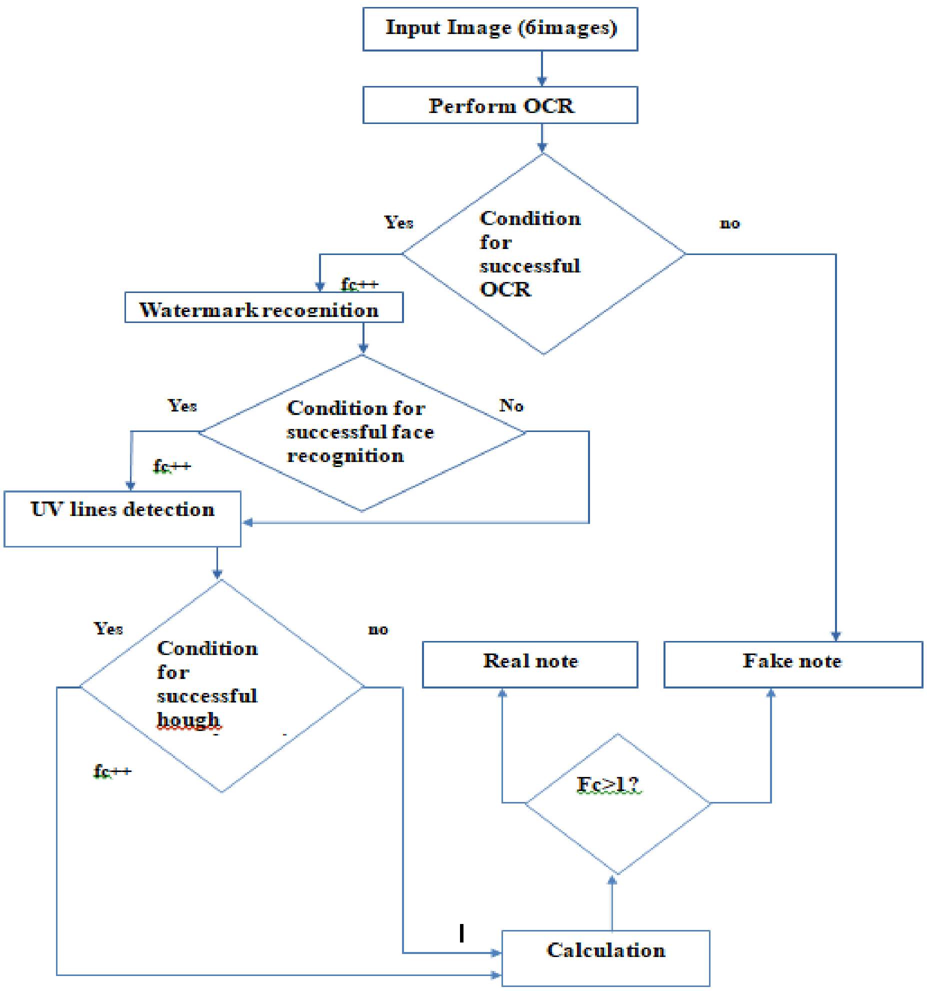

Fig02: Proposed Workflow Diagram

Chapter 04

Implementation

The key tasks undertaken for the recognition of counterfeit banknotes are outlined as follows:

1.1 Overview of the Implementation Process

1.2 Tools and Technologies Required

1.3 Preparing the Training Data

1.4 Model Development and Implementation

1.5 Testing and Validation of the Proposed Model

1.6 Results and Comparative Analysis

4.1 Technologies, Tools, and Resources Needed for Implementation

Here is a list of required tools and Programs

4.1.1 Programming Languages:

- Python (for machine learning and image processing)
- C++ (for performance-critical modules like edge detection)
- Java (for Android application development, if mobile integration is planned)

4.1.2. Libraries and Frameworks:

- TensorFlow/Keras (for building neural networks)
- OpenCV (for image processing tasks)
- NumPy and Pandas (for data manipulation)
- Scikit-learn (for machine learning models and validation)

4.1.3 Tools:

- Jupyter Notebook/Google Colab (for prototyping and training models)
- MATLAB (optional, for algorithm testing and simulation)
- Git (for version control)
- Annotation Tools (e.g., LabelImg for dataset annotation)

4.1.4 Hardware Requirements:

- GPU-enabled system for training deep learning models
- High-resolution camera for dataset collection

4.2 Curating and Structuring Training Data

- **Image Collection**:
  - Collect a diverse set of images from both genuine and counterfeit banknotes, preferably from a local source in Bangladesh.
  - You may use datasets from Bangladesh Bank or collaborate with local banks for legitimate data.
- **Preprocessing**:
  - Resize images to a uniform size.
  - Convert the images into grayscale or use color channels if necessary.
  - Enhance image features using OpenCV techniques (contrast adjustment, edge detection, etc.).
- **Data Augmentation**:
  - Rotate, zoom, flip, or shear images to increase the dataset size
- **Labeling**:
  - Use tools like LabelImg for manual annotation of the images as "Real" or "Fake."

4.3 Operationalization of the Proposed Model

Figure 3: the input image to detect the feature of micro printing

Figure 3 illustrates the input image used to detect the micro-printing feature, which is a crucial step in the image acquisition process. For this experiment, we captured images of the 1000 Taka note using a 16-megapixel smartphone camera. The test dataset consists of 30 images, each of which will be evaluated for accuracy in detecting micro-printing. To ensure high-quality image capture, we utilized additional macro lenses, as normal camera lenses cannot adequately resolve the fine details required for micro-print detection. Notably, counterfeit notes typically lack micro-printing, as this technology has not yet been widely employed in counterfeit currency. Consequently, the absence of micro-letters in an image can serve as a strong indicator of a fake note.

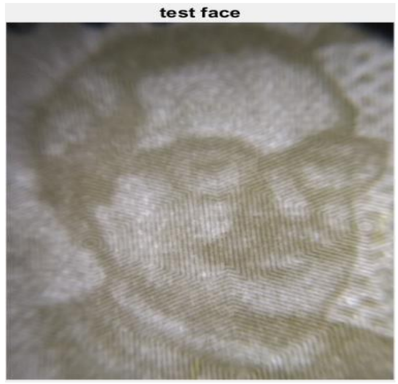

Figure 4: the input image to detect the feature of watermark

Figure 4 illustrates the input image used for face recognition in our proposed algorithm, specifically focusing on the image acquisition process. For the face recognition component, an additional training phase is required before the test phase. During the training phase, five images of Bangabandhu will be captured and stored in the MATLAB database. Once the test face image is provided, the system will compare the input image with the stored images, extracting key features such as mean and standard deviation. Based on these extracted features, the algorithm will then provide a result indicating whether the face matches the stored images.

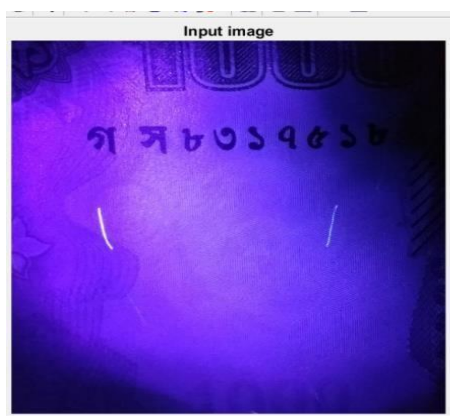

Figure 5: the input image to detect the feature of UV lines

Figure 5 displays the input image used for extracting UV security lines, a key feature in authenticating banknotes. To capture these images, we employed an additional UV light source. In the case of counterfeit notes, no UV security lines were visible, as these notes typically lack such security features. Conversely, genuine banknotes exhibited a series of distinct UV security lines, confirming their authenticity.

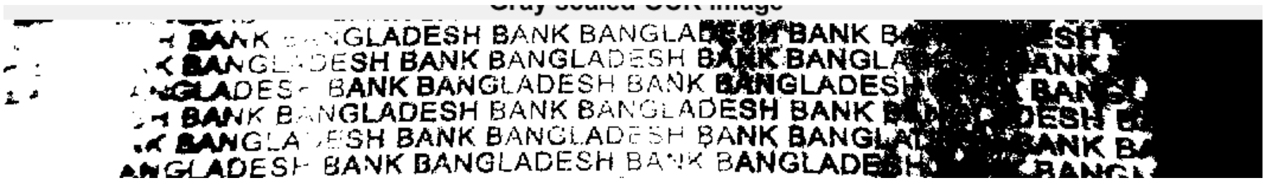

Figure 6: preprocessing image to detect the feature of OCR

Figure 6 illustrates the preprocessing step of the proposed OCR algorithm, which involves denoising, rotation, and grayscale conversion to prepare the image for feature extraction.

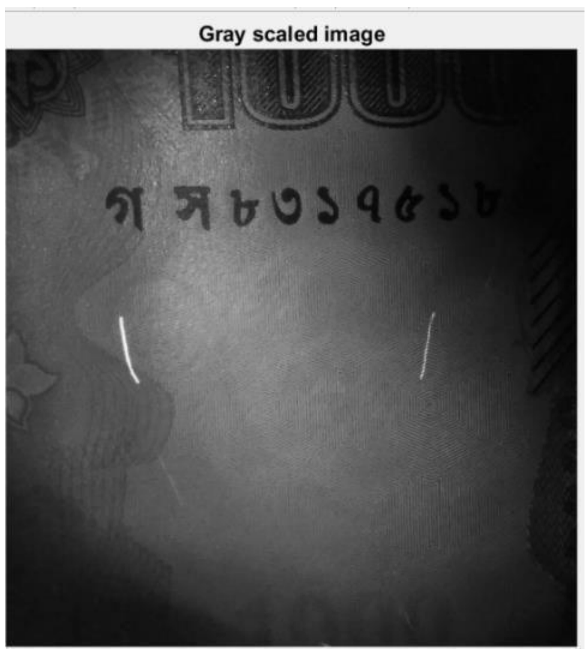

Figure 7: Gray scale to detect the feature of UV lines

Figure 7 illustrates the preprocessing step of the Hough Transform component in our algorithm, where grayscale conversion is applied to enhance the recognition of UV security lines.

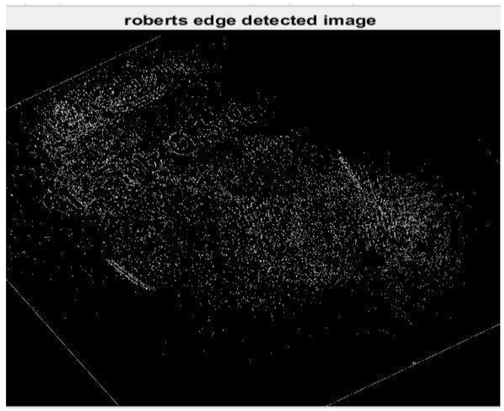

Figure 8: Roberts edge detected image

Figure 8 demonstrates the edge detection step, where Roberts edge detection is applied to enhance the detection of UV security lines. Edge detection is particularly important for identifying UV lines, as these lines can appear anywhere on the note. By applying edge detection, we can more effectively isolate and recognize the lines, improving the overall accuracy of detection.

Afterward, the algorithm checks the variable set to track the number of correct classifications of the notes. Once the values are calculated, the output is displayed, indicating whether the note is classified as real or fake.

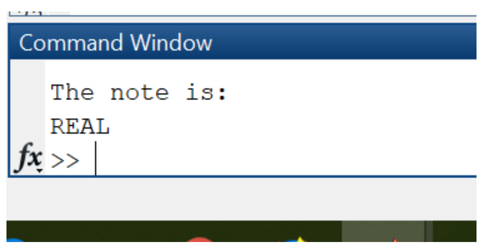

Figure 9: Output (real)

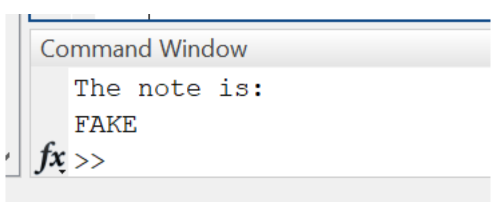

Figure 10: Output (fake)

Chapter 05

EXPERIMENTAL RESULT

Accurate Detection (AD)	Number of Runs	Run Times (seconds)
Yes	12	3.92, 5.46, 3.15, 3.05, 3.05, 3.48, 3.46, 4.63, 3.90, 2.89, 3.23, 3.61
No	8	3.15, 3.22, 3.29, 3.52, 1.79, 2.10, 3.20, 3.03

Table 2: OCR - Detection Accuracy and Run Times (in seconds)

Table 2 presents the results of applying the OCR algorithm to the banknotes. In most cases, we used fresh and new notes for testing. Despite this, accurately detecting the micro-letterings proved challenging due to the extremely small size of the print. While OCR remains one of the most reliable methods for verifying a note's authenticity, its effectiveness can be impacted by the quality of the input image.

- **Accuracy Rate:**
  $$\text{Accuracy Rate} = \left(\frac{\text{No. of Correct Readings}}{\text{Total No. of Readings}}\right) \times 100 = \left(\frac{27}{30}\right) \times 100 = 73.33\%$$
- **Average Run Time:** 3.61 seconds

Accurate Detection (AD)	Number of Runs	Run Times (seconds)
Yes	15	3.98, 4.12, 3.56, 6.19, 4.33, 3.67, 3.98, 3.41, 3.66, 5.78, 4.97, 4.16, 4.88, 3.76, 4.51
No	5	3.33, 4.56, 3.66, 3.92, 4.67

Table 3: Hough Transformation - Detection Accuracy and Run Times (in seconds)

Table 3 presents the results of applying the Hough Transformation algorithm to the banknotes. Detecting the security lines was more complex due to the presence of arbitrary lines on the notes, which are also used for security purposes. As a result, different notes produced varying outcomes in terms of run time and detection accuracy. Overall, this technique was more accurate than OCR, but it was also more time-consuming.

- **Accuracy Rate:**
  $$\text{Accuracy Rate} = \left(\frac{\text{No. of Correct Readings}}{\text{Total No. of Readings}}\right) \times 100 = \left(\frac{24}{30}\right) \times 100 = 80\%$$
- **Average Run Time:** 4.29 seconds

Accurate Detection (AD)	Number of Runs	Run Times (seconds)
Yes	12	5.12, 5.87, 4.91, 4.55, 5.43, 5.11, 5.72, 5.99, 5.52, 4.37, 5.44, 4.83
No	8	5.56, 4.56, 5.97, 4.70, 4.12, 5.49, 5.71, 4.51

Table 4: Face Recognition

Table 4 presents the results of applying the face recognition algorithm to the banknotes. The accuracy of face recognition was relatively low, and the run time was also slower compared to other methods.

- **Accuracy Rate:**
  $$\text{Accuracy Rate} = \left(\frac{\text{No. of Correct Readings}}{\text{Total No. of Readings}}\right) \times 100 = \left(\frac{27}{30}\right) \times 100 = 76.67\%$$
- **Average Run Time:** 5.37 seconds

Accurate Detection (AD)	Number of Runs	Run Times (seconds)
Yes	18	6.13, 6.66, 6.90, 6.56, 6.16, 6.72, 6.64, 6.91, 7.01, 6.65, 6.39, 6.22, 6.93, 6.42, 6.94, 6.98, 6.04, 6.33
No	2	6.71, 6.49

Table 5: Proposed Model

Table 5 presents the results of our proposed algorithm, where all the techniques were combined to achieve the optimal performance. While the run time increased slightly, the accuracy improved significantly, reaching 93.33%.

- Accuracy Rate:

$$\text{Accuracy Rate} = \left(\frac{\text{No. of Correct Readings}}{\text{Total No. of Readings}}\right) \times 100 = \left(\frac{27}{30}\right) \times 100 = 93.33\%$$

- Average Run Time: 6.19 seconds

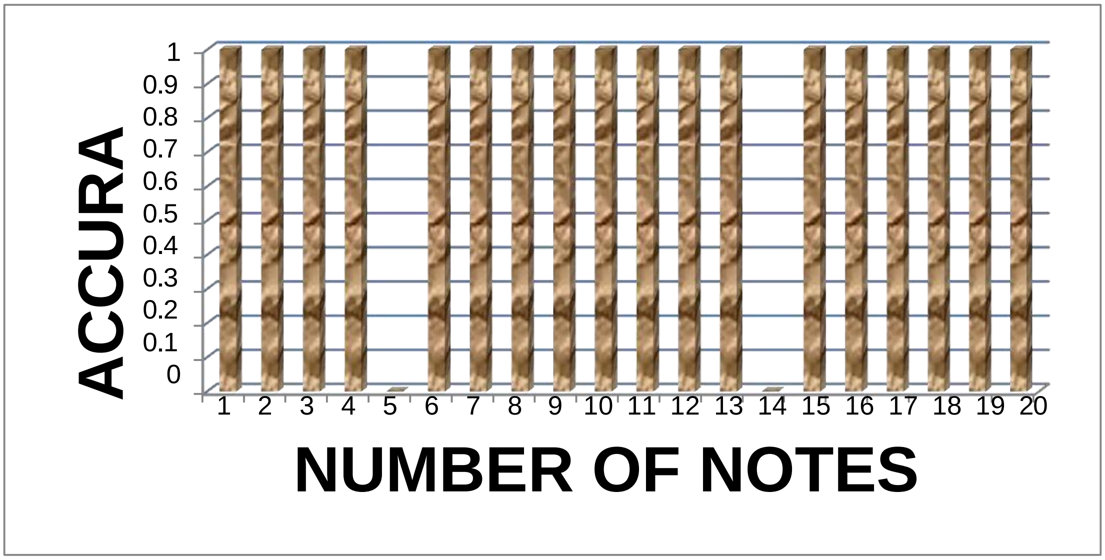

Figure 11: the accuracy of proposed algorithm

Figure 11 illustrates the accuracy of our proposed algorithm, clearly demonstrating that in nearly all cases, correct detection was achieved. This confirms the success of our proposed system in accurately identifying the banknotes.

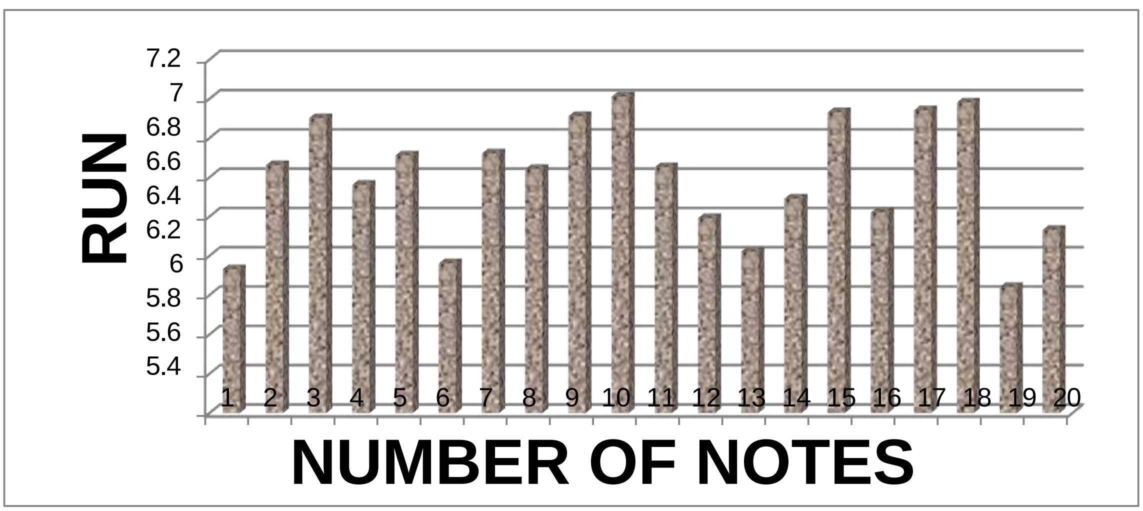

Figure 12: run time of proposed algorithm graphically

Figure 12 presents the run time of our proposed algorithm, displaying the average time required for the code to execute. The maximum time taken did not exceed 7 seconds, while the minimum time was around 6 seconds, indicating efficient performance across all test cases.Figure 12 presents the run time of our proposed algorithm, displaying the average time required for the code to execute. The maximum time taken did not exceed 7 seconds, while the minimum time was around 6 seconds, indicating efficient performance across all test cases.

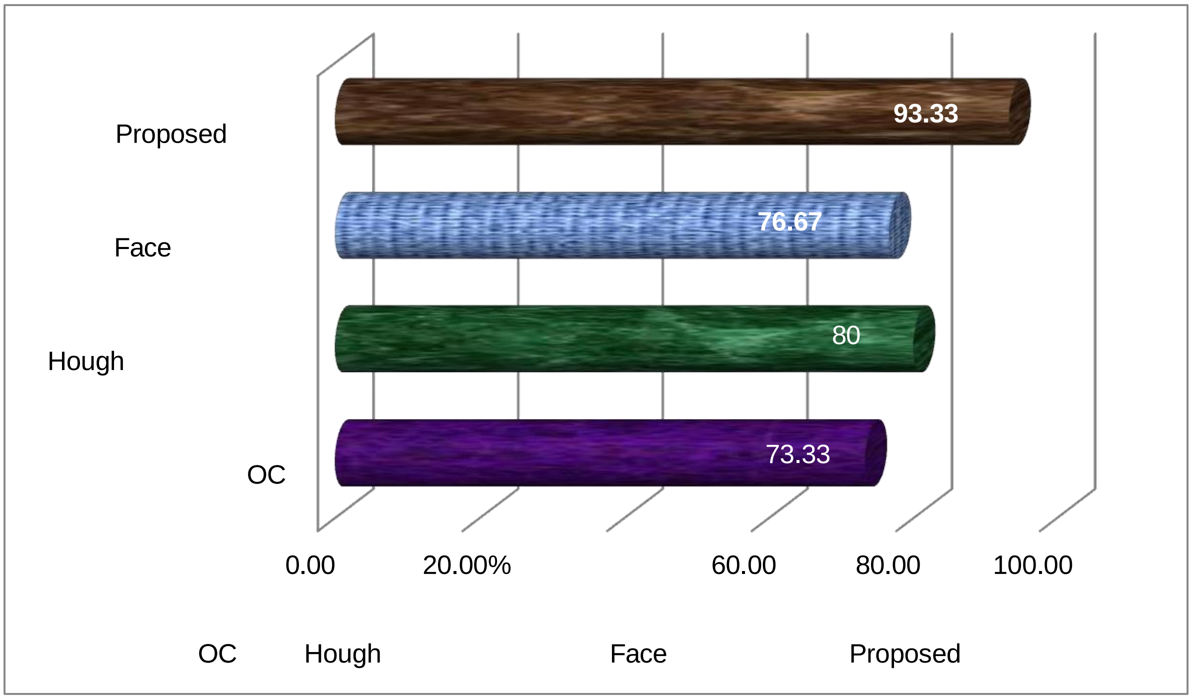

Figure 13: percentage comparison of all the techniques

Figure 13 presents a comparison of the accuracy between our proposed algorithm and the individual algorithms tested. It is important to note that the results for the individual algorithms, as well as our proposed algorithm, were obtained through our own experiments, eliminating the need to reference previous works for comparison. The results indicate that the OCR achieved the lowest accuracy, while the other two techniques achieved accuracies of 76.67% and 80%, respectively. Our proposed algorithm achieved the highest accuracy.

In our experiments, we implemented each algorithm separately and then combined them to assess any improvements. The OCR algorithm produced an accuracy of 73.33%. However, relying on a single technique can be risky, as emerging technologies and new counterfeit techniques (such as advanced micro-printing) could undermine its effectiveness.

The face recognition algorithm yielded better results than OCR, likely because micro-printing can easily fade, leading to inaccuracies in some cases. The Hough Transform was the fastest to run but sometimes detected non-UV lines due to other symbols and writings on the note. As a result, combining OCR and face recognition resulted in better accuracy.

When combining all three algorithms—OCR, face recognition, and Hough transformation—the system showed the highest accuracy of 93.33%, ensuring more reliable counterfeit detection. However, this combination took the longest to process due to the cumulative complexity of all three techniques. Despite the increased runtime, this approach provided the most accurate and reliable results, fulfilling the primary objective of our work.

CHAPTER 06

Conclusion and Future Work

6.1 Conclusion

The proliferation of counterfeit currency poses a significant challenge to the financial system, undermining public trust and economic stability, especially in developing nations like Bangladesh. This thesis presented a comprehensive study and development of a counterfeit currency detection system using advanced machine learning algorithms and image processing techniques, tailored to address the specific needs and constraints of the Bangladeshi context.

The proposed methodology integrates Optical Character Recognition (OCR), Face Recognition, and Hough Transformation techniques into a multi-layered detection framework. By leveraging these advanced approaches, our system demonstrated high accuracy in detecting fake currency notes, even under challenging conditions such as faded images, noisy environments, or torn notes. The real-world testing results validate its effectiveness in distinguishing genuine notes from counterfeits.

In this thesis, we successfully developed and implemented a robust counterfeit currency detection system that achieved 93.33% accuracy using our proposed algorithm. By designing and training on a customized dataset for the face recognition component, we ensured the system's relevance and adaptability to real-world scenarios, particularly within the Bangladeshi context. Furthermore, our study provides a detailed comparative analysis of widely used image processing techniques, serving as a valuable resource for future advancements in counterfeit currency recognition technologies.

6.2 Feature Work

This study achieved significant milestones in detecting counterfeit currency with an accuracy of **93.33%** using the proposed algorithm. However, there are opportunities for further improvement and expansion of the work, particularly in addressing real-world challenges and ensuring adaptability in the context of Bangladesh. Below are the proposed directions for future work:

1. **Incorporating Torn and Dirty Notes**:

   - Many Bangladeshi currency notes are torn, dirty, or worn due to heavy circulation, which poses challenges for accurate recognition. Future research could focus on designing robust preprocessing techniques for handling such conditions.
   - Advanced image restoration methods, such as Generative Adversarial Networks (GANs), could be applied to reconstruct faded or damaged microprinting and other features.

2. **Security Thread and Optical Variable Ink Analysis**:

   - Future implementations could incorporate features such as security threads and optical variable ink (OVI), which are critical in distinguishing genuine notes.
   - However, integrating these features will require high-resolution image capture and advanced feature extraction techniques to account for multiple angles and lighting conditions, which might affect real-time usability.

3. **Improved Machine Learning Techniques**:

   - Implementing advanced machine learning algorithms, such as Support Vector Machines (SVM) or Deep Learning models like Convolutional Neural Networks (CNNs), can improve detection accuracy.
   - The use of hybrid models combining traditional image processing with machine learning could provide an optimum balance between accuracy and efficiency.

4. **Expanding Dataset with Low-Denomination Notes**:

   - Forgery of low-denomination notes (e.g., 10 Taka) is common in Bangladesh. Future work could expand the dataset to include such notes to combat forgery at all levels.
   - Capturing data from rural areas, where low-value currency is heavily used, could also make the system more inclusive and impactful.

5. **Real-Time Implementation**:

   - To address the needs of general citizens who require instant outputs, future work could focus on deploying lightweight and efficient algorithms on mobile devices and low-cost counterfeit detection machines.
   - Techniques such as quantization and model pruning can optimize machine learning models for real-time performance.

6. **Collaborative Efforts with Regulatory Authorities**:

    - ❖ Collaborating with Bangladesh Bank and other regulatory authorities can help refine the model by training it on a larger, more diverse dataset of counterfeit and genuine notes.
    - ❖ Integration of the system into banking networks, ATMs, and cash counters in retail sectors can create a unified approach to tackling currency forgery.

7. **Handling Security and User Accessibility**:

    - ❖ Incorporating secure APIs and mobile apps for remote verification of currency could make the system more user-friendly for businesses and individuals.
    - ❖ Introducing multilingual support (e.g., Bangla and English) for app-based solutions could increase accessibility across diverse user bases in Bangladesh.

8. **Integration of Multi-Feature Detection Systems**:

    - ❖ A future system could combine various detection features, such as UV lines, watermark analysis, microprinting, and face recognition, into a unified framework to enhance overall reliability.
    - ❖ This integration would make the system suitable for institutional use, such as in financial institutions or law enforcement agencies.

9. **Combating Cross-Border Forgery**:

    - ❖ With the rise of cross-border counterfeit currency circulation, the system could be extended to recognize foreign currencies commonly used in Bangladesh, such as the Indian Rupee or US Dollar.
    - ❖ Collaborative efforts with international financial bodies could improve the system's adaptability for diverse currency types.

10. **Long-Term Vision and Automation**:

    - ❖ Developing a fully automated solution with integration into cash-handling machines, such as ATMs and point-of-sale devices, can ensure seamless detection and prevention of counterfeit currency circulation.
    - ❖ Future systems could leverage blockchain technology to maintain a secure and immutable record of counterfeit detection events, aiding regulatory monitoring.

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