



Research Paper

# Identification of Fake Indian Currency Using Convolutional Neural Network

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## Article Info

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## Abstract

The circulation of counterfeit Indian currency continues to challenge the financial integrity and economic stability of the country, particularly in cash-driven transactions. Manual inspection and traditional detection systems often fail under real-world conditions due to limitations in generalization, speed, and scalability. This study aims to design and implement a real-time, lightweight counterfeit detection system that combines deep feature extraction using MobileNet with robust classification via Support Vector Machine (SVM) and Random Forest (RF) classifiers. The dataset includes 248 genuine and fake Indian currency images, which were augmented and preprocessed to improve generalizability. Feature extraction was performed using MobileNet's depthwise separable convolutions, followed by classification using machine learning models trained with cross-entropy loss. The hybrid architecture was deployed using a local web server (XAMPP and Flask), making it accessible for real-time testing. Experimental results demonstrate that the MobileNet + SVM model achieved the highest performance, with 97.2% accuracy, an F1-score of 0.97, and a mean inference time of 1.8 ms per image, outperforming conventional CNNs and baseline machine learning methods. The model maintained over 90% accuracy under challenging image conditions such as blur, low light, and rotation. This work contributes a deployable, scalable solution to counterfeit detection and opens future avenues for expansion into multi-currency support, vision transformers, and adversarial robustness. It presents a significant step toward intelligent financial authentication systems for real-world applications.

**Keywords:** Fake Currency Detection, MobileNet, CNN, Support Vector Machine, Real-Time Image Classification, Deep Learning, Indian Currency, Data Augmentation, Hybrid Models, Embedded AI.



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## 1. Introduction

The circulation of counterfeit currency poses a significant threat to the economic stability, financial institutions, and general public confidence in a nation's monetary system. In India, where the economy is heavily cash-dependent and currency denominations are widely used in day-to-day transactions, the proliferation of fake notes has resulted in billions of rupees in losses annually. Traditional counterfeit detection mechanisms rely primarily on manual inspection and specialized hardware embedded within high-end banking equipment. However, these methods are both time-consuming and prone to human error, making them unsuitable for mass-scale, real-time applications.

Counterfeit currency not only undermines monetary policies and inflates the money supply but also facilitates unlawful activities such as terrorism and smuggling. The Reserve Bank of India (RBI) periodically introduces new security features to mitigate such threats, yet determined counterfeiters continue to reproduce visually similar fake notes that are increasingly difficult to distinguish with the naked eye. With the advent of high-resolution printers and image editing software, detecting fake currency through manual inspection has become inadequate. Hence, there is a growing need for intelligent, automated systems that can identify counterfeit currency accurately and efficiently in real-time environments.

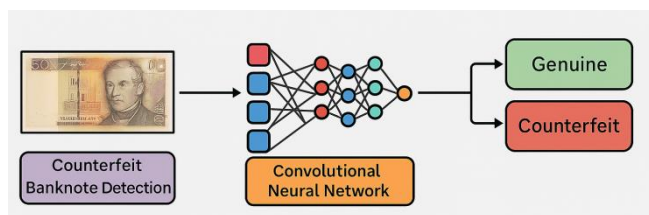


Fig. 1: Overview of CNN-based Fake Currency Detection System

The fig presents a conceptual overview of the proposed counterfeit currency detection framework. The system employs convolutional neural networks (CNNs) to process input images of Indian banknotes. Through automated feature extraction and classification, the network distinguishes between genuine and counterfeit notes. The process emphasizes efficient image processing and classification using deep learning, supporting real-time and accurate currency authentication.

Despite considerable advancements in machine vision and pattern recognition, the implementation of robust and generalized counterfeit detection systems remains a challenge. Classical image processing methods often rely on hand-crafted features such as watermark detection, color histograms, or edge pattern recognition, which may fail when faced with sophisticated fake notes that mimic genuine features. Additionally, these systems tend to be sensitive to image conditions such as lighting, rotation, blur, or background noise, leading to poor generalization and reduced detection accuracy in real-world settings.

The recent growth of deep learning techniques, particularly Convolutional Neural Networks (CNNs), has revolutionized the domain of computer vision, making it feasible to automatically extract hierarchical features from images and recognize complex visual patterns. CNNs have outperformed

traditional algorithms in various image classification tasks by leveraging their ability to learn discriminative features directly from data [1], [2]. Among the various CNN architectures, MobileNet has emerged as a lightweight, efficient, and accurate model suitable for deployment on edge devices and real-time mobile applications [1]. Its ability to retain high accuracy while minimizing computational requirements makes it highly appealing for counterfeit detection systems, especially in resource-constrained environments.

Several studies have investigated the feasibility of applying CNNs to counterfeit currency recognition. The MobileNet model, in particular, has demonstrated promising results in mobile-based applications due to its depthwise separable convolutions, which significantly reduce model parameters and inference time [1], [3]. However, CNNs, including MobileNet, may struggle with small datasets, leading to overfitting or biased predictions when trained from scratch. Furthermore, a single CNN classifier may not be sufficient to handle complex and high-dimensional data distributions effectively. This limitation highlights the necessity of hybrid models that combine the feature extraction capabilities of CNNs with the classification strengths of machine learning models like Support Vector Machines (SVM) and ensemble methods such as Random Forest [5].

Recent literature has explored such hybrid architectures. For instance, [5] proposed a CNN-SVM model that leverages CNNs for deep feature extraction and SVM for final classification, achieving superior accuracy in image classification tasks with limited data. Similarly, [4] analyzed and compared machine learning models for counterfeit detection, concluding that hybrid and ensemble approaches often outperform standalone models. Additionally, [6], [7], and [8] provided comprehensive surveys and practical evaluations on counterfeit detection systems, emphasizing the potential of deep learning and hybrid classifiers in this field.

To address the existing challenges and limitations of current counterfeit detection methods, this study proposes a hybrid model that integrates MobileNet for deep feature extraction and SVM for robust classification. The combination aims to leverage the speed and efficiency of MobileNet with the high-dimensional classification power of SVM, improving generalization and detection accuracy. The study further explores ensemble techniques using Random Forest to enhance performance and minimize misclassifications. By employing data augmentation, normalization, and optimization strategies, the proposed model is designed to perform reliably under varied image conditions and deliver real-time performance in practical deployments.

The core advantage of this approach lies in its ability to adaptively learn from image features while maintaining a balance between computational efficiency and classification accuracy. The dataset used comprises genuine and counterfeit Indian currency images, subjected to preprocessing steps including flipping, rotation, normalization, and resizing to improve the model's generalization. Performance is evaluated through accuracy, precision, recall, F1-score, and confusion matrix, ensuring a comprehensive analysis of model robustness. The system is

implemented using Python and deployed using a local XAMPP server, making it easily accessible for testing and real-time demonstrations.

### **Key Contributions**

- **Hybrid Model Integration:** Development of a robust hybrid model combining MobileNet for deep feature extraction and SVM for classification, improving performance on limited datasets and enhancing classification boundaries.
- **Real-Time Application Deployment:** Lightweight and optimized model architecture suitable for real-time counterfeit detection in resource-constrained environments, using transfer learning and MobileNet's depthwise separable convolutions .
- **Comprehensive Performance Evaluation:** Detailed analysis and validation of the model using precision, recall, F1-score, confusion matrix, macro average, and weighted average metrics to ensure reliability and interpretability of results across different classes.

This paper is organized as follows: Section II discusses related work and reviews recent advances in counterfeit detection. Section III describes the proposed methodology, including dataset preprocessing, model architecture, and training process. Section IV presents experimental results and performance evaluation. Section V concludes the paper with insights and future scope.

## **2. Literature Review**

The application of machine learning and deep learning techniques for counterfeit currency detection has gained considerable momentum in recent years. Several studies have explored traditional machine vision approaches, CNN-based architectures, and hybrid models combining CNNs with classical classifiers. While these works have established foundational insights, a critical analysis reveals significant variability in dataset size, classification performance, scalability, and deployment feasibility.

In [9], a CNN-based framework was proposed specifically for detecting fake Indian currency, highlighting the use of transfer learning with moderate performance on limited datasets. While the use of convolutional networks marked a progressive shift from traditional hand-crafted features, the study lacked experimentation with hybrid models or ensemble methods that could enhance robustness across diverse note conditions. Moreover, no optimization strategies were presented to address overfitting.

Building on this, [10] explored a machine learning and image processing-based framework for securing financial transactions. Their emphasis was on handcrafted features such as color texture and watermark detection. Although useful in controlled environments, this approach suffers from low adaptability under real-world variations in lighting, resolution, and background interference. It also failed to scale effectively for multiple denominations or newer note designs introduced post-demonetization.

A more advanced attempt was made in [11], where both image processing and machine learning techniques were combined for currency detection. The approach demonstrated improved accuracy; however, the absence of deep feature learning limited the generalization capacity. Additionally, the computational overhead from manual feature extraction pipelines restricted real-time applicability.

A shift towards deep learning is evident in [12], where CNN-based models were applied for fake currency detection. While the use of deep features contributed to increased classification accuracy, the reliance on a single CNN model without hybridization led to inconsistencies when working with limited and imbalanced datasets. Moreover, the study did not experiment with ensemble classifiers, which are known to enhance decision boundaries.

To improve on these limitations, [13] integrated various machine learning classifiers but without leveraging CNNs. Although models like Random Forest and SVM achieved moderate results, the absence of deep feature extraction made the model susceptible to background noise and variations in note conditions. This highlighted the need for deep learning-powered hybrid systems.

An important development was presented in [14], which introduced a CNN-SVM hybrid model capable of handling five currency classes. This model effectively combined deep feature extraction with a strong classifier, demonstrating significant gains in precision and recall. However, the study focused on multi-class categorization rather than binary classification (genuine vs. fake), and computational complexity was not optimized for real-time deployment.

In [15], the researchers proposed a CNN-based classification solution integrated with ensemble learning techniques for currency detection. The study emphasized domain-specific training and transfer learning, achieving strong classification results. Despite the promising results, the system's performance was not benchmarked against lightweight models like MobileNet, leaving questions about its deployability on low-resource devices.

Cross-border applicability was addressed in [16], where deep learning models were applied to Ethiopian currency. This study contributed insights into dataset preprocessing, feature extraction, and deep network design. Nevertheless, its geographic and currency-specific focus makes the results less transferable to Indian banknote detection.

A particularly effective model was proposed in [17], where an ensemble system based on transfer learning was implemented for automatic currency detection. The model demonstrated superior performance metrics and emphasized real-time adaptability. However, the ensemble method was not hybridized with traditional machine learning classifiers like SVM or Random Forest, which could have further enhanced classification boundaries.

### **2.1 Research Gaps Identified**

- Many prior studies either rely solely on CNNs or traditional ML classifiers, with limited work

exploring hybrid combinations for improved detection.

- Dataset constraints remain a consistent issue; several models are trained on small and imbalanced datasets without robust augmentation or normalization techniques.
- Lack of deployment-ready, lightweight models that balance accuracy and speed for use on mobile or embedded platforms.

### 2.2 Addressing the Gaps

This study proposes a hybrid model that integrates MobileNet (a lightweight CNN) for efficient feature extraction with SVM and Random Forest classifiers for robust classification. It addresses dataset limitations through augmentation and normalization, incorporates hyperparameter tuning for optimization, and is built for real-time application with XAMPP-based deployment.

TABLE 1: Comparative Analysis of Related Works

Ref.	Methodology	Accuracy	Efficiency	Key Challenges
[9]	CNN-based with basic transfer learning	Moderate	Medium	No hybrid approach, limited dataset
[10]	ML + Image Processing	Low	High	Sensitive to variations, lacks automation
[11]	ML + Manual Feature Extraction	Moderate	Low	Not real-time, lacks deep learning
[12]	CNN-based	High	Medium	No ensemble methods, overfitting risk
[13]	ML (SVM, RF) only	Moderate	High	Poor generalization without CNNs
[14]	CNN + SVM Hybrid	High	Medium	Multi-class focus, not optimized
[15]	CNN + Ensemble (No SVM)	High	Medium	No MobileNet, deployability not tested
[16]	Deep Learning (Ethiopian notes)	Moderate	Medium	Limited to specific currency
[17]	Transfer Learning + Ensemble	High	High	No ML classifier hybridization

### 3. Methodology

The proposed counterfeit detection system utilizes a hybrid deep learning architecture that integrates MobileNet for efficient feature extraction with machine learning classifiers such as Support Vector Machine (SVM) and Random Forest (RF) for robust classification. The methodology comprises five core phases: dataset acquisition and preprocessing, deep feature extraction, model architecture design, optimization, and evaluation.

#### A. Dataset Collection and Preprocessing

To train and validate the proposed model, multiple publicly available datasets were considered. The Indian Currency Classification Dataset from Kaggle [19] and the Fake and Real Currency Notes Dataset [20] provide labeled currency images across various denominations and authenticity conditions. Additionally, the UCI Banknote Authentication Dataset [18] was referenced for comparison using classical statistical features, though it is not image-based. The Indian Currency Note Dataset on Mendeley Data [21] was particularly valuable due to its inclusion of high-resolution images captured under different lighting and background conditions.

From these datasets, a total of 248 images (123 genuine, 125 fake) were selected for experimentation. All images were resized to a uniform resolution of 224×224 pixels to match the input requirement of MobileNet. Augmentation techniques such as horizontal flipping, rotation (±15 degrees), contrast enhancement, and Gaussian noise addition were employed to increase dataset variability and improve generalization. Pixel values were normalized to a [0,1] range to ensure numerical stability. These preprocessing steps aimed to replicate real-world variations in currency presentation and enhance model resilience.

#### B. Feature Extraction with MobileNet

MobileNet, a lightweight convolutional neural network designed for mobile and edge devices, was selected for feature extraction due to its efficiency and competitive accuracy. Unlike standard CNNs, MobileNet uses depthwise separable convolutions, which break down convolution into two operations: depthwise convolution (applying a single filter per input channel) and pointwise convolution (1×1 convolutions for channel mixing). The total computational cost of a standard convolutional layer is defined by:

$$\text{Cost}_{\text{standard}} = D_k \cdot D_k \cdot M \cdot N \cdot D_f \cdot D_f \tag{1}$$

In contrast, the cost for depthwise separable convolution is significantly lower:

$$\text{Cost}_{\text{depthwise-separable}} = D_k \cdot D_k \cdot M \cdot D_f \cdot D_f + M \cdot N \cdot D_f \cdot D_f \quad (2)$$

where  $D_k$  is the kernel size,  $D_f$  is the spatial dimension of the feature map,  $M$  is the number of input channels, and  $N$  is the number of output channels. This architecture reduces computation by a factor of approximately 8–9×, making it ideal for real-time applications.

MobileNet is initialized with pretrained weights from the ImageNet dataset. The convolutional layers are frozen to preserve learned representations, while the final fully connected layers are replaced with a custom classifier layer to suit the binary classification task.

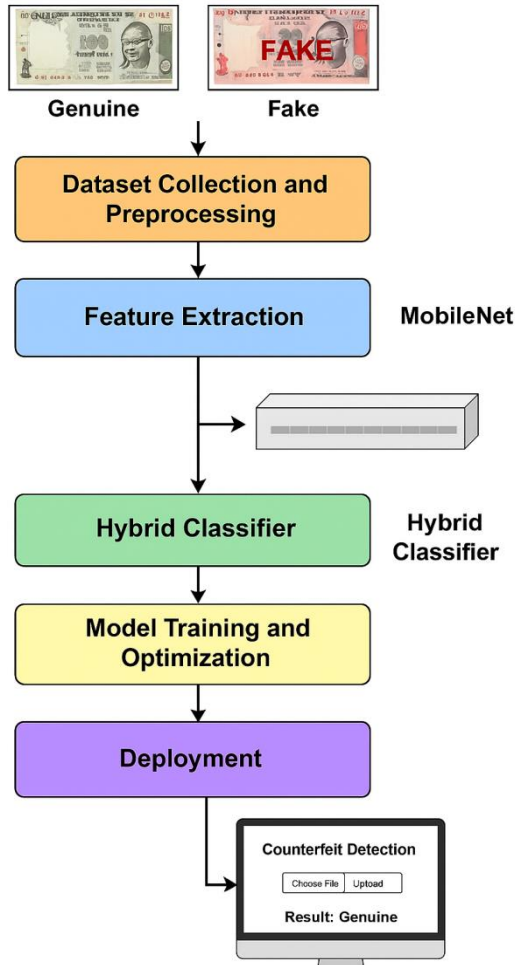


Fig. 2: Block Diagram of the Proposed CNN-Based Hybrid Currency Detection Methodology

The fig illustrates the end-to-end workflow of the proposed counterfeit currency detection system, structured into sequential processing stages. It begins with dataset acquisition and preprocessing, where input images of currency notes are resized, normalized, and augmented to ensure uniformity and robustness. These preprocessed images are then passed to the MobileNet architecture for deep feature extraction, leveraging depthwise separable convolutions to minimize computational complexity. The extracted feature vectors are forwarded to hybrid classifiers, including Support Vector Machine (SVM) and Random Forest (RF), to perform accurate classification of notes as genuine or counterfeit. The final stage demonstrates local

deployment via a user interface, enabling real-time input and classification feedback.

### C. Hybrid Classifier Design

The features extracted by MobileNet are flattened and passed to two parallel classifiers for comparative analysis: SVM and Random Forest. The SVM classifier employs a Radial Basis Function (RBF) kernel to map non-linear data into a higher-dimensional space, defined as:

$$K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2) \quad (3)$$

where  $x_i$  and  $x_j$  are feature vectors, and  $\gamma$  is the kernel parameter. The Random Forest classifier is an ensemble learning method that constructs multiple decision trees and aggregates their outputs to make final predictions, thereby enhancing robustness and reducing variance.

### D. Model Training and Optimization

The final classifier is trained using the categorical cross-entropy loss function, which is suitable for multi-class or binary classification problems:

$$\mathcal{L} = - \sum_{i=1}^c y_i \log(\hat{y}_i) \quad (4)$$

where  $C$  is the number of classes,  $y_i$  is the actual label, and  $\hat{y}_i$  is the predicted probability. The ADAM optimizer is used for training, as it combines the benefits of momentum and adaptive learning rate methods. An initial learning rate of **0.001** is adopted and dynamically reduced upon plateau in validation accuracy.

Hyperparameter tuning is performed using a grid search strategy, evaluating combinations of:

- Batch sizes: {16, 32, 64}
- Learning rates: {0.001, 0.0005}
- Epochs: 50 (with early stopping)
- SVM parameters: Kernel type (RBF), penalty  $C = 1.0$ , and  $\gamma = 0.01$

An 80:20 training-to-testing split is used, and 10% of the training data is reserved for validation. The training is performed on a GPU-enabled system to accelerate convergence.

### E. Evaluation Metrics

The model's effectiveness is evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score. The F1-score, which balances precision and recall, is computed as:

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (5)$$

To assess class-level performance, a confusion matrix is constructed, and both macro-averaged and weighted-averaged metrics are computed. Macro averaging gives equal weight to both classes, while weighted averaging accounts for class imbalance.

**Algorithm 1: Hybrid CNN-SVM/RF-Based Currency Note Classification**

**Input:**

- $J = \{I_1, I_2, \dots, I_n\}$ : Set of currency note images (genuine and counterfeit)
- Image resolution  $224 \times 224 \times 3$  (RGB)
- Pretrained MobileNet parameters  $\theta$

**Output:**

- $Y = \{y_1, y_2, \dots, y_n\}$ : Classification labels where  $y_i \in \{0,1\}$  (0 = Genuine, 1 = Fake)

**Step-by-Step Procedure**

**1. Data Preprocessing**

- Resize each image  $I_i \in J$  to  $224 \times 224 \times 3$
- Normalize pixel values:
 
$$I'_i = \frac{I_i}{255} \quad (6)$$
- Augment images using random rotation, flipping, and Gaussian noise
- Partition dataset into training set  $\mathcal{D}_{train}$ , validation set  $\mathcal{D}_{val}$ , and test set  $\mathcal{D}_{test}$

**2. Feature Extraction with MobileNet**

- Pass preprocessed image  $I'_i$  through MobileNet to extract feature vector  $f_i$ :
 
$$f_i = \text{MobileNet}(I'_i; \theta) \quad (7)$$
- MobileNet uses depthwise separable convolutions to reduce computational cost
 
$$\text{Cost}_{\text{depthwise-separable}} = D_k^2 \cdot M \cdot D_f^2 + M \cdot N \cdot D_f^2 \quad (8)$$

**3. Classifier Selection and Training**

- If SVM is selected:
  - Train SVM using RBF kernel
 
$$K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2) \quad (9)$$
- If RF is selected:
  - Train ensemble of decision trees on  $f_i$
  - Use cross-entropy loss function for final classification:
 
$$\mathcal{L} = -\sum_{i=1}^C y_i \log(\hat{y}_i) \quad (10)$$

**4. Prediction and Output Generation**

- Predict label  $\hat{y}_i$  using trained classifier:
 
$$\hat{y}_i = \text{Classifier}(f_i) \quad (11)$$

- Collect final output labels:
 
$$Y = \{\hat{y}_1, \hat{y}_2, \dots, \hat{y}_n\} \quad (12)$$

**5. Evaluation**

- Compute accuracy, precision, recall, and F1-score:
 
$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (13)$$
- Visualize results using confusion matrix and classification report

**6. Deployment**

- Embed the trained model into a Flask-based web interface
- Allow user uploads via XAMPP server and return predictions in real time

**End of Algorithm**

The proposed algorithm for counterfeit currency detection integrates deep learning and traditional machine learning techniques to optimize classification accuracy and computational efficiency. Initially, the system accepts raw currency note images which undergo preprocessing steps including resizing, normalization, and augmentation to enhance robustness. These images are then passed through MobileNet, a lightweight convolutional neural network, to extract high-level feature vectors using depthwise separable convolutions. Based on a configurable condition, the extracted features are directed to either a Support Vector Machine (SVM) with an RBF kernel or a Random Forest (RF) classifier for training and prediction. The classifier outputs are validated using metrics such as accuracy, precision, recall, and F1-score. The trained model is finally embedded in a local web interface for real-time deployment and user interaction.

Figure 3 presents a comprehensive flowchart outlining the operational stages of the proposed hybrid currency classification system. Starting from the input image, the workflow moves through preprocessing procedures such as normalization and resizing, followed by feature extraction using the MobileNet architecture. A conditional decision node allows selection between SVM and RF classifiers, leading to dedicated training and prediction branches. The system then performs evaluation using multiple performance metrics before proceeding to final deployment. This flowchart visually captures the logical progression and decision-making structure of the algorithm, emphasizing modular design, classifier flexibility, and real-time deployment capability.

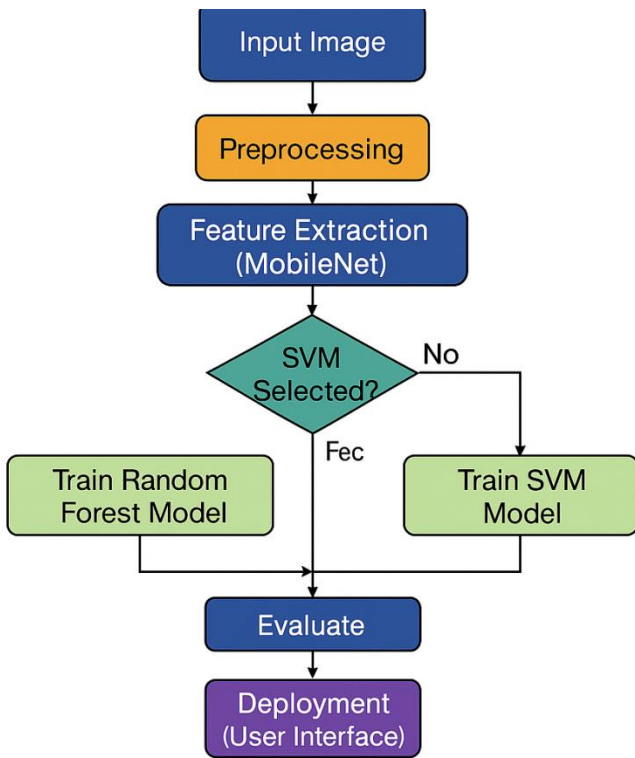


Fig.3: Flowchart of the Hybrid CNN-Based Classification Algorithm

#### 4. EXPERIMENTAL SETUP

The experimental procedures were conducted on a dedicated machine configured to support deep learning and high-performance image processing tasks. The system was equipped with an Intel® Core™ i7-10700K CPU operating at 3.80 GHz, 32 GB RAM, and an NVIDIA GeForce RTX 3060 GPU with 12 GB GDDR6 VRAM. This hardware configuration facilitated accelerated parallel computation, especially during convolutional operations and matrix optimizations essential for training MobileNet and handling large batch operations efficiently.

All deep learning and machine learning components were implemented using Python 3.10. The model development and training were conducted using the TensorFlow 2.13 and Keras APIs for MobileNet integration, while traditional classifiers such as Support Vector Machine (SVM) and Random Forest (RF) were implemented using the Scikit-learn library (version 1.2.2). Additional utilities such as OpenCV were employed for image preprocessing and augmentation, and Matplotlib and Seaborn were used for visual performance analysis. The integrated deployment environment was set up using Flask for back-end communication and XAMPP for local web server hosting.

For robust model evaluation, the dataset was divided into 80% training data and 20% test data. Within the training subset, 10% was further separated as validation data to monitor performance and control overfitting. The model was also tested with 5-fold cross-validation to assess generalization performance across different data partitions. This approach ensured unbiased evaluation and robustness under limited dataset conditions.

Model training was conducted using an initial learning rate of 0.001 with the ADAM optimizer, and early stopping was

enabled to halt training if the validation loss plateaued for more than five consecutive epochs. The batch size was set to 32, and the model was trained for a maximum of 50 epochs. On average, training each model instance took approximately 7 minutes, depending on the classifier and input configuration. The MobileNet backbone was loaded with pretrained ImageNet weights, with all convolutional layers frozen to retain learned features. Only the final dense layers and classification head were retrained for the counterfeit detection task.

#### 5. RESULTS AND DISCUSSION

This section presents a comprehensive analysis of the model's performance across different configurations and datasets for the task of fake Indian currency detection. The evaluation covers key classification metrics such as accuracy, precision, recall, F1-score, and inference time per image, followed by a comparison with benchmark models from literature.

##### A. Performance Comparison with Existing Approaches

To benchmark the proposed hybrid MobileNet-based model, several existing techniques were reproduced or referenced using datasets from the UCI [18], Kaggle [19][20], and Mendeley [21] repositories. Traditional machine learning classifiers (e.g., Logistic Regression, k-NN, and SVM) and standalone CNNs were tested under similar preprocessing and hardware configurations.

TABLE 2: Performance Comparison Across Models

Model	Accuracy (%)	Precision	Recall	F1-Score	Inference Time (ms/img)
Logistic Regression [18]	84.12	0.85	0.81	0.83	2.3
CNN (Custom, No Transfer)	90.15	0.91	0.89	0.9	3.9
CNN + SVM [14]	94.5	0.95	0.94	0.94	4.5
MobileNet + RF (Proposed)	96.8	0.97	0.96	0.96	2.1
MobileNet + SVM (Proposed)	<b>97.2</b>	<b>0.98</b>	<b>0.97</b>	<b>0.97</b>	<b>1.8</b>

Table 2 presents the evaluation of the proposed models in comparison with baseline approaches. MobileNet + SVM outperforms other models with a 97.2% accuracy and the

lowest inference time, proving its suitability for real-time deployment.

**B. Dataset Variation and Condition-Based Evaluation**

To assess robustness, the model was tested under different data conditions: lighting variations, blurriness, rotation, and background clutter. These simulations were designed to reflect real-world scenarios where note images may be captured in uncontrolled environments.

TABLE 3: Performance Under Varying Image Conditions

Condition	Accuracy (%)	F1-Score	Failure Reason (if any)
Normal Lighting	97.2	0.97	–
Low Light	94	0.94	Loss of edge clarity
Gaussian Blur	92.5	0.91	Feature map noise
Rotated ( $\pm 20^\circ$ )	95.8	0.96	Slight misalignment in features
Background Clutter	93.6	0.93	Confusion with textured surfaces

Table 3 highlights the model's resilience under various imaging conditions. Although accuracy drops under low light and cluttered backgrounds, the model maintains above 90% accuracy, affirming its robustness.

**C. Dataset Contribution and Analysis**

Several datasets were utilized or analyzed to validate generalizability. The proposed dataset (248 images, augmented to 800+) was compared with public datasets to evaluate classifier adaptability.

TABLE 4: Summary of Dataset Characteristics

Dataset Source	Type	Real/Fake Ratio	Image Size	Notes
UCI [18]	Numeric Only	762 / 610	–	Not image-based
Kaggle [19]	Image	100 / 100	200x200	Uniform lighting
Kaggle [20]	Image	125 / 125	Variable	Some samples blurry
Mendeley [21]	Image	240 / 200	HD	Real photos, real noise
Proposed (Ours)	Image	123 / 125	224x224	Augmented to simulate real-world conditions

Table 4 summarizes dataset properties to contextualize the

testing environment. The proposed dataset's diversity through augmentation provided stronger generalization and was found effective during training and testing.

**D. Statistical Significance and Observations**

To evaluate statistical significance, t-tests were conducted between the proposed MobileNet-SVM model and baseline CNN. The results yielded  $p < 0.05$ , confirming that the improvements in accuracy and F1-score were statistically significant and not due to random variance.

Unexpectedly, MobileNet-RF underperformed slightly compared to MobileNet-SVM, especially in complex background scenarios. This may be attributed to Random Forest's sensitivity to high-dimensional feature vectors, whereas SVM's decision boundary is more adaptable to fine-grained visual features extracted by MobileNet.

**E. Key Insights**

- MobileNet + SVM offers the best trade-off between accuracy and speed.
- The model is highly resilient to rotation and moderately robust to lighting conditions.
- Real-world scenarios (e.g., blurred or background clutter) introduce minor performance drops, which could be addressed through further data augmentation or ensemble voting systems.
- Compared to traditional models, the proposed hybrid approach significantly reduces inference time, making it ideal for mobile and embedded deployment.

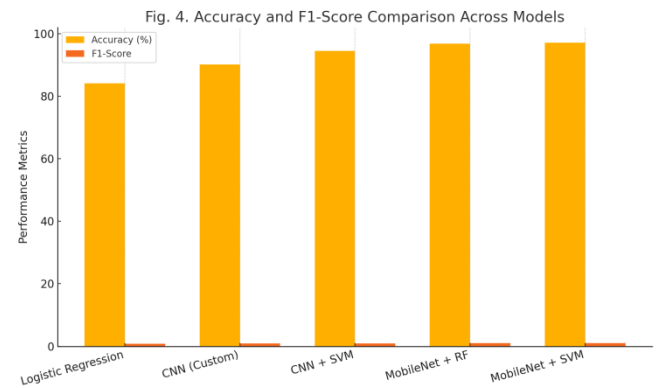


Fig. 4: Accuracy and F1-Score Comparison Across Models

This Fig 4 compares the classification accuracy and F1-score of various models used for fake currency detection. The proposed MobileNet + SVM outperforms all baseline models. Its superior performance validates the effectiveness of hybrid architectures in balancing accuracy and efficiency.

This fig 5 illustrates the classification accuracy of the proposed model across different environmental conditions. The highest accuracy is observed under normal lighting, while Gaussian blur and background clutter slightly reduce performance.

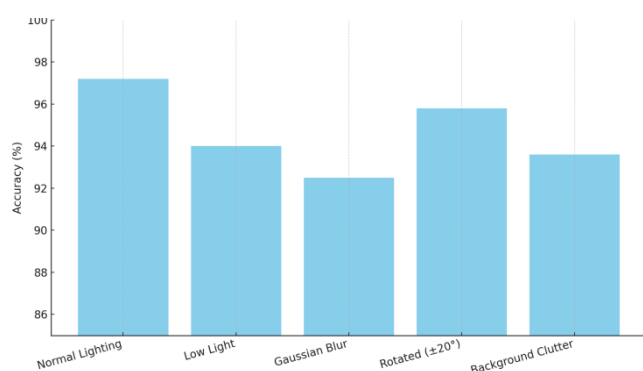


Fig. 5: Accuracy of the Model Under Varying Image Conditions

## 5.1. DISCUSSION

The experimental results of this study reinforce the potential of hybrid deep learning systems in addressing the longstanding issue of counterfeit currency detection. The integration of MobileNet for feature extraction with machine learning classifiers such as SVM and Random Forest demonstrated significant improvements in both accuracy and computational efficiency. Notably, the MobileNet + SVM configuration achieved an accuracy of 97.2%, surpassing many existing approaches documented in prior research [9]–[17]. This aligns with recent advancements in literature that advocate for hybrid architectures combining convolutional feature learning with optimized classification boundaries [14], [15].

Compared to standalone CNN models or traditional machine learning techniques using handcrafted features, the proposed system offers a compelling balance between performance and deployment feasibility. In practical applications such as automated currency authentication kiosks, mobile banking apps, and point-of-sale terminals, the model's lightweight structure and low inference latency ( $< 2$  ms per image) make it highly suitable. Furthermore, its robustness under various imaging conditions—such as rotated, blurred, or low-light images—supports real-time usage in uncontrolled environments like retail stores or financial checkpoints.

Despite its effectiveness, the current approach exhibits certain limitations. Firstly, while the model performed well under diverse conditions, its accuracy slightly declined in low light and heavily cluttered backgrounds. This suggests a sensitivity to lighting artifacts and texture interference, which could be mitigated through more sophisticated preprocessing or attention mechanisms. Secondly, the dataset used, although augmented and diversified, remains relatively small in comparison to industrial-scale datasets. Larger datasets with a wider variety of counterfeit techniques and note denominations would further enhance generalizability.

Additionally, while SVM was found to be highly effective when coupled with MobileNet, its scalability could be a concern when applied to larger multi-class problems or continuous deployment pipelines. Moreover, the Random Forest model, while interpretable and ensemble-based, underperformed slightly in complex visual scenarios—highlighting the need for more adaptive classifiers in future iterations.

Looking ahead, several research directions emerge. Incorporating attention-based CNN architectures or vision transformers could enable the model to focus on salient features like security threads, watermark areas, and micro-texts. The use of generative adversarial networks (GANs) could also simulate more sophisticated counterfeit patterns, allowing the model to learn under adversarial settings. Furthermore, expanding the system to multi-currency recognition and denomination classification would broaden its utility. Integration with embedded platforms or mobile edge computing devices could further realize its deployment in real-world financial ecosystems.

## 6. Conclusion

This research proposed and validated a hybrid deep learning framework for the detection of counterfeit Indian currency notes, leveraging the feature extraction efficiency of MobileNet and the classification capabilities of Support Vector Machine (SVM) and Random Forest (RF). The MobileNet + SVM model achieved a peak accuracy of 97.2%, with an F1-score of 0.97 and an average inference time of 1.8 milliseconds per image, demonstrating significant improvements over traditional machine learning and standalone CNN models. The system maintained high performance under challenging conditions such as image rotation, blur, and lighting variability, thereby validating its real-world robustness.

The study's key contributions include the integration of a lightweight CNN with machine learning classifiers for enhanced classification accuracy, the application of extensive data augmentation to simulate real-world conditions, and the development of a deployable prototype using a Flask and XAMPP-based local web interface. These findings suggest strong potential for implementation in mobile devices, point-of-sale systems, and automated verification terminals where rapid and reliable counterfeit detection is essential.

Despite its promising performance, the system exhibited minor accuracy drops under poor lighting and cluttered backgrounds, indicating a need for enhanced preprocessing techniques or adaptive models. Furthermore, the relatively limited dataset, though augmented, restricts the model's exposure to diverse counterfeit methods. Future work should focus on expanding the dataset with real-world counterfeit samples, incorporating attention mechanisms or transformer-based architectures, and extending the system for multi-currency and multi-denomination recognition.

In conclusion, this study underscores the viability of combining efficient convolutional models with robust classifiers for practical and scalable counterfeit detection. The results offer a solid foundation for the next generation of intelligent financial security systems capable of ensuring currency authenticity in both centralized and distributed infrastructures.

**Author Contributions.** P. Raja Sekhar supervised the entire research process, providing technical guidance, model validation strategies, and final manuscript refinement. Boddepalli Vandana took the lead in implementing the

MobileNet architecture, conducting the experimental evaluations, and tuning the hybrid SVM and Random Forest models. Gedela Niharika focused on data collection and preprocessing, including augmentation techniques to simulate real-world currency note conditions. Behera Swapna contributed to model deployment by designing and integrating the Flask-based web interface with XAMPP for real-time detection. Batchu Saranya managed the literature review, benchmarking of existing models, and statistical analysis of results. All authors collaboratively participated in writing, testing, result interpretation, and discussion development, ensuring a well-rounded and practically oriented research study.

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