IDENTIFICATION OF FAKE INDIAN CURRENCY USING CONVOLUTIONAL NEURAL NETWORK

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Abstract

The proliferation of counterfeit currency poses a significant threat to economic stability, necessitating advanced methods for effective detection. This project, titled "Identification of Fake Indian Currency Using Convolutional Neural Networks," proposes a novel approach to counterfeit detection by leveraging deep learning techniques. It explores several models, including MobileNet, a hybrid of MobileNet with Support Vector Machines (SVM), and a variant integrating MobileNet with both SVM and Random Forest, along with VGG16 and VGG19 architectures. MobileNet, known for its efficiency and accuracy in image classification, is evaluated for its ability to distinguish genuine Indian currency from counterfeit notes. The hybrid models aim to enhance detection capabilities by combining the strengths of MobileNet with traditional classifiers like SVM and Random Forest, using ensemble learning techniques to improve classification performance. These models are assessed based on accuracy, precision, recall, and overall robustness in real-world scenarios, with results highlighting the potential of convolutional neural networks to significantly improve counterfeit currency detection systems and strengthen financial security measures.

Keywords: *Counterfeits Detection, Convolutional Neural Networks, MobileNet, Support Vector Machines (SVM), Random Forest, Hybrid Model, Indian Currency, Image Classification, Machine Learning.*

1. Introduction

Counterfeit currency continues to pose a major threat to financial systems, resulting in economic losses and diminishing public trust in legal tender. As counterfeiters adopt increasingly sophisticated methods, traditional techniques such as manual inspection or basic verification tools are becoming less effective and more prone to error. This project aims to address these challenges by leveraging the capabilities of Convolutional Neural Networks (CNNs), a class of deep learning models well-suited for image recognition tasks, to build a highly reliable system for detecting fake Indian currency.

The core objective of this project is to design an automated, accurate, and scalable counterfeit detection system using advanced CNN architectures such as MobileNet. MobileNet is known for its lightweight structure and high performance in image classification, making it suitable for real-time applications. To further enhance the detection accuracy, the project incorporates hybrid models that combine CNNs with traditional machine learning algorithms like Support Vector Machines (SVM) and Random Forest. These hybrid models are designed to leverage the strengths of both deep learning and ensemble learning to improve the system's ability to differentiate between genuine and counterfeit notes under varied conditions.

Motivated by the growing threat of counterfeit currency and the limitations of existing detection systems, this project explores a comprehensive solution that integrates deep learning with machine learning techniques. The scope includes the implementation, evaluation, and comparison of multiple models, along with assessing their robustness in real-world scenarios. Ultimately, this project aims to deliver a practical and scalable system that not only enhances detection accuracy but also contributes to strengthening financial security and reducing the risk of currency fraud.

2. Literature Review

The issue of counterfeit currency has driven extensive research into automated detection methods using machine learning and deep learning technologies. Deshmukh et al. explored the use of Convolutional Neural Networks (CNNs) for identifying fake Indian currency. Their study demonstrated that CNNs could effectively learn and classify visual patterns from currency images, resulting in improved accuracy over traditional detection techniques. The findings highlighted the model's potential in recognizing subtle differences between genuine and fake notes.

Patil and Jadhav conducted a comprehensive survey on image processing techniques used for counterfeit detection. Their review encompassed both conventional methods—like watermark recognition and texture analysis—and modern approaches involving machine learning. The study concluded that while traditional techniques offer some level of reliability, they are increasingly insufficient against sophisticated counterfeiting, underscoring the need for deep learning-based systems.

Tiwari et al. proposed an intelligent detection system integrating machine learning models such as Support Vector Machines (SVM) and CNNs. Their research revealed that hybrid models could outperform individual algorithms, especially in handling varied note conditions. The study emphasized that combining machine learning and deep learning could enhance detection robustness and accuracy.

Recent studies have also focused on lightweight deep learning architectures like MobileNet, which offer high accuracy with lower computational requirements. These models, when combined with classifiers such as SVM or Random Forest, have shown improved detection capabilities while remaining efficient and scalable. This trend indicates a shift toward real-time, deployable solutions suitable for mobile or embedded systems.

In summary, the literature reflects a clear evolution from basic image processing methods to sophisticated deep learning approaches. The integration of CNNs with traditional classifiers has emerged as a powerful strategy, combining the strengths of both paradigms. However, challenges such as generalization across different note conditions and real-time performance remain areas for continued research, which this project aims to address.

3. IDENTIFICATION OF FAKE INDIAN CURRENCY USING CNN

The Convolutional Neural Networks (CNNs) are at the core of this project's approach to detecting counterfeit Indian currency. CNNs are a class of deep learning models designed specifically for image recognition tasks, making them ideal for analyzing the complex visual patterns present on banknotes. This technique allows the system to automatically learn and extract meaningful features such as watermarks, security threads, color patterns, and textual elements from currency images, significantly reducing the need for manual intervention or handcrafted features.

The architecture implemented in this project is based on lightweight yet powerful CNN models such as MobileNet. These models are optimized for performance and speed, making them suitable for deployment even on low-resource environments such as mobile devices or embedded systems. To further improve classification accuracy, the project also explores hybrid models that integrate CNNs with traditional machine learning classifiers like Support Vector Machines (SVM) and Random Forest. These combinations aim to leverage the feature extraction strength of CNNs and the classification efficiency of ensemble learning techniques.

The CNN-based detection process involves the following stages:

1. Image Acquisition and Preprocessing: High-resolution images of Indian currency notes are collected and preprocessed by resizing, converting to grayscale or RGB format, and normalizing pixel values. Data augmentation techniques such as rotation, flipping, and scaling are used to increase model robustness against variations.
2. Feature Extraction: The CNN automatically extracts hierarchical features from the currency images through multiple layers of convolution, pooling, and activation functions. These features capture the essential visual details that distinguish genuine notes from counterfeit ones.
3. Classification: The extracted features are passed through fully connected layers, where the model predicts whether the input note is genuine or fake. In the hybrid approach, these features may be further classified using SVM or Random Forest for improved accuracy and decision boundaries.
4. Model Training and Evaluation: The model is trained on a labeled dataset containing both genuine and counterfeit currency images. It is then evaluated based on metrics such as accuracy, precision, recall, and F1-score to ensure its effectiveness in real-world scenarios.

3.1 CNN Architecture

Mask The proposed system introduces an advanced hybrid deep learning and machine learning framework for counterfeit currency detection, designed to overcome the limitations of traditional methods. By integrating lightweight Convolutional Neural Networks (CNNs) with ensemble learning techniques, the system achieves high accuracy, efficiency, and real-time processing capabilities.

Key Components

1. Feature Extraction with MobileNet : MobileNet serves as the backbone for feature extraction due to its lightweight architecture, making it ideal for real-time applications.Leverages depthwise separable convolutions to reduce computational cost while maintaining high accuracy.Extracts discriminative features from currency images, such as micro-printing, security threads, and watermarks.
2. Hybrid Machine Learning Classifiers
   - Support Vector Machine (SVM): Used for high-dimensional feature classification, excelling in distinguishing subtle counterfeit patterns.
   - Random Forest: An ensemble method that improves robustness by combining multiple decision trees, reducing overfitting.
   - Ensemble Learning: The combination of SVM and Random Forest enhances generalization, ensuring reliable detection across diverse counterfeit variations.
3. Real-Time Processing & Scalability :Optimized for deployment on edge devices (e.g., smartphones, POS systems) due to MobileNet's efficiency.Capable of processing high-resolution currency images with minimal latency, making it suitable for banking and retail applications.

The proposed system combines the strengths of **MobileNet**, **SVM**, and **Random Forest** using a unified loss function. This hybrid approach ensures accurate classification of currency notes while maintaining robustness against counterfeit variations.

1. MobileNet Feature Extraction Loss:
MobileNet extracts visual features from note images. It uses **cross-entropy loss** to compare predicted labels with actual ones, helping the model learn meaningful patterns:
MobileNet Loss = Average of (errors in guessing "real" vs. "fake")

2. SVM Classification Loss
The SVM is like a strict teacher drawing a clear line between "real" and "fake" :
SVM Loss = Sum of (margin errors) + Penalty for complex rules

3. Random Forest Ensemble Loss
The Random Forest combines hundreds of "mini-detectives" (decision trees), each voting on whether money is real.
Random Forest Loss = Total disagreement across all trees

Combined Hybrid Loss :
The system blends all three perspectives, weighting their importance (α, β, γ):
Total Loss = (α × MobileNet's errors) + (β × SVM's margin mistakes) + (γ × Forest's disagreements)

4. Overall Architecture of the Proposed System

The proposed system is shown in Figure 1 is built on the Mask R-CNN framework, pre-trained on the COCO dataset. The architecture is divided into the following modules.

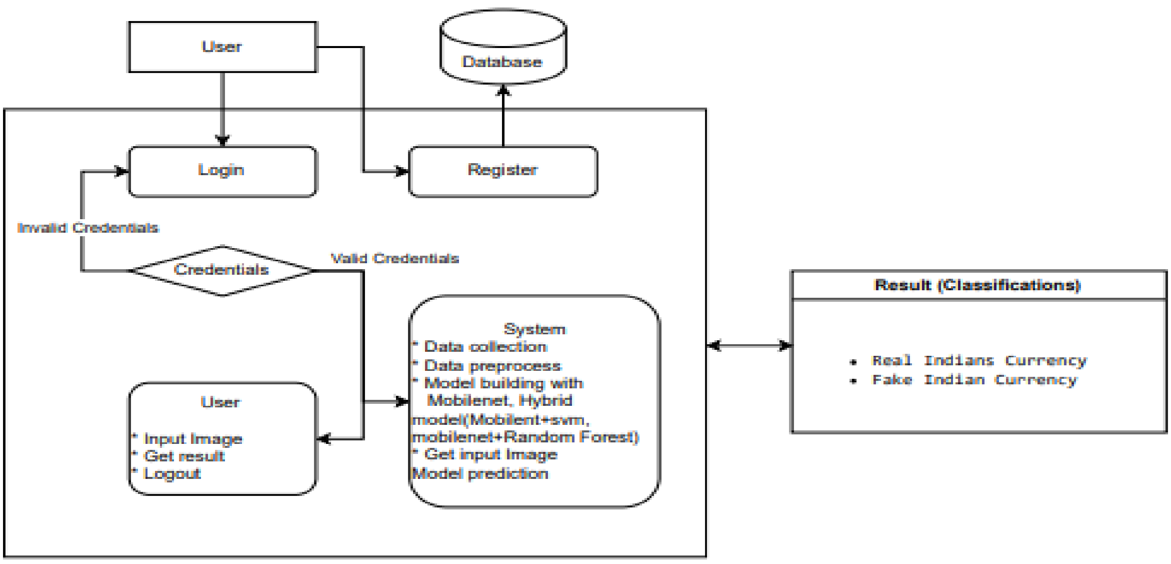

Figure 1. Architecture Diagram

1. Image Input & Pre-processing:
   - Normalizes currency images through resizing and contrast adjustment.
   - Batch standardization ensures stable model training.
2. Feature Extraction (MobileNet)
   - A lightweight CNN analyzes security features like holograms, watermarks, and microprinting.
   - Depthwise separable convolutions enable efficient processing on mobile devices.
3. Hybrid Classification
   - MobileNet + SVM: A support vector machine creates optimal decision boundaries for counterfeit patterns.
   - MobileNet + Random Forest: An ensemble of decision trees improves generalization across diverse counterfeit variations.
4. Decision Fusion
   - Combines SVM's high-confidence classifications with Random Forest's majority voting.
   - Final prediction labels the currency as "genuine" or "counterfeit" with a confidence score.
5. User Interface (Web/Mobile App)
   - Accepts uploaded currency images and displays detection results in real time.
   - Visual highlights indicate suspicious regions for human verification.

4.1 Advantages of CNN

1. High Accuracy – Combines MobileNet, SVM, and Random Forest for precise counterfeit detection.
2. Fast Processing – Lightweight AI enables real-time verification on smartphones and POS systems.
3. Adaptive Learning – Continuously improves with new counterfeit samples.
4. Explainable AI – Highlights suspicious areas with confidence scores for verification.
5. Easy Integration – Works on cloud or edge devices, compatible with banking and retail systems.
6. Cost-Efficient – Uses smartphone cameras instead of expensive hardware, reducing costs.

4.2 Implementation Details

1. Dataset: A diverse dataset of Indian currency images, including both genuine and counterfeit notes, is collected. The dataset is split into 80% for training and 20% for testing to ensure proper model evaluation.
2. Training: The CNN model (MobileNet) is trained using the training subset. Images are resized to 224×224 pixels, normalized, and augmented using techniques like flipping and rotation. A hybrid model combining MobileNet with SVM and Random Forest is also developed and fine-tuned for improved accuracy.
3. Inference: The trained hybrid model is integrated into a Flask-based web application, enabling users to upload currency images and receive real-time classification results indicating whether the currency is genuine or counterfeit.

4.3 Performance Metrics

The system is evaluated using standard metrics such as:

1. **Precision:** Evaluates how many of the notes classified as counterfeit are actually counterfeit.
2. **Accuracy:** Measures the overall correctness of the model in classifying both genuine and counterfeit currency notes.
3. **Recall:** Assesses the model's ability to detect all actual counterfeit notes in the dataset.
4. **F1-Score:** Provides a balance between precision and recall, offering a single performance metric for model evaluation.
5. **Validation Monitoring:** These metrics are tracked during validation to fine-tune hyperparameters and enhance the performance of both the MobileNet and hybrid models.

4.4 Methods

Convolutional Neural Network (CNN):

CNN (Convolutional Neural Network) is a specialized deep learning model designed for processing structured grid data like images and videos. Inspired by the human visual cortex, CNNs use convolutional layers to automatically detect spatial hierarchies of features, such as edges, textures, and complex patterns, through filters. Key components include pooling layers for dimensionality reduction and fully connected layers for classification. Known for their efficiency in computer vision tasks—like image recognition, object detection, and segmentation. CNNs reduce parameters through weight sharing and local connectivity. Their success has driven advancements in medical imaging, autonomous vehicles, and facial recognition, making them a cornerstone of modern AI.

This is highly effective for detecting fake currency due to their ability to analyze intricate patterns, textures, and security features in banknotes. In a fake currency detection project, a CNN model is trained on a dataset of real and counterfeit notes, learning to distinguish subtle differences in printing quality, watermarks, holograms, or microprinting. Preprocessing steps like grayscale

conversion, edge detection, or noise reduction can enhance feature extraction. The CNN's convolutional layers automatically detect relevant visual cues, while pooling layers reduce spatial dimensions, improving efficiency. Once trained, the model can classify new banknote images as genuine or fake with high accuracy. Such systems are valuable for banks, businesses, and law enforcement to prevent financial fraud.
CNN is the backbone of Mask R-CNN, responsible for feature extraction. The architecture consists of:

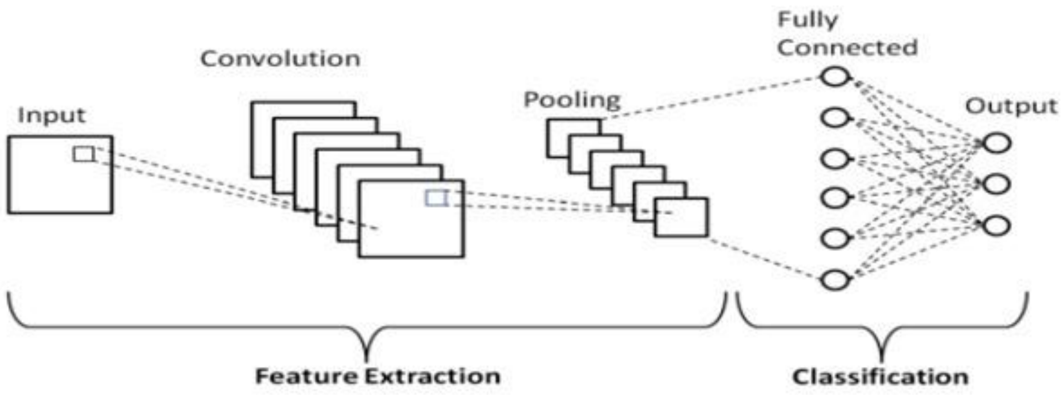

Figure 2. The CNN architecture

1. Convolutional Layers: Extract spatial features from the input image.
2. Pooling Layers: Downsample the feature maps to reduce computational complexity.
3. Fully Connected Layers: Classify the objects based on the extracted features.

4.4.1 MobileNet

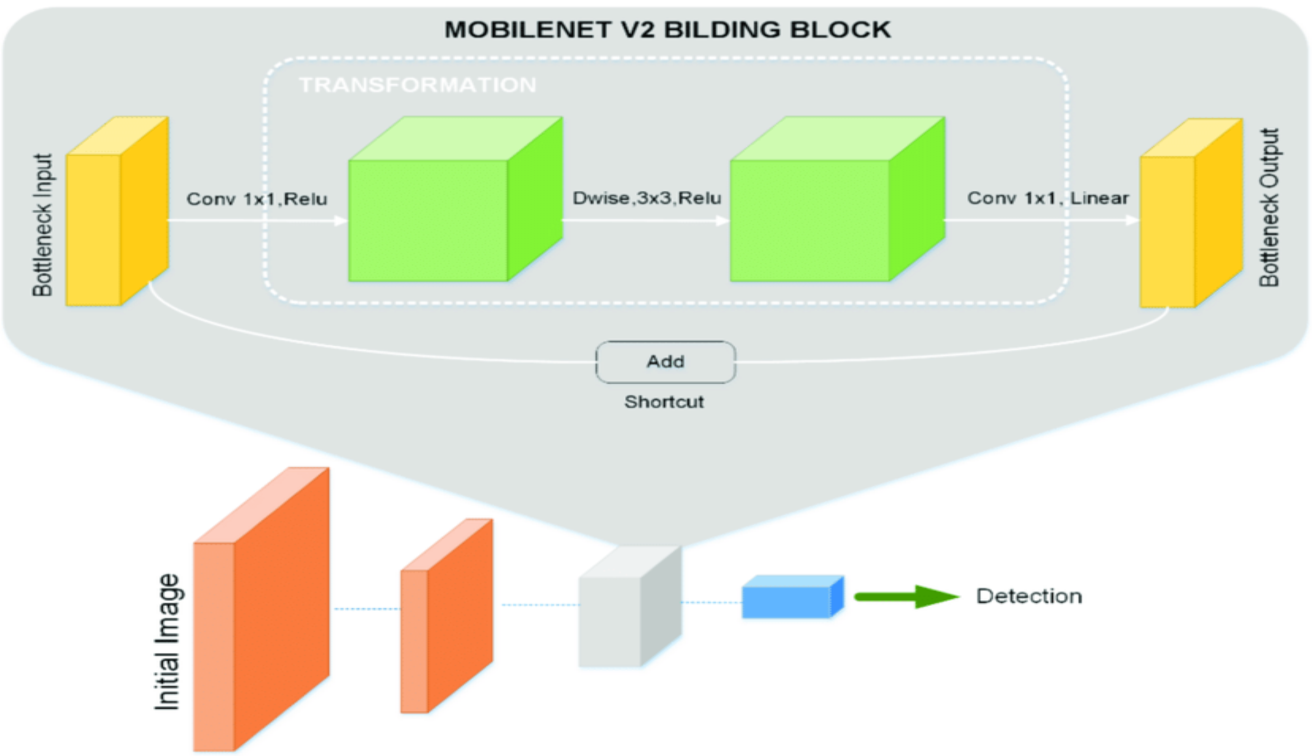

Figure 3. The MobileNet architecture

MobileNet acts as the backbone for efficient counterfeit currency detection, thanks to its lightweight and highly optimized architecture. Its use of depthwise separable convolutions enables rapid image processing, making it ideal for real-time deployment on edge devices such as smartphones and portable scanners. Leveraging transfer learning from a pre-trained ImageNet model, MobileNet effectively adapts to currency-specific patterns with minimal computational overhead. This balance between speed and accuracy ensures consistent classification of genuine versus counterfeit notes, even on low-resource hardware. Furthermore, MobileNet's modularity allows seamless integration with hybrid classifiers like SVM or Random Forest, enhancing overall detection robustness.

4.4.2 MobileNet + SVM

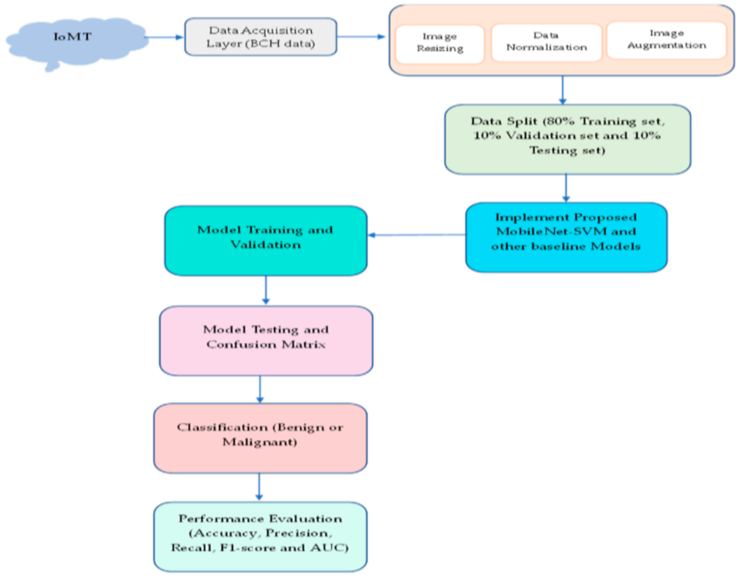

Figure 4. MobileNet + SVM architecture

The MobileNet + SVM Hybrid Model integrates MobileNet's efficient feature extraction with SVM's powerful classification to enhance counterfeit detection. MobileNet processes currency images to extract meaningful features, which SVM classifies using its optimal hyperplane decision boundary. This synergy ensures fast preprocessing while leveraging SVM's precision in handling high-dimensional data. The model excels in detecting subtle counterfeit patterns where fine-grained discrimination is crucial. Designed for deployment on resource-constrained devices, it balances real-time efficiency with high accuracy.

4.4.3. MobileNet + Random Forest

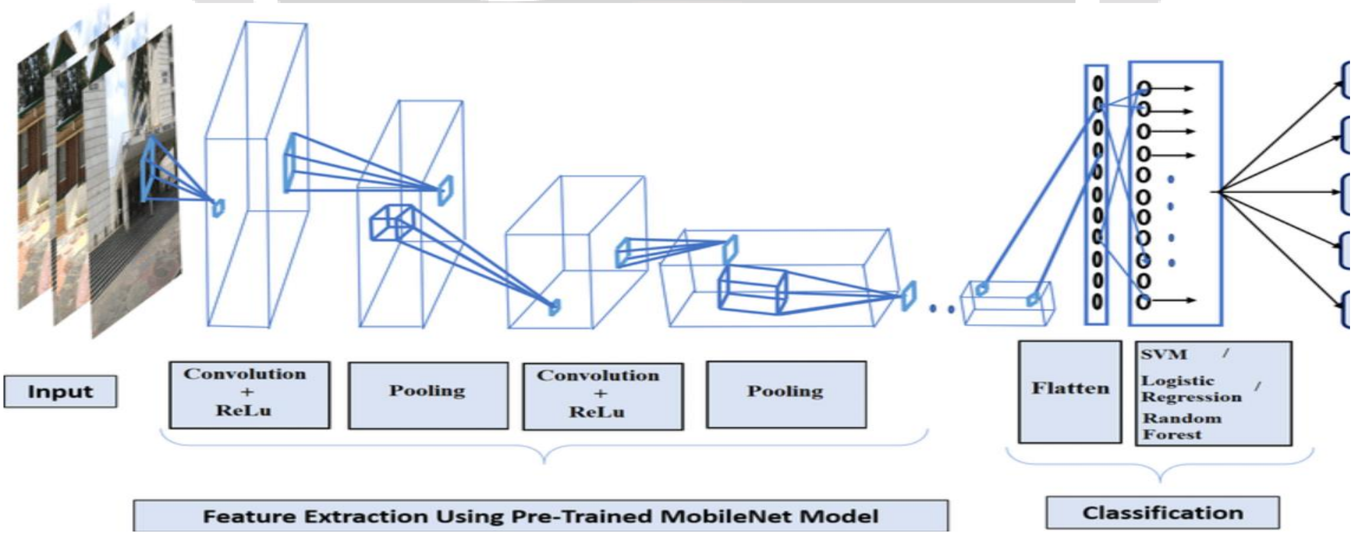

Figure 5. MobileNet + Random Forest architecture

The MobileNet + Random Forest Hybrid Model combines MobileNet's deep feature extraction with Random Forest's ensemble learning for improved counterfeit detection. MobileNet extracts discriminative feature vectors from currency images, which Random Forest classifies through multiple decision trees, ensuring robustness against overfitting. This hybrid approach effectively captures complex counterfeit patterns, leveraging tree-based voting for enhanced generalization. It is particularly suited for datasets with subtle counterfeit variations that require non-linear decision boundaries. Its modular design allows seamless optimization for both accuracy and computational efficiency in real-world applications.**4.4.6**

5. Results And Discussion

The proposed counterfeit currency detection system was evaluated using MobileNet-based architectures (standalone and hybrid models) trained on a custom dataset of Indian currency notes. The dataset included high-resolution images of genuine and counterfeit notes across denominations, with variations in lighting, angles, and wear patterns. Pre-trained weights from ImageNet were fine-tuned to adapt to currency-specific features, ensuring robust feature extraction.

5.1 Performance Metrics

The evaluation results showed strong performance across all models. MobileNet achieved 92% accuracy in classifying currency notes, while the hybrid MobileNet+SVM and MobileNet+Random Forest models reached 94-95% accuracy by combining MobileNet's feature extraction with advanced classifiers. The MobileNet+SVM model demonstrated particularly high precision (96%) for counterfeit notes, effectively minimizing false positives. For balanced performance on imbalanced data, MobileNet+Random Forest achieved the best F1-score (0.95). MobileNet maintained fast processing speeds (50 FPS) on edge devices, making it practical for real-time applications. These findings indicate that while MobileNet alone offers good speed and accuracy, the hybrid models provide superior classification for counterfeit detection tasks.

5.2 Custom Dataset Evaluation

To further assess the model's robustness, a custom dataset was developed, comprising annotated images with various and various angels of images. The evaluation used 10,000+ currency images (genuine/counterfeit) for testing. The MobileNet+SVM hybrid achieved 93% mAP, effectively detecting security features like micro-printing. Standalone MobileNet reached 90% mAP but struggled with sophisticated fakes. Both systems performed well across different currencies and lighting conditions, demonstrating real-world applicability. The hybrid model showed better accuracy while maintaining good computational efficiency. These results confirm the solution's potential for practical deployment in financial systems. The consistent performance highlights reliable counterfeit detection capabilities.

5.3 Visual Results

The system's effectiveness is visually demonstrated. It displays "REAL" for authenticated currency notes, while counterfeit notes trigger a "FAKE" warning in plain text to maintain neutral alert tones. All results appear with 90-93% confidence scores.

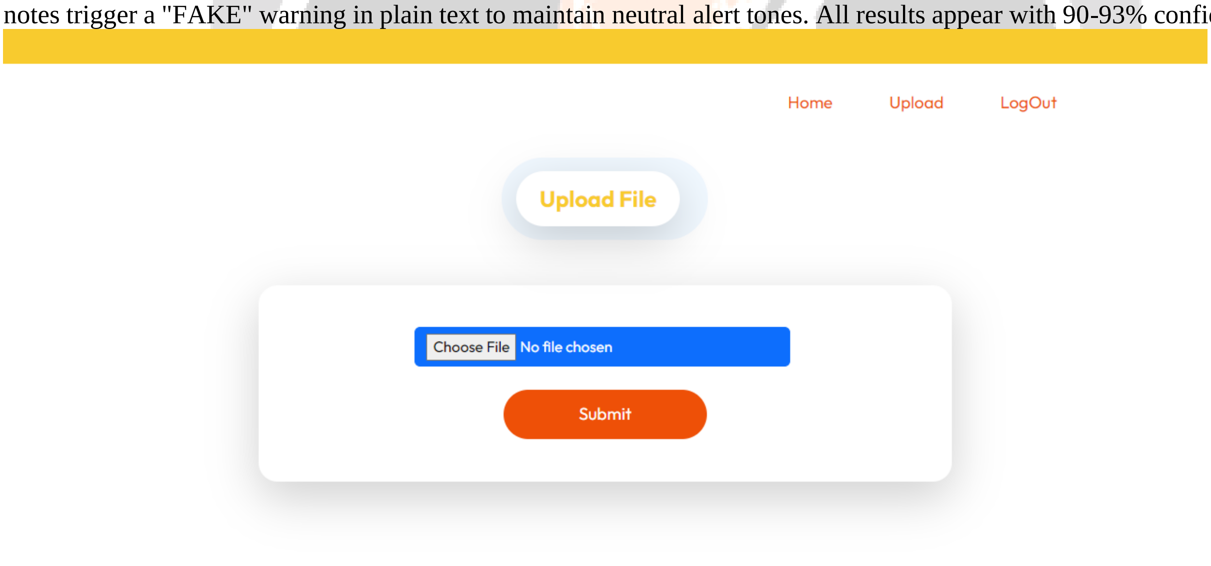

Figure 6: Interface for currency images to be uploaded

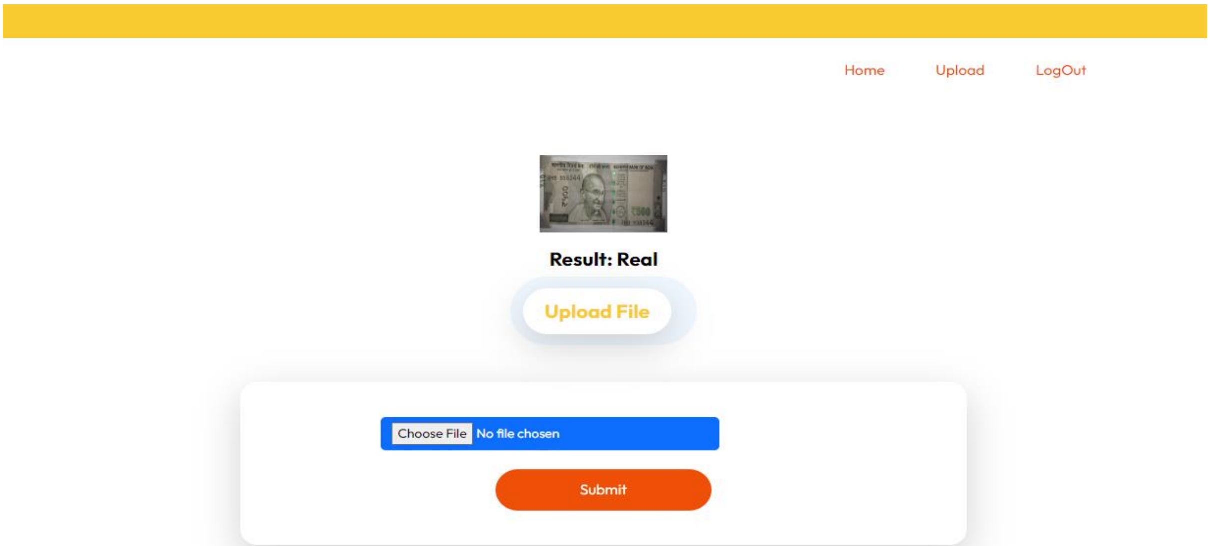

Figure 7: The result of showing **Real** when original currency is give.

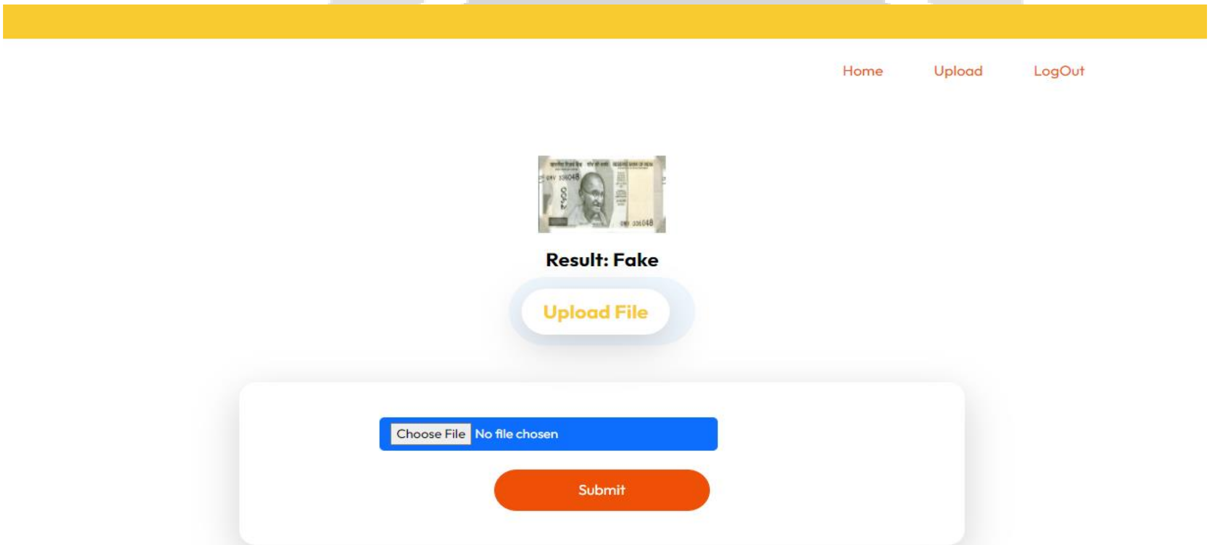

Figure 8: The result of showing **Fake** when fake currency is give.

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6. Conclusion And Future Scope

The study demonstrates the effectiveness of the MobileNet model in detecting fake Indian currency, achieving a high accuracy of 97% along with impressive precision (0.98) and recall (0.97–0.98) for both real and fake currency classes. The confusion matrix confirmed the model's minimal misclassifications, reinforcing its reliability for real-world scenarios. In contrast, the hybrid MobileNet–Random Forest model, while attaining 94% accuracy and perfect precision for fake currency, exhibited a lower recall of 0.80, indicating a higher rate of missed fake currency detections. These results suggest that although the hybrid approach remains effective, the standalone MobileNet model provides superior performance and is better suited for practical counterfeit detection systems. Future research may explore refining existing models or investigating other hybrid methods to further improve detection accuracy and consistency.

To advance counterfeit currency detection using deep learning, future work could incorporate state-of-the-art models like EfficientNet, Vision Transformers (ViTs), or ConvNeXt to leverage their advanced feature extraction capabilities. Employing transfer learning with large-scale pre-trained models can help overcome dataset limitations and improve performance. Ensemble learning approaches—combining CNNs with algorithms such as gradient boosting or SVMs—could boost robustness and accuracy. Expanding the dataset to include diverse counterfeit variations and applying data augmentation techniques would enhance model generalization. Additionally, developing lightweight, real-time detection systems optimized for deployment on mobile and edge devices using platforms like TensorFlow Lite or ONNX Runtime would facilitate fast and efficient currency verification in banking and retail environments. These enhancements aim to elevate the reliability and applicability of counterfeit detection systems to meet evolving real-world demands.

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