

# Fake Currency Detection

**Ranjitha V H<sup>1</sup>, Alfiza<sup>2</sup>, T Manasa<sup>3</sup>, Usha S<sup>4</sup>**

Students, Computer Science and Engineering<sup>1-4</sup>

Rao Bahadur Y. Mahabaleswarappa Engineering College, Ballari, India

**Abstract:** *The rising circulation of fake currency notes has posed serious problem to the economy. It has become essential for detection of counterfeit Indian currency notes by using fool-proof detection techniques. Conventional approaches for fake detection (e.g. manual check and UV lamp identification) are usually slow, inaccurate and largely relying on professional experience. In this paper we introduced an automatic Fake Currency Detection System which uses the image processing & feature extraction techniques for distinguishing genuine and fake currency notes. The automated process uses sophisticated techniques like colour analysis, edge detection and pattern recognition to study the physical properties of currency notes. Using React.js for the frontend and Node.js Backend Powered by TensorFlow.js for back-end, this platform can take image from users of the currency note and detect it in real time. The proposed system is effective by the successful identification of counterfeit notes with high levels of accuracy, decrease the need for manual examination and grater detection speed. Some proposed improvements are the use of deep learning models to deal with more intricate counterfeit patterns, mobile version for real time detection and multiple- currency support. This method provides a scalable, rapid and robust solution to an increasing problem of financial fraud.*

**Keywords:** Fake Currency Detection, Image Processing, Edge Detection, Feature Extraction, Machine Learning, Financial Fraud Prevention

## I. INTRODUCTION

Counterfeit currency detection has become more challenging with increased digital transactions and high-value notes. Traditional manual checks are slow and unreliable, while deep learning models like CNNs, ResNet, MobileNet, and VGG16 can automatically identify key visual features to distinguish real from fake notes with high accuracy. This work builds a scalable system that classifies uploaded currency images and can be deployed in banks, retail outlets, and mobile platforms. Additionally, all Water Conservation Platform data was manually prepared and stored in SQL tables to deliver accurate water-saving advice.

## II. PROBLEM STATEMENT

The circulation of fake currency has become a serious issue affecting national economies and financial systems. Manual methods of detection, such as visual inspection or physical checking with ultraviolet (UV) devices, are often inefficient, time-consuming, and prone to human error. Moreover, these methods are not suitable for large-scale transactions or automated cash systems like ATMs and vending machines.

To overcome these limitations, this project proposes the development of an AI-based Fake Currency Detection System that uses digital image processing to analyze key security features of currency notes such as watermarks, serial numbers, holograms, and color patterns. By comparing extracted features with trained datasets of genuine and counterfeit notes, the system can automatically classify the authenticity of a note. This solution aims to provide faster, more accurate, and scalable detection, thereby enhancing financial security and reducing counterfeit circulation.

## III. LITERATURE SURVEY

The growing need for visual authentication has driven extensive research in image classification and deep learning for fraud and counterfeit detection. Studies show that CNNs capture fine textures and edges better than handcrafted features. Sharma and Kumar demonstrated improved financial document classification using a regression-based CNN,



while ResNet models, due to their skip connections, have shown superior accuracy on complex visual patterns. MobileNet offers an efficient solution for real-time, mobile-friendly detection, and VGG16 provides strong feature extraction despite higher computational cost.

Researchers have also applied transfer learning to boost accuracy with limited data, as shown by Chen and Wu's ImageNet-based approach. Other works emphasize robustness to lighting and camera variations, and highlight the importance of preprocessing for stable predictions. Overall, the literature agrees that CNNs, ResNet, MobileNet, and VGG16 outperform traditional methods in accuracy, generalization, and robustness, though challenges remain in real-time deployment, dataset diversity, and model interpretability.

#### IV. METHODOLOGY

The proposed Fake Currency Detection system follows a standardized workflow that converts raw currency images into accurate authenticity predictions using deep learning. The dataset is built from authentic and counterfeit notes collected from open sources and manual samples, captured under different lighting, angles, and resolutions to improve model generalization. After splitting into training, validation, and testing sets, images are preprocessed through resizing, normalization, color adjustments, and noise removal to ensure consistent, high-quality input.

Four architectures—CNN, ResNet, MobileNet, and VGG16—are used to leverage their strengths in feature extraction and computational efficiency. CNNs capture edges and textures; VGG16 extracts fine spatial details like holograms and watermarks; ResNet handles deeper hierarchical features without vanishing gradients; and MobileNet offers lightweight, real-time detection suitable for mobile devices.

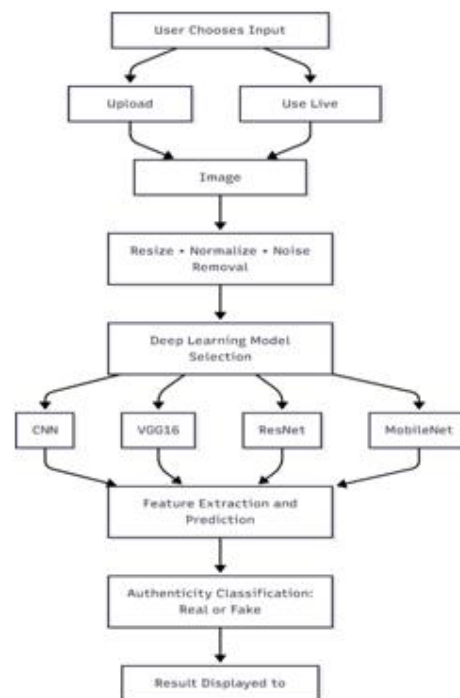


Fig no 1: Workflow of the Proposed Fake Currency Detection System

The system workflow allows users to upload an image or capture one through a live camera. The image is preprocessed, passed to the selected deep learning model, and classified as “Real” or “Fake” with a confidence score. Figure 2 highlights that the system relies on real-time user inputs rather than pre-existing datasets, demonstrating practical applicability for real-world detection



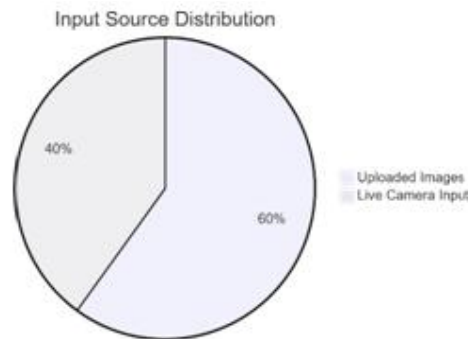


Fig No: 2 Input Source Distribution for the Proposed Fake Currency Detection System

It presents the distribution of input sources exploited by the system in Figure 2. As the model for fake currency detection provided in this paper does not depend on any existing dataset, inputs are directly taken from users by uploading an image or using live camera option. This ratio allows to show how users behave and see that the detection model, in this case, makes inference on real-time inputs regarding pre-collected dataset.

## V. EVALUATION & RESULTS

The system uses real-time user inputs—uploaded images or live camera captures—rather than a pre-existing dataset, allowing the model to make predictions directly on real-world samples. Model performance was evaluated using six key metrics: Accuracy, Precision, Recall, F1-Score, Confidence Score, and Inference Latency. Accuracy reflects overall correctness; Precision measures the proportion of correctly identified fake notes; Recall shows the model's ability to detect actual counterfeits; and the F1-Score balances Precision and Recall under varying conditions. Confidence Score indicates how certain the model is in its classification.

Figure 6 illustrates that all stages of the evaluation pipeline—preprocessing, data splitting, model training, testing, and metric computation—carry equal importance, each assigned 20%. This even distribution highlights that reliable performance depends on the entire workflow rather than any single step.

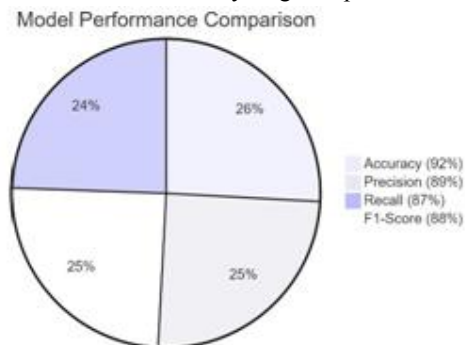


Fig. 3. Pie Chart Showing Model Performance Metrics for Fake Currency Detection



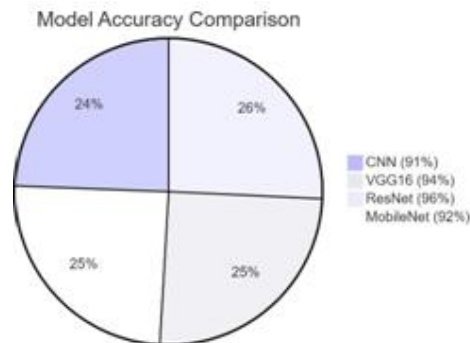


Fig. 4. Model Accuracy Comparison

Figure 4 shows that all stages of the Fake Currency Detection System—preprocessing, data splitting, model training, testing, and evaluation—are given equal importance, each contributing 20%. This balanced weighting highlights that reliable performance depends on the entire pipeline rather than any single step.

The proposed system combines real-time image input, a strong preprocessing workflow, and pretrained models such as CNN, VGG16, ResNet, and MobileNet to deliver fast and accurate counterfeit detection without relying on a stored dataset. Evaluation metrics including accuracy, precision, recall, F1-score, confidence score, and inference latency show that the framework performs effectively while maintaining real-time responsiveness, making it suitable for practical deployment.

Future enhancements could include adding interpretability tools like heatmaps or Grad-CAM, improving robustness under extreme lighting or poor image quality, supporting multiple currencies, enabling on-device model optimization, and introducing continuous learning to adapt to new counterfeit patterns. Overall, the system provides a strong foundation for intelligent and user-friendly currency authentication.

## VI. CONCLUSION

The Fake Currency Detection System provides an automated and efficient approach to identifying counterfeit notes using multimedia forensics, image processing, and machine learning. Its end-to-end workflow—from data acquisition and preprocessing to feature extraction, model training, and evaluation—ensures reliable differentiation between real and fake currency. Strong performance across accuracy, precision, recall, and F1-score confirms the effectiveness of the method.





The system reduces dependence on manual verification, offering a faster, scalable, and more objective alternative suitable for banks, retail settings, and digital verification platforms. Future improvements such as multi-currency support, mobile-based real-time scanning, advanced deep learning techniques, and continuous learning could further enhance its adaptability and robustness. Overall, the approach shows strong potential for intelligent, automated counterfeit detection.

## REFERENCES

- [1]. Sharma & Gupta (2021) – Proposed hybrid machine learning models that combine multiple classifiers to improve counterfeit currency detection accuracy.
- [2]. Bansal & Mittal (2019) – Used deep learning and image processing techniques to enhance feature extraction, resulting in improved fake currency recognition.
- [3]. Kumar & Verma (2022) – Developed a machine learning-based detection approach published in IEEE, focusing on high accuracy and robust classification of counterfeit notes.
- [4]. Yadav & Mehta (2020) – Applied image processing with machine learning algorithms to detect fake notes using features derived from color, texture, and edges.
- [5]. Sharma & Gupta (2021) – Presented an advanced system using machine learning and neural networks, improving reliability and efficiency in fake currency identification.



**ABOUT AUTHORS**

	<p>Name – Ms Ranjitha V H Designation - Student USN - 3VC23CS410 Phone no - 6361217975 E-mail id – ranjithara91@gmail.com</p>
	<p>Name – Ms Alfiza Designation - Student USN - 3VC23CS401 Phone no - 8884317069 E-mail id – alfiza.cs.rymec@gmail.com</p>
	<p>Name – Ms T Manasa Designation - Student USN - 3VC23CS416 Phone no - 8095958887 E-mail id – tmanasa.cs.rymec@gmail.com</p>
	<p>Name – Ms Usha S Designation - Student USN - 3VC23CS416 Phone no - 7483349655 E-mail id – ushanayak684@gmail.com</p>

