

Identification of Counterfeit Currency for Visually Impaired People using Hybrid Model

Palak Shrivastava¹ and Dr. Meghana Lokhande²

¹⁻²Dept. Computer Engineering, PCCOE, Pune, India

Email: palak_shrivastava@hotmail.com, meghana.lokhande@pccoe.org

Abstract—Counterfeit currency detection is a significant challenge for visually impaired individuals. This project proposes a hybrid model that combines image processing and machine learning techniques to assist in identifying fake currency. The system uses a ML Algorithms to classify notes as genuine or counterfeit by analyzing security features such as watermarks and holograms. Designed for accessibility, it provides result via audio, allowing visually impaired users to verify currency easily and accurately. The solution is portable, cost-effective, and enhances financial independence for visually impaired individuals.

Index Terms— Counterfeit, Visually Impaired, Feature Extraction, Financial Independence.

I. INTRODUCTION

Although electronic financial transactions are becoming more popular and the use of paper money has been decreasing recently, banknotes remain in recirculation owing to their reliability and simplicity in usage. As a result, the problems of the automatic handling of banknotes are still relevant. These tasks include the recognition of the banknote type and denomination, counterfeit detection, fitness, classification, and serial number recognition, which are mostly conducted on automated transaction facilities, such as counting machines or vending machines, based on image processing techniques.

Anti-counterfeit technologies, which are now being applied to banknotes in general, consist of various features, such as security threads, anti-copier patterns, watermarks, or hologram patterns. In some circumstances, this technology can also be used by novices to create counterfeit banknotes by reproduction from the genuine ones, which may be not recognized by general users, especially in low-visibility environments, or by visually impaired people. This study aim at recognition of fake banknotes created by reproduction with general-purpose imaging devices for visually impaired people.

II. BACKGROUND

India is home to one of the largest populations of visually impaired individuals globally. According to the World Health Organization (WHO) and National Programme for Control of Blindness and Visual Impairment (NPCBVI), India accounts for approximately 20% of the world's blind population. The main causes of visual impairment include cataracts, refractive errors, glaucoma, corneal diseases, and retinal disorders. Despite advancements in medical science and policy interventions, a significant number of individuals continue to face challenges due to limited access to healthcare and assistive technologies.

Issues Faced by Visually Impaired People in Financial Situations. Despite legal provisions and efforts from

various organizations, visually impaired individuals face significant challenges in financial transactions. These challenges stem from their dependence on cash transactions and the lack of inclusive financial infrastructure.

A. Challenges in Cash Transactions

Difficulty in Currency Recognition

Indian banknotes differ in size and texture across denominations, but distinguishing these features can be challenging, especially with worn-out notes. Counterfeit currency is often indistinguishable by touch, making visually impaired individuals vulnerable to fraud.

Reliance on Trust

Many visually impaired individuals depend on others to verify the authenticity and denomination of banknotes, which exposes them to the risk of deceit or exploitation.

Inconsistent Features for Assistance

Features like tactile marks on currency notes are often poorly designed, fade with use, or are missing on older notes.

B. Accessibility Issues in Banking

Limited Access to ATMs

While many ATMs claim to be "talking ATMs," only a fraction function as intended, and accessibility is not always user-friendly.

Digital Banking Barriers

Although digital banking reduces dependence on physical cash, navigating apps and websites is challenging due to inconsistent implementation of accessibility standards (e.g., screen reader compatibility).

C. Vulnerability to Financial Fraud

Exploitation by Unethical Individuals

Due to their reliance on assistance, visually impaired individuals are often given incorrect change or counterfeit notes.

Lack of Verification Tools

There are limited tools designed specifically to help visually impaired people independently verify currency authenticity.

D. Limited Employment Opportunities

Low-Income Levels

Many visually impaired individuals rely on small businesses or informal jobs, where cash transactions dominate. Their inability to independently handle finances further limits their employment opportunities.

E. Psychological and Social Impact

Loss of Confidence

The inability to manage finances independently often leads to a sense of helplessness and loss of dignity.

Social Exclusion

The dependence on others for financial transactions limits their participation in social and economic activities.

III. LITERATURE SURVEY AND RELATED WORK

The paper [1] introduces new method uses convolutional neural networks to detect counterfeit banknotes using smartphone cameras. This method, which uses preprocessed images, outperforms existing techniques and identifies critical security features. However, blurriness and low resolution could affect performance. Future work aims to improve the method's ability to locate and classify banknotes more effectively, enhancing financial transaction security and accessibility. The study evaluated various CNN architectures, alongside data augmentation techniques, to improve robustness against variations in note presentation.

The proposed model [2] uses advanced image processing techniques and machine learning to detect genuine and counterfeit Indian currency. It aims to assist the visually impaired by reducing dependence on others. The system uses MATLAB for image feature extraction and Android Studio for a user-friendly mobile application. The

Teachable Machine achieves a high accuracy rate of 89% for certain currency types, enabling blind users to engage in monetary transactions independently. This model enhances accessibility for the visually impaired. The model provides an efficient and cost-effective solution for detecting genuine currency, achieving an overall accuracy of 95% or higher. It enhances accessibility for the visually impaired by enabling reliable real-time identification of currency notes.

This study [3] aims to improve the identification of fake Indian currency notes using an Ensemble Decision Tree (EDT) and compares its performance with Ridge Linear Classification. The dataset consists of 1,050 unique currency values, with the EDT model trained using 80% of the dataset. The results show an average accuracy of 88.47% for the EDT, while Ridge Linear Classification achieved 85.91%. The study highlights the cost-efficiency of digital image processing in detecting fake notes and suggests further improvements through deep learning techniques and expanded datasets.

The study presents [4] a hybrid approach to counterfeit currency detection using Convolutional Neural Networks (CNN) and Residual Networks (ResNet). The method, which combines image processing and feature extraction stages, achieves a testing accuracy of approximately 98.3%. This method is particularly useful in banking and finance, where swift and reliable identification of counterfeit currency is essential. The system uses a dataset of approximately 4000 Indian currency denominations, divided into real and fake categories. The CNN architecture, which excels in image recognition tasks, is used to extract features, pool for down-sampling, and flatten for classification. The findings have significant implications for further research and practical applications in currency detection technologies.

This research proposes [5] an automated approach using ensemble learning for detecting counterfeit currency, backed by a comprehensive dataset of genuine and counterfeit images. The model is evaluated against traditional algorithms like Naive Bayes, Random Forest, and Decision Trees, yielding a high accuracy of 89% for the ensemble learning technique. The study underscores the importance of efficient counterfeit detection methods in safeguarding financial integrity.

The paper [6] presents a method for detecting counterfeit currency notes using image processing techniques in MATLAB. The system uses Canny's algorithm to extract key features, specifically for Indian currency denominations like 500 and 2000 rupee notes. The detection process includes image acquisition, gray scale conversion, edge detection, image segmentation, and feature extraction. The method, which uses a 70% intensity threshold, classifies genuine notes as counterfeit. The paper emphasizes the practicality of this method for the latest denominations and its potential for broader applications.

The paper [7] discusses the growing issue of counterfeit banknotes in the financial market and the need for automated detection systems. It applies six supervised machine learning algorithms to classify banknotes accurately. The algorithms are tested under various train-test ratios and some achieve up to 100% accuracy. The study confirms the effectiveness of various supervised machine learning algorithms in banknote authentication, with KNN and DT emerging as the top performers. The findings underscore the potential for machine learning to enhance security measures in financial transactions by reliably identifying counterfeit notes. Further research could explore the integration of additional algorithms or feature extraction techniques to improve performance.

This project [8] proposes a new approach using Generative Adversarial Networks (GANs) to classify Indian paper currency notes as real or fake. The process involves extracting currency features through Convolutional Neural Networks (CNNs) and classification using GANs, consisting of a Generator and a Discriminator. The proposed system is trained on a dataset of approximately 4,000 images of Indian currency notes across different denominations. The GAN framework alternates training between the Generator and the Discriminator to improve accuracy in classification. The implementation of GANs for currency recognition proved highly effective, particularly the Discriminator's performance in classification.

The proposed project [9] aims to detect counterfeit Indian currency notes using mobile cameras and image processing techniques. The system targets tourists who are often unaware of the differences between real and fake notes. It comprises four key components: image scanning, web application, image registration, and currency conversion. The system demonstrates a comprehensive approach to counterfeit detection and currency conversion. The paper [10] discusses the growing issue of counterfeit currency, particularly in India, and proposes an image processing-based system using MATLAB to differentiate between real and fake notes. The system involves capturing images, preprocessing to remove noise, and extracting features like the latent image, RBI logo, and denomination numeral with rupee symbols. The system was tested on 30 images, yielding accurate results for 23 of them, resulting in an accuracy rate of 76.66%. The work emphasizes the importance of technology in safeguarding economic integrity against counterfeiting.

IV. METHODOLOGY

The project, titled Identification of Counterfeit Currency for Visually Impaired People Using Hybrid Model, follows a structured methodology that integrates advanced image processing techniques, machine learning models, and user-centered design principles. The initial phase involves a thorough requirement analysis to understand the challenges faced by visually impaired individuals in handling currency and detecting counterfeits. This includes identifying gaps in existing tools and collecting Indian currency samples, both genuine and counterfeit, under diverse conditions for dataset preparation. High-resolution images are captured using smartphone cameras, and these are annotated with labels indicating denomination, authenticity, and key distinguishing features. Preprocessing steps, such as noise reduction, normalization, and segmentation, are applied to enhance the dataset for model training.

The image processing module focuses on extracting critical features from currency images. Techniques such as grayscale conversion simplify the analysis, while noise reduction filters ensure clarity by removing artifacts. Edge detection algorithms, like the Canny Edge Detector, and segmentation methods are employed to highlight significant regions, including holograms, watermarks, and security threads. These processed images serve as input for feature extraction, where advanced algorithms identify texture, color, and holographic attributes. The extracted features are further analyzed to detect anomalies indicative of counterfeit notes.

A hybrid model combining machine learning and deep learning is developed to classify currency authenticity. The machine learning component employs classifiers, such as Support Vector Machines (SVM) or Decision Trees, trained on extracted features for initial classification. Concurrently, a Convolutional Neural Network (CNN) is utilized to learn patterns directly from images. The outputs from these components are integrated using ensemble techniques to enhance accuracy and robustness. Performance is evaluated using metrics such as accuracy, precision, recall, and F1 score.

To ensure accessibility, a user interaction module is designed with features tailored for visually impaired individuals. This includes voice-assisted guidance through Text-to-Speech (TTS) technology, enabling users to capture images and receive results through auditory feedback. The system is implemented as a lightweight Android application with simple input mechanisms, such as voice commands or tactile buttons, ensuring usability across skill levels. Multilingual support and offline functionality further enhance its inclusivity.

The solution undergoes rigorous testing and validation to ensure reliability and user satisfaction. Technical tests evaluate the model's performance on unseen data, while user testing with visually impaired individuals assesses the app's usability. After successful testing, the system is deployed as a scalable application available for widespread use. Periodic updates to the dataset and system features address emerging counterfeit techniques and incorporate user feedback, ensuring long-term reliability and adaptability. This methodology aims to empower visually impaired individuals by providing a reliable, accessible, and user-friendly solution for counterfeit currency detection.

V. ARCHITECTURE

Voice-Controlled User Interface: Enables users to interact with the system using voice commands. Guides users with audio instructions for capturing the image and interpreting results.

Image Acquisition Module: Captures high-resolution images of currency notes using a camera. Ensures that the captured image meets predefined criteria for clarity and dimensions.

Image Pre-Processing: Enhances image quality through: Noise reduction, Contrast adjustment, Image resizing and alignment. Converts the image to a suitable format for feature extraction.

Noise reduction, Contrast adjustment, Image resizing and alignment. Converts the image to a suitable format for feature extraction.

Feature Extraction: Extracts key features from the currency note, such as: Watermarks, Serial Numbers, Micro-Text, Security Threads, Colour Patterns. Utilizes image processing libraries like OpenCV for this task.

Hybrid Model for Classification: Combines image processing and machine learning for counterfeit detection. Utilizes a Convolutional Neural Network (CNN) for feature classification. Trains on a dataset of genuine and counterfeit Indian currency notes.

Result Module: Audio Output: Speaks out whether the currency is genuine or counterfeit. Visual Output: Displays the result on the device screen for confirmation.

VI. PROPOSED MODEL

The proposed system for Identification of Counterfeit Currency for Visually Impaired People Using Hybrid

Model follows a sequential workflow designed to ensure efficiency, accuracy, and accessibility. The system begins with the user capturing an image of the currency note using a smartphone camera. This process is voice-assisted, guiding visually impaired users through Text-to-Speech (TTS) technology to position the note correctly and ensure a clear image is taken. The captured image is then processed by the system to prepare it for analysis. Preprocessing steps include noise reduction using filters to remove any distortions, grayscale conversion to simplify the image, and segmentation to extract key regions of interest, such as holograms, watermarks, and serial numbers.

Once pre-processed, the image undergoes feature extraction, where critical attributes, such as texture patterns, color distribution, and security features, are analyzed. Advanced techniques, such as Gabor filters and Fourier transforms, identify anomalies that distinguish genuine notes from counterfeits. These features are then fed into the hybrid detection model, which combines machine learning and deep learning techniques. The machine learning component, using classifiers like Support Vector Machines (SVM), performs an initial analysis of the extracted features, while the deep learning component, powered by a Convolutional Neural Network (CNN), conducts a detailed examination of the entire image. The results from both models are integrated using ensemble techniques to ensure high accuracy and robustness.

The final classification result is then conveyed to the user through the voice-assisted interface. The system announces whether the note is genuine or counterfeit and identifies its denomination. If necessary, additional feedback is provided to guide the user in re-capturing the image for improved accuracy. The interface is designed to be simple and intuitive, ensuring usability even for individuals with minimal technical expertise. The application supports offline functionality, allowing users to operate it without internet connectivity, and includes multilingual options to cater to diverse user groups.

The workflow concludes with periodic updates to the system's dataset and algorithms to adapt to emerging counterfeit methods and maintain reliability. This descriptive workflow ensures a seamless process for visually impaired individuals, empowering them with the ability to independently detect counterfeit currency while fostering financial security and autonomy.

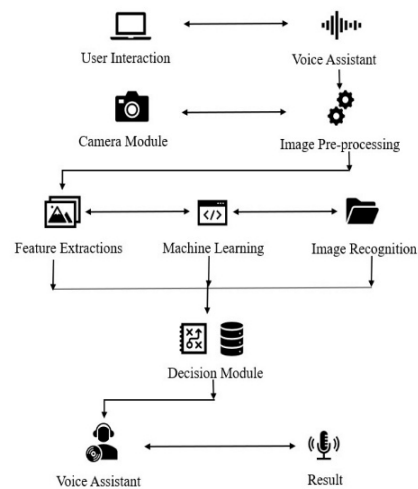


Fig.1: System Architecture



Fig.2: Currency With Identification Marks

VII. DATASET

The dataset is a critical component of the system, containing images of genuine and counterfeit Indian currency notes. It is used to train, validate, and test the hybrid model for accurate counterfeit detection. The dataset needs to be comprehensive, diverse, and well-labeled to ensure robustness against variations in counterfeit techniques and real-world conditions.

A. Dataset Composition

Categories:

- a) Genuine Currency Notes: High-quality images of authentic Indian currency notes across different denominations.
 - b) Counterfeit Currency Notes: Images of known counterfeit notes obtained from publicly available sources or synthesized.
2. Denominations: ₹10, ₹20, ₹50, ₹100, ₹200, ₹500, and ₹2000.
 3. Image Features: Front and back views of each denomination. Inclusion of distinct security features: Watermarks, Micro-text, Security thread patterns, Serial number fonts and position, Dimensions and corner patterns.



Fig.3: Real Indian Currency Data

VIII. COMPARITATIVE STUDY OF ALGORITHMS

In the context of the project Identification of Counterfeit Currency for Visually Impaired People Using Hybrid Model, different algorithms are analyzed based on their relevance, effectiveness, and suitability for the task. Below is a detailed comparative study of Convolutional Neural Networks (CNN), Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Feedforward Neural Networks (FNN), and Decision Trees (DT) with respect to their performance in counterfeit currency detection.

A. Convolutional Neural Networks (CNN)

Description: CNNs are deep learning models designed for image analysis and feature extraction. They automatically learn hierarchical features, making them highly effective for image-based tasks like counterfeit currency detection.

Advantages: High accuracy in image classification tasks due to automated feature learning. Robust to variations in lighting, rotation, and background. Can capture intricate patterns like watermarks, textures, and holograms.

Limitations: Requires large datasets for effective training.

Computationally intensive, needing GPUs for faster processing.

Suitability for Project: Ideal for this project due to its capability to analyze intricate security features of currency notes with minimal manual intervention.

B. Support Vector Machines (SVM)

Description: SVMs are supervised machine learning algorithms used for classification tasks. They work by finding the hyperplane that best separates different classes.

Advantages: Effective for small to medium-sized datasets. Performs well with high-dimensional data (e.g., texture and color features). Can handle linear and non-linear classification using kernels.

Limitations: Performance drops with large datasets. Requires manual feature extraction before training. Sensitive to parameter tuning.

Suitability for Project: Useful as a supporting algorithm to analyze specific extracted features like textures and colors. Not ideal as a standalone due to the manual feature extraction requirement.

C. K-Nearest Neighbors (KNN)

Description: KNN is a simple, instance-based learning algorithm that classifies data points based on the majority class of their nearest neighbors.

Advantages: Easy to implement and requires no training phase. Effective for small datasets with clear boundaries.

Limitations: Computationally expensive during testing as it requires comparing each test instance to all training instances. Sensitive to noise and irrelevant features.

Suitability for Project: Not optimal for this project due to the high-dimensional and noisy nature of image data.

D. Feedforward Neural Networks (FNN)

Description: FNNs are basic artificial neural networks where connections do not form cycles, making them suitable for structured input data.

Advantages: Flexible architecture for structured data. Can model complex relationships in data with multiple hidden layers.

Limitations: Requires extensive manual feature engineering for image-based tasks. Less effective than CNNs for visual tasks due to the absence of spatial feature extraction capabilities.

Suitability for Project: Applicable for structured inputs like extracted features but less efficient for raw image analysis compared to CNN.

E. Decision Tree (DT)

Description: Decision Trees classify data by recursively splitting it based on feature thresholds, creating a tree-like structure.

Advantages: Easy to understand and interpret. Works well with smaller datasets and structured data. Handles non-linear relationships between features.

Limitations: Prone to overfitting with noisy data. Requires careful feature selection.

Suitability for Project: Good for analyzing specific extracted features like security patterns but not suitable for raw image data.

TABLE I: COMPARATIVE STUDY OF ALGORITHMS

Algorithm	Accuracy	Complexity	Dataset Dependency	Training Speed	Image Analysis Capability	Suitable for Project
CNN	High	High	Large	Slow	Excellent	High
SVM	Medium	Medium	Small to Medium	Medium	Limited	Moderate
KNN	Low	High	Small to Medium	Fast	Poor	Low
FNN	Medium	Medium	Medium	Medium	Moderate	Moderate
DT	Medium	Low	Small to Medium	Fast	Poor	Low

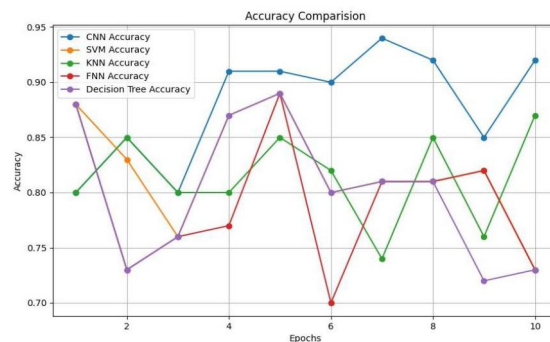


Fig.4: Accuracy Comparison of the Algorithms

IX. RESULT ANALYSIS

A. Implementation

The system is implemented as a voice-guided application that captures an image of a currency note using a webcam. The image is preprocessed by resizing and normalizing it to ensure compatibility with the trained CNN

model. The CNN, trained on a dataset of real and fake currency images, extracts intricate features such as watermarks, security threads, and patterns to classify the note as real or fake. The project ensures a user-friendly experience by guiding users to capture images with correct dimensions and releasing resources like the camera after processing.

B. Training Models

The training phase of the implementation involves developing a Convolutional Neural Network (CNN) to classify Indian currency as real or fake. A labeled dataset of currency images is used, containing examples of authentic and counterfeit notes. The CNN, consisting of convolutional, pooling, and fully connected layers, learns hierarchical features from the data, such as patterns, textures, and security markings unique to genuine notes. During training, the model adjusts its weights using backpropagation and gradient descent to minimize classification errors. The trained model is then saved as a .h5 file for deployment, allowing the system to accurately predict the authenticity of currency in real-time.

C. Genuine Currency

The training model successfully identifies a currency note as real by analyzing its unique features, such as watermarks, security threads, micro-text, and patterns, learned during training. When an image of a real currency note is input into the system, the model processes it through its convolutional layers, extracting key characteristics that match those of authentic notes. The fully connected layers combine these features and produce a prediction with a high probability for the "real" class. For example, if the model outputs [0.95, 0.05], it indicates a 95% confidence that the note is real. This result is then displayed and conveyed via the voice-guided system, providing an accessible and accurate verification for the user.

D. Counterfeit Currency

The training model identifies a currency note as fake when the extracted features from the input image do not match those of authentic notes learned during training. Features such as missing watermarks, incorrect patterns, or distorted micro-text, commonly found in counterfeit currency, are recognized by the model. The processed image passes through the convolutional and fully connected layers, and the model predicts a high probability for the "fake" class. For instance, an output like [0.10, 0.90] signifies a 90% confidence that the note is fake. This result is displayed on the screen and announced through the voice-guided system, enabling the user to identify counterfeit currency easily and effectively.

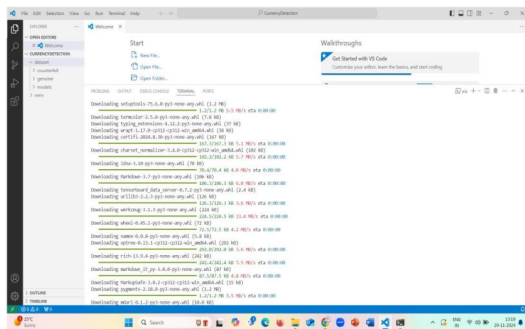


Fig.5: Implementing Module

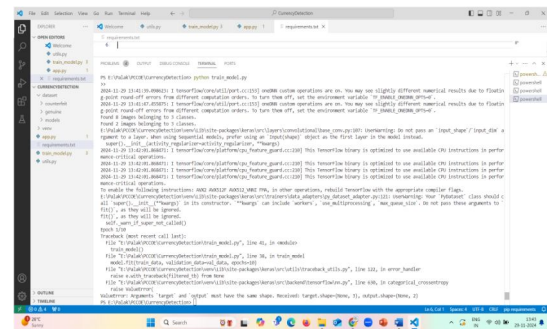


Fig.6: Training Model

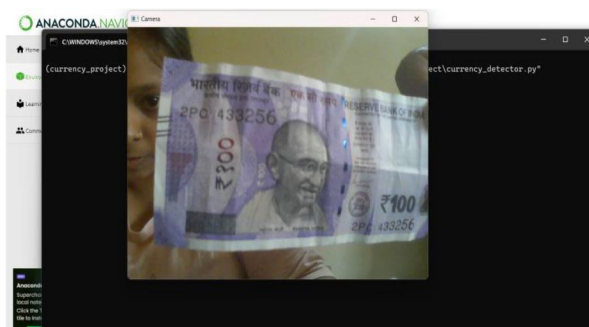


Fig.7: Genuine Currency Input

```

(currency_project) C:\Users\DELL>python "E:\Palak\PCODE\Project\CurrencyDetectionProject\currency_detector.py"
2024-12-01 11:34:13.675977: I tensorflow/core/platform/cpu_feature_guard.cc:182] This TensorFlow binary is opt
imized to use available CPU instructions in performance-critical operations.
To enable the following instructions: SSE SSE2 SSE3 SSE4.1 SSE4.2 AVX AVX2 AVXS12F AVXS12F_VNNI FMA, in other o
perations, rebuild TensorFlow with the appropriate compiler flags.
1/1 [=====] - 0s 177ms/step
Prediction: Real Currency

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Fig.8



Fig.9: Counterfeit Currency Input

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(currency_project) C:\Users\DELL>python "E:\Palak\PCODE\Project\CurrencyDetectionProject\currency_detector.py"
2024-12-01 11:29:23.479276: I tensorflow/core/platform/cpu_feature_guard.cc:182] This TensorFlow binary is opt
imized to use available CPU instructions in performance-critical operations.
To enable the following instructions: SSE SSE2 SSE3 SSE4.1 SSE4.2 AVX AVX2 AVXS12F AVXS12F_VNNI FMA, in other o
perations, rebuild TensorFlow with the appropriate compiler flags.
1/1 [=====] - 0s 393ms/step
Prediction: Fake Currency

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Fig.10: Counterfeit Currency Output

X. CONCLUSION

The development and implementation of the hybrid model successfully provided a reliable and accessible solution for visually impaired individuals to identify counterfeit currency. The integration of advanced technologies, such as machine learning and voice feedback, ensured high accuracy in currency verification.

The system proved to be user-friendly and effective, empowering visually impaired users to independently authenticate currency without relying on others. This innovation not only enhances financial independence but also contributes to broader societal efforts towards inclusivity and accessibility.

The project presents an innovative solution to a critical problem faced by visually impaired individuals in financial transactions. By leveraging advancements in image processing, machine learning, and voice-assisted technology, the system provides a user-friendly platform that empowers users to independently verify the authenticity of Indian currency notes.

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