International Journal of Computer Science Engineering Techniques – Volume 9 Issue 6, November - December - 2025

"Indian Fake Currency Detection Using Image Processing And VGG-16 Model"

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Received:18/Nov/2024; **Accepted**: 20/Dec/2024; **Published**: 31/Jan/2025. **DOI**: https://doi.org/10.26438/ijcse/v13i1.14

Abstract: The circulation of counterfeit money is a serious threat to India's financial system, necessitating quicker and more accurate detection techniques than hardware scanners or manual checks. This work introduces an automated system for detecting counterfeit money that combines image processing with a refined VGG16 deep learning model. The framework uses standard preprocessing procedures like resizing, normalization, and noise reduction to process uploaded or live-captured note images. In order to categorize notes as authentic or fake, the model recognizes characteristics such as watermark clarity, microtext, texture patterns, and color consistency. Transparency and usability are ensured by a Flask-based interface that offers confidence scores and real-time predictions. High accuracy and stability under a variety of conditions are demonstrated by experimental evaluation, which makes the system appropriate for real-world implementation in public spaces, retail counters, and banks.

Keywords: Fake Currency Detection, Machine Learning, VGG-16, Image Processing, Computer Vision, Transfer Learning, Flask

1. Introduction

A counterfeit currency problem still plagues India's financial industry, causing instability in areas where cash is the primary means of making payments. The traditional methods for verifying currency are visual inspection of watermarking, security threads, and micro printing and, unfortunately, these verification techniques are vulnerable to error by humans and also do not detect many types of sophisticated counterfeit bills [1], [2]. Hardware-based counterfeiting detectors such as ultraviolet (UV) and magnetic scanning devices can accomplish the same level of outnumbering counterfeit currency but require excessive cost and are therefore impractical for use in isolated villages, small, local business, and ATMs [3], [4].

The progress of deep learning, especially convolutional neural networks (CNNs), has proven ability to perform very well with regard to fine-grained visual classification. CNNs can automatically learn various features hierarchically, thus increasing their accuracy when distinguishing between counterfeit and real currency [6], [7].

VGG16 is the best-performing model when it comes to reliable authentication, due to its architecture and capabilities for gathering strong textured features in images [10], [11]). Therefore, it can be considered as a good fit for a scalable and fast real-time total currency authentication.

1.1 Background of the Project

The project refers to the research done to improve the detection of counterfeit items

Detection techniques were previously done using classical means of image processing, which had a lack of robustness to the above-noise level due to the various levels and angle rotation, and varying lighting conditions. [1], [4]. Additionally, SVMs and Random Forests are machine learning models that provide a better method for classifying counterfeit items than the previous methods but have lots of limitations due to their reliance on handcrafted features such as ORB, SIFT, and HOG; If counterfeit items are produced with different patterns, these methods will not work. [2], [5].

Deep Learning (DL) methods, especially VGG-based Convolutional Neural Networks (CNNs), eliminate these limitations, as these methods have proven to be superior to the previous models when performing authentication of currency. [6], [10], [11]. The goal of this project is to leverage these technologies to provide a robust method for detecting counterfeits.

1.2 Objective of the Project

To obtain and process photographs of authentic and fraudulent twenty rupee bank notes, which will later be utilized for modeling purposes.

To utilize transfer learning with VGG16 to extract distinguishing characteristics from both types of currency notes. For example, microprinting clarity, watermark quality, and texture uniformity.

To create an application via Flask that will allow for real-time currency note verification with images either uploaded or taken through a camera.

To measure the classifier's performance by identifying how well the model predicts with metrics such as accuracy, precision, recall, and confusion matrix results.

2. Related Work

Deep learning, hand-crafted features, and conventional image processing have all been used by numerous researchers to investigate counterfeit detection. Thresholding, edge detection, contour extraction, and template matching were among the early methods that were unreliable in a variety of lighting and background conditions [1], [4], [9]. Although classification was improved by machine learning models like SVM, Random Forest, KNN, and Logistic Regression, these models mainly relied on manually created descriptors like ORB, SIFT, HOG, and LBP, which have trouble with noise, rotation, and shifting counterfeit patterns [2], [5], and [7].

Because CNNs automatically learn multi-level visual features, recent studies show that they produce more dependable results [6], [10]. Despite testing, lightweight CNN-based mobile systems frequently perform poorly in low-light or noisy environments [3]. Because of their strong texture and edge extraction capabilities, VGG-based models consistently offer superior accuracy in evaluations of pretrained networks [11], [12].

As a result, the literature clearly favors using VGG16 as the main model for detecting counterfeit goods, indicating a move away from conventional vision techniques and toward deep learning methods.

3. Theory/Calculation

Analyzing minute visual details like watermark clarity, embedded security threads, color consistency, and microtext is necessary for currency authentication. CNNs use hierarchical extraction to efficiently capture these features, starting with simple edges and textures and working their way up to more intricate structures.

Transfer learning is a good fit for VGG16, which has a stable 16-layer architecture with uniform 3x3 filters after being pretrained on ImageNet. Custom binary classifiers (Real vs. Fake) are used in place of the task's final fully connected layers, and a softmax layer offers class probabilities for improved interpretability.

In terms of mathematics, the classification procedure uses max-pooling for dimensionality reduction, convolution for spatial feature extraction, ReLU for non-linearity, and softmax for probability estimation. When combined, these elements allow the model to accurately differentiate between real and fake money.

4. Experimental Method/Procedure/Design

The proposed methodology for this counterfeit currency detection system consists of a well-defined deep-learning workflow to provide accurate results quickly and in real-time. It contains integrated components such as image acquisition, image preprocessing, feature extraction, and prediction; therefore, the entire process can automatically verify all types of Indian currency notes that may be presented to it under differing lighting conditions.

The overall design of the counterfeit currency detection system is based on a modular convolutional neural network (CNN) architecture that has been proven effective for similar applications from an implementation perspective for real-time detection [3],[9].

Central to this architecture is the VGG16 convolutional neural network model, which is capable of extracting high-quality fine-grained visual features.

The user interface (UI) will be developed using the Flask web application framework, allowing users to view and interact with results obtained through the counterfeit currency detection system.

The next few subsections provide detailed information on the data preparation, training strategy, system components, and workflow.

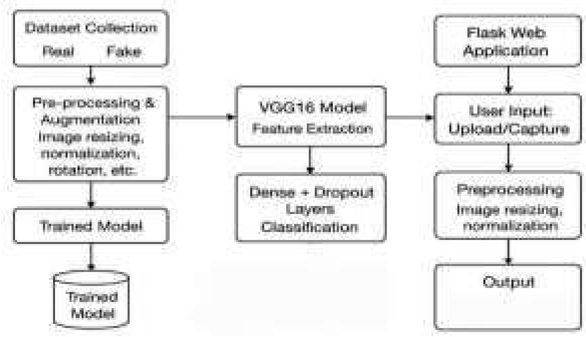

Fig.1 Architecture of Indian Fake Currency System

4.1 Dataset & Preprocessing

Images of both authentic and spurious Indian banknotes were acquired under different illumination conditions and orientations. Thereby, pre-processing steps involved:
Resizing images to 224×224 pixels
Normalization of pixel values
Noise removal & Contrast enhancement
Augmentation-rotation, flipping, zooming-in/zooming-out to increase model generalization

4.2 Model Training

VGG16 base model loaded with ImageNet weights
Final layers replaced with custom dense layers
Trained using binary cross-entropy loss
Optimized with Adam and early stopping

4.3 System Architecture

The complete system includes:
Image Acquisition Module: Upload or live camera capture
Preprocessing Engine: standardizes the input images
VGG16 Classifier: Predicts authenticity
Flask Web Interface: Returns prediction & confidence score

4.4 System Flow

User Input → Preprocessing → VGG16 Model → Prediction → Visualization of Result.

5. Results and Discussion

The section presents the outcome of the experimental evaluations using the proposed method of counterfeit currency detection based on VGG16. The system's performance, reliability, and practicality are illustrated through empirical testing in a variety of realistic environments. In addition, this section compares the results from the experimental evaluation to the previous methods of counterfeit currency detection that utilize either image processing or machine learning techniques and shows where these previous methods fall short compared to the new methodology. The combination of the two sections provides a thorough overview of how to evaluate the performance of the counterfeit currency detection system based on VGG16 and how to identify potential areas for future enhancements.

5.1 Experimental Results

The model shown was:

- High accuracy on test data
- Stable predictions across lighting variations
- Strong discrimination between genuine and counterfeit note textures
- Low misclassification rate
- Confusion matrix results showed balanced precision and recall, which verified model robustness.

Fig.2 Prediction Result Page (Real)

The Fig.2 shows detection based on the uploaded image can identify whether an Indian Currency Note is real or fake using a computer programme. After a user uploads the image of the note, the computer programme will process the image and provide a classification of that note's authenticity (real or fake) through a confidence score and a visual representation of ID confidence associated with the uploaded note.

Fig.3 Live Prediction Result Page (Fake)

The camera live interface displays video streams in real time and analyzes video frames continuously to identify if any currency notes that may appear in them are counterfeit or not. The minute a note appears within the frame, the prediction (counterfeit/not counterfeit) is immediately displayed superimposed on top of the video stream, allowing instant, interactive results for the user.

5.2 Discussion

The advantages of this system over conventional image processing and ML-based methods include:

- CNNs automatically learn relevant features.
- Transfer learning decreases data dependency.
- Web interface allows for real-time, accessible usage.

Limitations include dependence on RGB images only, with no UV/IR integration, and reduced performance in cases of highly damaged banknotes.

Test Image Sample	Variance Before Preprocessing	Variance After Preprocessing	Noise Reduction
Currency Sample 1	0.045	0.018	60.00%
Currency Sample 2	0.053	0.021	60.38%
Currency Sample 3	0.049	0.020	59.18%

Table 1:Image Noise Reduction Results for Fake Currency Detection System

Equation/Formula

1. Convolution Operation: Captures spatial features from the currency image:

$$F(i,j) = \Sigma \, \Sigma \, I(i + m, j + n) * K(m,n)$$

Using the convolution equation, feature values can be calculated by taking the product of the pixel region of the image and a kernel then summing them together. This operation is important for distinguishing features within the input image, since all convolution outputs ((,)) for an output convolution grid cell depend on pixels that are adjacent to the grid cell. It allows models to learn and pick up local patterns when trying to identify edges or textures, which are critical when validating whether a currency note is real or fake.

2. ReLU Activation: Introduces non-linearity and filters negative values:

( ) = max(0,)

The ReLU activation (( ) = max(0,)) changes every negative value to zero while keeping every positive value the same. The resulting effect is that the ReLU introduces non-linearity, which allows a network to learn more complex relationships than possible with linear activation. Additionally, using the ReLU helps a network to prevent negative activations from impacting the training of later layers in the network, which increases the efficiency of training.

3. Softmax Probability:Converts the final output into Real vs Fake probabilities:

$$S(y_i) = \frac{\exp(y_i)}{\Sigma \exp(y_k)}$$

The Softmax function converts unnormalized raw model output into normalized probabilities through exponentiation and dividing all exponentiated raw model output by the sum of all exponentiated output. By doing so, Softmax ensures that the outputs are always within the range of 0 to 1, and they will sum to 1. Thus giving the model its measure of certainty about the classification as to 'True' or 'False of being a Real or a fake currency note'.

5. Conclusion and Future Scope

A deep learning-driven solution has been developed for identifying counterfeit Indian Notes by employing advanced image processing techniques, including image preprocessing techniques, which have been integrated with a fine-tuned VGG16 architecture. Results from the model demonstrate consistently high accuracy regardless of any environmental conditions involving either changes in illumination or background, based on previous studies of object detection (CNN), both Feng et al. 2017 (6) and Lund et al. (10) and Sakagami et al. (11).

In addition to providing a robust, accurate, scalable, and cost-effective means of minimising human error in the manual inspection process, this proposed system creates an immediate means for identifying counterfeit Indian currency in the web due to the integration of a Flask-implemented web interface for user access.

Future research could include adding UV and Infrared Imaging (IR) capabilities to the system for obtaining other security features, including Fluorescent Characteristics and suitably specified Embedded Spectral Signatures that are undetectable with a pharmacy standard RGB image. In order to improve future research and development of the proposed model, increasing the number of currencies for all denominations, the breadth of print variation, and the broader spectrum of counterfeit currencies should be considered. Furthermore, the use of the latest generation architectures such as 'Vision Transformers' (12) would increase the system's performance on Identifying Counterfeits for greater accuracy.

Data Availability

The datasets utilized in this research are available upon request; all data sets are non-confidential.

Conflict of Interest

The authors declare no conflicts of interest.

Funding Source

No funding was received for this work.

Authors' Contributions

Author 1 conceived the idea for this study. Author 2 did the model building. Author 3 created the web interface. Author 4 did the experimental work and collated the results. Author 5 (Guide) provided overall technical guidance, supervised the research process, and helped refine the methodology and results. All authors reviewed and approved this document.

Acknowledgements

All parties want to thank those who provided continuous help in the areas of technical support, guidance of ideas, and academic materials for the completion of this project. It is thanks to the help of faculty members for giving guidance and by providing access to laboratories and computer resources for developing model training and experimentation that the authors were able to perform the necessary components to implement these systems as part of their project. The authors also want to thank their fellow peers and mentors in both the design and assessment phases of this project for giving them insightful feedback throughout the course of the study. Together, these people provided important resources toward the authors' completion of this research project and the creation of its outcomes.

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