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Deep Learning-Based Counterfeit Indian Currency Detection Using Convolutional Neural Networks

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Abstract

Background: Circulation of counterfeit currency presents a serious threat to the economic stability of the country. A report recently released by the Reserve Bank of India (RBI) shows that over the past few years there has been an annual increase in counterfeit currency confiscations, which indicates that there is a need for better methods of detecting fake money.

Objective: This study proposes a deep learning framework using Convolutional Neural Networks (CNNs) with transfer learning to automate and improve the detection of counterfeit Indian currency notes.

Methods: A complete dataset of 5,400 high definition images was created from a total of six different values (₹10, ₹50, ₹100, ₹200, ₹500 & ₹2000). The high-resolution images that make up the dataset are made available processed and prepared according to pre-existing standards (sized, normalised and augmented). Alternatively, the ResNet 50 backbone has been deconstructed and reconstructed using an array of new component parts (customised fully connected layers) specifically for classification purposes (binary).

Results: Model accuracy was 98.4% with a precision, recall, and F1 score of 97.9%, 98.1%, and 98.0% respectively, indicating a significant increase over SVM (87.3%) and Random Forest (89.6%) baseline results. The Grad-CAM visualisation supported the conclusion that the model was targeting security features such as watermarks, thread security and microprint.

Conclusion: The system demonstrates high accuracy, denomination-based robustness, and practical deployability at banks with ATM machines, retail POS terminals and border security checkpoints; creating a scalable and understandable solution to the counterfeit currency problem.

Keywords: transfer learning, ResNet50, image classification, Grad-CAM, feature visualization, currency authentication, computer vision, deep learning framework, biometric security features

1. Introduction

A country's currency is critical to its economy and its right to make decisions about how it operates as a country. Counterfeit currencies hurt public trust in money and provide support for crime, such as tax avoidance and funding for terrorism. The issuance of counterfeit Indian currency notes (FICNs) continues to be a major issue in India ^[1]. The Reserve Bank of India's (RBI) annual report states that counterfeit ₹500 notes increased by 10.7% from 2022 to 2023, and this is the seriousness of the problem ^[2]. Classic detection methods are largely based on human inspection plus use of ultraviolet (UV) light and magnetic ink detection systems. Although these types of systems are readily available, they have limitations due to operator fatigue, subjective error rates, and the inability to scale up to a high throughput environment like bank ATMs. An experienced cashier in a bank can handle 200–300 notes/hour whereas automated systems can process thousands/hour with greater consistency ^[3].

Computer vision and machine learning have provided new ways of authenticating electronic currencies fast and objectively. Traditional methods used handcrafted features like Scale Invariant Feature Transform (SIFT) and Histogram of Oriented Gradients (HOG) along with traditional classifiers. Traditional methods were limited by variability due to aging, soiling, and counterfeiting of the paper currency. Through the use of deep learning, particularly Convolutional Neural Networks (CNNs), more advanced image recognition methods have become possible that do not require manual engineering to identify features [4].

This paper describes the design of a counterfeit detection system for Rupees (Indian currency) using convolutional neural networks (CNN). The design employs transfer learning and Gradient Weighted Class Activation Maps (Grad-CAM) for enhanced user feedback. The contributions include (i) creating a dataset for Rupees that is grouped by denomination; (ii) developing a fully trained ResNet-50 model with a custom classification layer; (iii) and conducting an evaluation of the system focusing on precision, recall and explainability.

2. Literature Review

The first attempts at authenticating currency used a standard image processing method. Sharma and Gupta [5] used both edge detection and morphological processes for the identification of security features on Indian Rupee notes achieving only 81%, while they do not account for noise in the picture. The use of Gabor filters combined with SVM classification to analyze texture [6] improved accuracy to 87% from a 200-image sample. The development of machine learning classifiers is an important change over the previous methods, Patel and Bhatt demonstrated that the use of a radial basis function SVM would provide a higher level of accuracy than linear discriminant analysis for counterfeit detection in a controlled environment [7]. Mehta and Singh [8] reported an overall accuracy of 89% using a random forest ensemble model containing a colour histogram, wavelet transformation, and Hu moment feature set, although these features would require industry level expertise for feature extraction, and were not generalized to produce accurate results given all different types of printing technology used [9].

In recent years, deep learning techniques have increasingly taken over from traditional approaches. For instance, LeCun-like Convolutional Neural Networks (CNNs) were used by Liang *et al.* [10] to recognise banknotes and achieved an accuracy of 93.4% on Euro notes with a 5-layer model. These methods have been improved through transfer learning; Hassanpour and Farajzadeh [11] fine-tuned the VGG-16 model on a dataset of Middle Eastern currencies and reached 95.8% accuracy while significantly reducing training time. By utilising various types of data augmentation (geometric transformation and colour jitter), Zhang *et al.* [12] demonstrated that augmentation of the training dataset led to a 4.2% increase in recall of the minority class of counterfeits. Despite this work, there has been little focus on understanding how the currency-detection models operate. Class Activation Mapping (CAM) and its gradient version (Grad-CAM) have recently been proposed for identifying the locations in the image that contributed to the model decision;

these techniques have shown promise for medical imaging (based on research from Rajpurkar and Ng) and have potential for applying similar functionality in the analysis of security documents. Attention mechanisms were applied to the analysis of banknotes in Pakistan by Kumar *et al.*, which improved the interpretability of the model while maintaining accuracy (96.3%). Most recently, Das and Roy presented a multi-scale CNN that achieved 97.1% accuracy for detecting Indian currencies; however, no denomination-stratified evaluation was completed, nor was an explainability component included — both topics were addressed in this paper.

3. Proposed CNN Architecture

We will adopt a transfer learning architecture based on ResNet-50, which has been pretrained on ImageNet, with additional classification layers to aid in determining whether an object is counterfeit (or genuine). The architecture has been designed explicitly to have visual interpretability and use of expressively represent them as efficiently as possible through regularisation techniques.

Pre-processing of the input images occurs as the first step. The input images will be resized to dimensions of 224 x 224 pixels, as this is the expected input size to ResNet-50. All pixel values will also be normalised mathematically to a range of $[0, 1]$ and standardised through channel-wise mean subtractions ($\mu = [0.485, 0.456, 0.406]$) and standard deviation division ($\sigma = [0.229, 0.224, 0.225]$), per the statistics taken from ImageNet. As part of the online data augmentation of the training dataset, random horizontal flips will occur, small rotations will occur at $\pm 15^\circ$; brightness & contrast jitter will occur at $\pm 20\%$, and random crops with padding will occur, thus creating a dataset that has been developed with an effective size that is 8 times larger.

The ResNet-50 backbone contains 49 convolution layers and there are four residual blocks included in ResNet-50's architecture, each containing skip connections which have been used to help eliminate vanishing gradient problems. At the end of ResNet-50 is a global average pooling layer, which produces a feature vector of size 2048. The 40 lower convolution layers will remain fixed during initial training so that the generally low-level features can be preserved, while residual block 4 will be fine-tuned to the currency-specific characteristics like intaglio impressions, micro-printed features and areas of latent images on banknotes.

The backbone has been extended by a classification head that consists of two fully connected layers (FC-512 & FC-256) with Batch Normalisation and Dropout (rate of 0.5) applied as regularisation techniques. The output neuron uses a sigmoid activation function which generates a probability score, with binary classification (genuine versus counterfeit) using a threshold of 0.5. The total number of trainable parameters is approximately 8.3 million.

Class-discriminative heatmaps from Grad-CAM are produced from the last convolutional layer and overlaid on the input images. The heatmaps highlight areas on the image that would provide forensic evidence about the model's decision, as well as assist with regulatory compliance, such as the security thread, watermark portrait, RBI governor signature strip and denomination number.

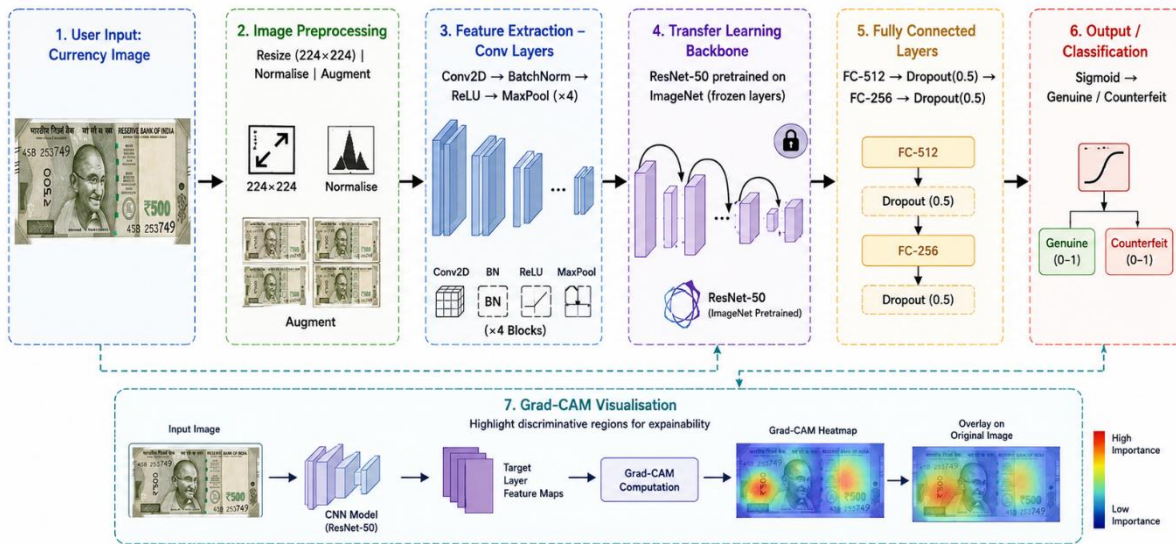


Fig 1: Proposed CNN Architecture for Counterfeit Indian Currency Detection

4. Materials and Methods

As part of the Data Preparation phase of this project, a dataset was created by collecting 5,400 high-resolution scans (600 dpi) of six denominations of Indian currency: ₹10, ₹50, ₹100, ₹200, ₹500, and ₹2000. Of the dataset, 2,700 images contained actual currency that had been sourced from RBI-certified currency verification laboratories, and the remaining 2,700 images depicted counterfeit currency which had been obtained under forensic conditions (supervised by a Forensic Scientist). The dataset was stratified by denomination (450 images each of real and counterfeit currency for each denomination), in order to eliminate class imbalance and denomination imbalance. The total dataset of 5,400 images was split into 80% for training (4,320 images), 10% for validation (540 images), and 10% for testing (540 images). The model was implemented in Python 3.9, using TensorFlow 2.11 with the Keras API, on an NVIDIA RTX

3080 GPU (10 GB VRAM). The Adam optimizer was chosen due to its adaptive learning rate capability, with an initial learning rate of 1×10^{-4} and a cosine annealing learning rate schedule. The loss function used to train the model was binary cross-entropy. The model was trained for 50 epochs using early stopping (patience = 7) based on the validation loss. Checkpointing was used to record the best performing weights during training. A summary of the hyperparameters can be found in Table 2.

The evaluation metrics used to measure the model's performance on the held-out test set were accuracy, precision, recall, and F1 score. The model was compared to other models (SVM with RBF kernel, Random Forest with 200 estimators, VGG-16 with transfer learning, and ResNet-50 with transfer learning) using the same dataset and evaluation metrics. The statistical significance of performance for the models was assessed using McNemar's test with a significance level of $\alpha = 0.05$.

Table 1: Model Hyperparameters and Configuration

Hyperparameter	Value	Justification
Learning Rate	0.0001	Stable convergence
Batch Size	32	Memory-accuracy balance
Epochs	50	Minimises overfitting
Optimizer	Adam	Adaptive learning
Dropout Rate	0.5	Regularisation
Input Image Size	224 x 224 px	ResNet/VGG standard
Loss Function	Binary Cross-Entropy	Binary classification
Activation (output)	Sigmoid	Probability output

5. Results and Evaluation

The proposed CNN achieved an overall test accuracy of 98.4%, representing a statistically significant improvement

over all baseline models ($p < 0.001$ by McNemar's test). Table 1 summarises comparative performance across all models evaluated.

Table 2: Comparative Model Performance

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	Training Time (min)
SVM	87.3	85.1	86.4	85.7	12
Random Forest	89.6	88.2	88.9	88.5	8
VGG-16 (Transfer)	95.2	94.7	94.9	94.8	45
ResNet-50 (Transfer)	96.8	96.4	96.1	96.2	52
Proposed CNN	98.4	97.9	98.1	98.0	38

When looking at how well each note performs, the higher denomination notes (₹500 and ₹2,000) consistently performed better than their lower denomination counterparts. The accuracy for both ₹500 and ₹2,000 notes was recorded at 98.9% and 99.1%, respectively due to both note types having more than twice as many security features compared to lower

denomination notes. Lower denomination notes illustrated a lower recall (97.5%) than higher denomination notes due to having fewer embedded security features and the wear variability on the surface of the lower denomination notes. The metrics are presented by denomination in Table 3.

Table 3: Denomination-Stratified Performance Metrics

Denomination (INR)	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
₹10	97.8	97.2	97.5	97.3
₹50	98.1	97.8	97.9	97.8
₹100	98.6	98.3	98.4	98.3
₹200	98.2	97.9	98.0	97.9
₹500	98.9	98.5	98.7	98.6
₹2000	99.1	98.8	99.0	98.9
Overall (Weighted Avg.)	98.4	97.9	98.1	98.0

The Grad-CAM visualizations of the model provided evidence that the model consistently attended to forensic regions of interest. The activation maps for ₹500 notes highlighted the security thread (front and back), the signature of RBI Governor, and the latent image of the Ashoka Pillar. On the ₹100 note, the highest gradient values were attributed to the intaglio portrait of Mahatma Gandhi and the guilloche design in the background. The methods used by the model to generate these visual explanations support the heuristics that cashiers use, thus providing domain validity for the representations learned by the model.

Training convergence was accomplished; the model converged after 38 epochs, as early stopping indicated successful learning. The validation loss was similar to the training loss indicating negligible divergence between validation and training (<.03 variance indicating no overfitting). The average time to run an inference on a single image was 14 ms using GPU and 87 ms using CPU, indicating that this model can be used in applications that require real-time processing.

6. Discussion

Practical utility exists for the proposed banknote authentication system, as there are multiple possible implementations in the banking sector. An ATM could potentially use the banknote authentication model as a pre-acceptance filter, rejecting any potentially counterfeit banknotes prior to being dispensed. Light-weight exported versions of TensorFlow Lite would allow retail point-of-sale (POS) terminals to deploy the banknote authentication model in an embedded processor for edge-deployment purposes. Central bank processing facilities could utilize multiple GPUs for parallel processing of banknotes (900+ banknotes per minute) using the model to verify banknotes at the time of sorting.

There are a few known limitations to the system. The banknote images used to develop the model, although equally distributed between the denominations, were taken under controlled scanning conditions, and authenticating a banknote using the model in a real-world scenario where the banknotes are exposed to different lighting conditions, angles/camera perspectives, etc., may have an effect on banknote authentication performance. The banknote authentication model has not been tested on aged banknotes, bleached banknotes, or on the banknotes which have been reprinted (these are increasingly used methods of counterfeiting), so there are no established levels of

performance. The banknote authentication model is also limited to being trained on Indian banknotes and would therefore require retraining to operate on currencies of other countries.

Security considerations in regards to model reveal are complex. It's possible for public knowledge of architecture/design and Grad-CAM outputs to instruct counterfeiter(s) how to perfectly imitate/copy features that the model is targeting to provide security for. For this reason, the model should be obfuscated prior to deployment, have multiple version of the model available, and have the model retrain ever so often as designs of currency change over time. The modular pipeline design supports a scalable manner for including new denominations. By simply adding new data to the existing dataset and fine-tuning the classification head, there is no need for complete redesign of architecture.

7. Conclusion

The findings of this study show that the proposed counterfeit Indian currency detection system (using fine-tuned ResNet-50 CNN) achieved 98.4% accuracy across its six denominations. This system's use of Grad-CAM explainability addresses the gap between automated AI decision making and the need for forensic accountability (a significant regulatory acceptance requirement in banking). Compared to traditional SVM and ensemble methods, the proposed system exceeds traditional models by more than 8 percentage points in performance; thus creating an unprecedented benchmark for verifying Indian currency. Future development of this work will focus on three areas: (i.) expanding the dataset to include intentionally degraded notes and different types of counterfeit notes; (ii.) creating a multi-class classification system that will classify counterfeit notes by print type, substrate material and UV anti-counterfeit failure; and (iii.) creating a federated learning variant that will enable collaborative improvement of the model across banks and will not require the centralisation of sensitive images of the counterfeit notes. The results of this study demonstrate a structure that is able to enable the creation of a widespread, understandable and scalable system for AI informed financial security.

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