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Indian Currency Note Classification Using Deep Learning

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Abstract
Detecting and classifying currency notes is very important to protect financial security, especially in a cash-based country like India. Even though online payments are growing, people still use cash widely, and fake note detection remains a big challenge. Traditional image processing and machine learning methods are still often used, but the performance is unsatisfactory when there are changes in lighting, note orientation, or note quality. In this study, towards increasing performance propose a Convolutional Neural Network (CNN)-based deep learning model is proposed for Indian currency detection. The model classifies the currency note images in the seven denominations: ₹10, ₹20, ₹50, ₹100, ₹200, ₹500, and ₹2000. The dataset, collected from the Kaggle repository with a total of 3,166 images, was expanded using augmentation techniques to improve feature learning. The CNN architecture includes two convolutional layers with max pooling, two dense layers, and a softmax classifier. The proposed model achieved a training accuracy of 98.93% and a validation accuracy of 90.82% at 15 epochs. Furthermore, when the ₹2000 denomination (which is no longer in circulation) was excluded, the model achieved a training accuracy of 99.50% and validation accuracy of 83.95%.

Keywords: *Convolutional Neural Network (CNN); Deep Learning; Data Augmentation; Image Classification; Softmax Classifier.*

1. Introduction

In the modern world, Technology is developing very rapidly these days, and due to that, every sector is getting more contemporary, such as the banking industry. From online transactions to digital wallets, the handling of money is undergoing a sea change. But despite all this development, cash remains a significant part of life, particularly in nations like India. Whether spending cash on something from a local store or paying in cash for services, currency notes are still used by people regularly. But one of the huge drawbacks of doing so is the issue of counterfeit or fake notes. The fake notes are also created so well that they are almost the same as real notes. For shopkeepers, bank employees, and even ordinary citizens, verifying all the notes manually is not just tiring but also not always accurate. And for visually impaired persons, it is simply impossible. Therefore, Automatic recognition of fake Indian currency notes has become an essential requirement in automated teller machines, vending machines, and other financial systems to ensure secure and reliable transactions [1]. Fake currency detection is a serious issue worldwide, affecting the economy of almost every country, including India, where duplication of notes has become common due to advanced printing and scanning technology [2]. In the past, people used simple image processing or basic machine learning methods to identify currency, but those often failed when the note was crumpled, tilted, or under poor lighting. With the arrival of deep learning and advanced computer vision, we now have tools that can see and learn like humans. These modern techniques make it much easier and faster to build reliable currency recognition systems that actually work in the real world. In This Paper, a Convolutional Neural Network (CNN) was utilized to recognize Indian currency notes. This paper describes the classification of Indian currency into seven classes, including the Rs. 10, Rs. 20, Rs. 50, Rs. 100, Rs. 200, Rs. 500, and Rs. 2000. CNNs are really good at working with images because they can learn to detect patterns, shapes, and textures all on their own. it will

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be able to learn automatically the features that separate each denomination and correctly identify them even if the note is tilted or degraded. The organization of the rest of the paper is followed by a literature review in section 2, methodology, along with a customized CNN architecture described in section 3, section 4 illustrates the implementation process, followed by the results and discussion in section 5. Section 6 concluded the paper.

2. Literature Review

Reddy, K et. al. [3] proposed a deep learning-based framework to help physically challenged individuals identify Indian currency notes. The system classified seven denominations using multiple CNN models, including Basic customized Sequential CNN, VGG16, MobileNet, and AlexNet. The datasets used from Kaggle and the author customized. The dataset from the Kaggle dataset, a total of 995 images, was utilized, where the dataset does not contain the 1000 Rs. And 500 Rs. Banned notes and the custom dataset of 1280 images, including 10 Rs, 20 Rs, 50 Rs, 100 Rs, 200 Rs, 500 Rs, and 2000 Rs Indian currency notes images. The proposed sequential CNN model achieved an accuracy of 97.98% which is higher than VGG16, MobileNet, and AlexNet models, where models achieved 92.71%, 89.07%, and 71.66% respectively. Smitha, K. et. al. [4] Researchers used different methods for fake Indian currency detection, like KNN, Logistic Regression, SVM, Random Forest, and deep CNN models. Some works achieved high accuracy, for example, Logistic Regression (99%) and CNN with SSD (96.6%), while MobileNetV2 gave 85%. In this paper, a Custom CNN was developed to classify ₹10, ₹50, ₹100, ₹500, and ₹2000 notes. It performed better than ResNet50 (83.44%) and VGG16 (91.6%), reaching 94.4% accuracy, making it effective for fake note detection. Kumar et. al. [5] created a system to find out fake Indian notes using a Deep CNN. They made their own dataset by clicking photos of ₹200, ₹500, and ₹2000 notes (both real and fake) with a Samsung mobile camera. At first, they had 218 images; later increased to 306 using rotation and zoom. They built a three-layer CNN model that checked the images and decided if the note was real or fake. The model gave 96.9% training accuracy and about an 80% overall success rate. Jadhav et. al. [6] The research paper "Currency Identification and Forged Banknote Detection using Deep Learning" employed its own images of Indian (₹100, ₹500) and Saudi (1 Riyal, 10 Riyal) currency, scanned and photographed. A deep learning model was utilized to verify characteristics such as size, color, and texture of the currency. This model performed more accurately than previous methods and demonstrated high precision, although no specific percentage was reported. The data was entirely constructed from Indian and Saudi currency real-time images. Padmaja, B., et. al. [7] This paper used a dataset of 4002 images covering all major Indian denominations (₹10 to ₹2000). A three-layer CNN achieved 98.5% accuracy for denomination recognition. For counterfeit detection, multiscale template matching with OpenCV was applied to verify security features. While results were promising, the system currently works only with the front side of notes, leaving scope for future improvement. Laavanya, M. et. al. [8] The authors built a fake note detection system using AlexNet with transfer learning on ₹50, ₹200, ₹500, and ₹2000 notes. With around 100 images per note (augmented), the model checked the security thread and gave 81.5% accuracy for real and 75% for fake notes, about 26% better than VGG. It was also fast, taking only 3 seconds per note. Singh, Karandeep, et. al. [9] proposed a Hybrid CNN-LSTM based framework for Indian currency recognition. Earlier studies had used image processing methods like template matching, ORB, YOLO, CNN, and Faster R-CNN, but these approaches either gave low accuracy on unclear notes or were slow and required powerful devices. In this work, the authors created a dataset of 300 Indian currency images (₹10, ₹20, ₹50, ₹100, ₹200, ₹500, and ₹2000) and applied a Hybrid CNN-LSTM model. With the support of cloud deployment, improved scanning, crash detection, and audio output, the system became faster, more reliable, and achieved an accuracy of 92.55%, which was higher and more practical compared to older methods. Bhutkar, et. al. [10] focused on Indian currency recognition and created a custom dataset of about 4000 images of notes (10,20,50,100,200,500, and 2000) captured under different lighting, angles, and worn-out conditions. Earlier feature-based methods using texture, size, and RBI seals were unreliable on unclear notes. While LBP worked only on clear images and Faster R-CNN gave good accuracy but was too heavy for mobile devices, the authors proposed a CNN with transfer learning (MobileNetV2) and deployed it on TensorFlow Lite. Their system achieved 94.38% accuracy. Lakshmi, B. N et. al. [11] Researchers have used different techniques for fake currency detection. Earlier works applied image processing with features like texture, watermark, and serial numbers, while others used MATLAB and basic ML classifiers for Indian notes. Later, deep learning methods, especially CNNs, showed much better performance by automatically learning features and giving high accuracy. Some studies even combined CNN with advanced image filters, though they needed more time. Overall, CNN-based approaches proved more reliable than traditional methods, and the present paper improves further by combining CNN with SVM, achieving 98.5% accuracy in detecting counterfeit notes. Kumar et. al. [12] Studies on fake currency detection using the UCI banknote dataset show that supervised ML algorithms like Decision Tree, SVM, and KNN can classify real and fake notes effectively. Among them, KNN performed best with 100% accuracy, while Decision Tree (~99%) and SVM (~98%) followed closely.

3. Methodology

We implemented a Convolutional Neural Network (CNN) model to classify Indian banknotes, which had seven denominations which were ₹10, ₹20, ₹50, ₹100, ₹200, ₹500, and ₹2000. The data was downloaded from Kaggle, "Indian Currency Note Images Dataset 2020," containing 3,166 real currency note images. The dataset does not include any banned notes, ensuring that the training process was based only on valid denominations. The overall process of our suggested system is illustrated in Figure 1, in which the process steps are as follows: (1) image capture, (2) preprocessing, (3) feature extraction, (4) CNN-based classification, and (5) output creation. Although the referenced diagram typically represents binary classification of fake vs. real currency, our work extends the concept to multi-class classification of seven denominations. This makes the system more robust and practical for real-world applications.

3.1. CNN Architecture

A Convolutional Neural Network (CNN) is capable of learning to label new images into pre-specified categories after being trained on a collection of labeled images. It processes the input image through successive layers, gradually extracting important features for classification. The proposed CNN architecture is composed of convolutional layers, pooling layers, and fully connected layers, which together transform raw image data into class predictions for the seven banknote denominations used in this study.

3.2. Convolutional Layer

In CNN architecture, the most significant component is the convolutional layer. It consists of a collection of convolutional filters (so-called kernels). The input image, expressed as N-dimensional metrics, is convolved with these filters to generate the output feature map [13].

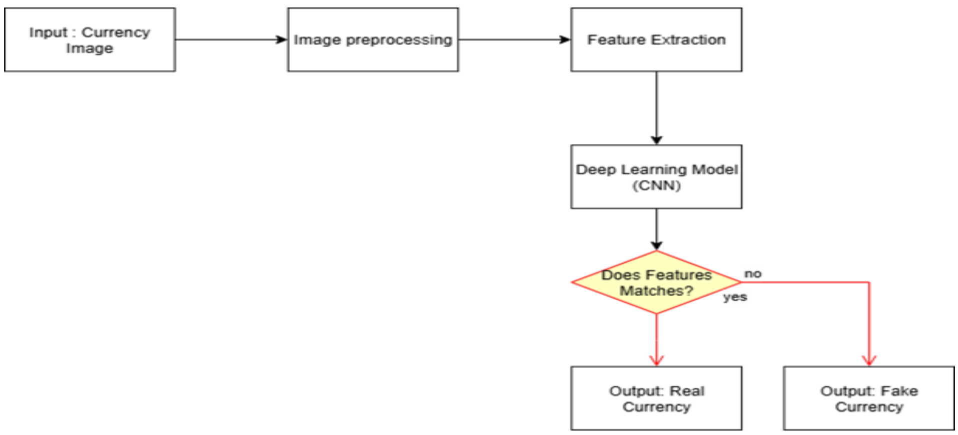

Figure 1 General Steps of Currency Detection System

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3.3. Pooling Layers

The pooling layer, which is responsible for reducing the size of activation maps, is also referred to as the down-sampling layer. This is achieved by the application of a filter and stride of the same length to the input volume, and in essence, while shrinking the feature maps, it always preserves the most dominant features in each pool step [14].

3.4. Fully Connected Layers

A model with fully connected layers allows each pixel to connect to every other pixel in the image to capture long-range correlations in natural scenes. This layer learns complex combinations of features extracted in the earlier layers [15].

3.5. Activation Function

The activation function plays an important role in the training of neural networks. They provide the necessary non-linearity of the model to be able to learn complex representations [16]. In our work, we first trained the proposed CNN model without any augmentation, but the accuracy was relatively lower due to variations in lighting, orientation, and note quality. To overcome this limitation and enhance model generalization, we applied image rotation augmentation, where images were rotated at different angles ranging from 5% to 95% to generate more variations. This increased the dataset size significantly, resulting in 63,280 augmented images. We also resized all input images to 124 × 124 pixels to ensure that the CNN received a consistent input size.The dataset was divided into 80% for training and 20% for validation, so that most of the data could be used for learning and the remaining data for unbiased performance evaluation. Furthermore, since the ₹2000 denomination is no longer in circulation, we removed it from the dataset, which reduced the total number of augmented images to 54,520, and also evaluated the accuracy after exclusion. The proposed CNN model consisted of two convolutional layers, each with 32 filters of size 3×3 and ReLU activation, with max pooling layers (2×2) applied after each convolution for dimensionality reduction. The extracted features were then flattened and passed through a fully connected dense layer with 256 neurons and ReLU activation. Finally, a softmax output layer classified the input images into seven categories corresponding to the denominations of Indian currency. The detailed proposed CNN model layers are shown in Table 1.

Table 1 The Proposed Model CNN Layer Wise Detail

Layer (Type)	Parameters / Details
Input Image	(224×224×3 RGB)
Conv2D_1	32 filters, 3×3 kernel, ReLU
MaxPooling2D_1	2×2 pool size
Conv2D_2	32 filters, 3×3 kernel, ReLU
MaxPooling2D_2	2×2 pool size
Flatten	-
Dense_1	256 neurons, ReLU
Dense_2 (Output)	7 neurons (Softmax activation → 7 classes)

4. Experiments

4.1. Dataset Collection

The dataset used in this study is the "Indian Currency Note Images Dataset (2020)" from Kaggle, which contains 3,166 images of Indian banknotes in different denominations (₹10, ₹20, ₹50, ₹100, ₹200, ₹500, and ₹2000). The dataset includes both front and back side images of the notes. For preprocessing, all images were resized to 224×224 pixels and divided into 80% for training and 20% for validation. To make the model more accurate and reliable, rotation-based augmentation was applied, where images were rotated at different angles (from 5% to 95%). This augmentation helps the model learn to correctly identify notes even when they are tilted or placed in different orientations, improving its performance in real-life situations.

4.2. Model Implementation

The CNN model was developed in Python using TensorFlow / Keras and implemented in Visual Studio Code. The architecture included two convolutional layers with 32 filters each, using a 3×3 kernel and ReLU activation, followed by max pooling layers of size 2×2. After these layers, a flatten layer was used to convert the feature maps into a one-dimensional vector, which was then passed through a dense layer with 256 neurons and ReLU activation. Finally, a softmax output layer with seven neurons

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was used to classify the seven denominations of Indian currency notes. The dataset originally contained 3,166 images, all resized to 224×224 pixels. To improve diversity and robustness, rotation-based augmentation was applied at different angles ranging from 5° to 95°, which expanded the dataset size to 63,280 images. This augmented dataset was then divided into 80% for training and 20% for validation, ensuring that the model had enough samples to learn effectively and generalize well. The model was trained using the Adam optimizer with a learning rate of 0.001 and a categorical crossentropy loss function. Training experiments were conducted for 5, 10, and 15 epochs with a batch size of 32 to analyze performance. The model quickly learned features in the initial epochs, while longer training of 15 epochs helped achieve more stable generalization. The highest validation accuracy recorded was approximately 90.82%.

5. Results and Discussion

In the beginning, the model was trained using the 2020 dataset with ₹2000 notes and no augmentation. The results showed that the training accuracy was very high, reaching 95.20% at 5 epochs and 97.72% at 25 epochs. But the validation accuracy was much lower, starting at 43.38% for 5 epochs and dropping further to 34.56% for 25 epochs. The training loss was very small (0.17 to 0.10), while the validation loss kept increasing from 2.57 to 4.32. The accuracy and loss graphs shown in Figure 2 represent the difference, which means the model was overfitting it. It performed well on the training data but did not work properly on the validation data. Since the validation accuracy was very low in the first experiment, data augmentation was applied by rotating the images between 5° to 95°. This made the dataset more diverse and helped the model learn better. After augmentation, the results improved a lot. At 5 epochs, the training accuracy was 97.95% and the validation accuracy reached 86.67%. At 10 epochs, training accuracy increased to 99.04% with validation accuracy of 86.84%. Finally, at 15 epochs, the model achieved 98.93% training accuracy and the highest validation accuracy of 90.82%. The training and validation loss values also became much closer, as seen in the graphs Shown in Figure 3 & 4. These results show that augmentation reduced overfitting and helped the model perform well on both training and validation data Shown in Table 2.

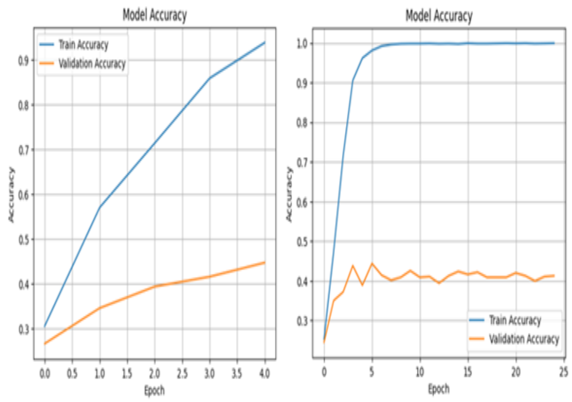

Figure 2 The proposed CNN Model Performance on Datasets without Augmentation: Epoch Vs Accuracy and Epoch Vs Loss

Table 2 The Proposed Model CNN Performance Epoch Wise

Epochs	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
5	97.95	86.67	0.0696	0.6057
10	99.04	86.84	0.031	0.612
15	98.93	90.82	0.0402	0.4286

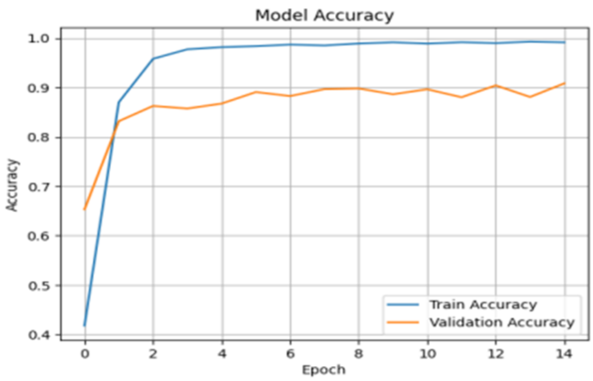

Figure 3 **The proposed model Epoch Vs Accuracy for 15 Epochs**

The dataset originally had ₹2000 denomination notes, but since these notes are no longer in circulation, they were removed, and the model was retrained. After removing ₹2000 notes, the model still showed good performance. At 5 epochs, the training accuracy was 98.09% and validation accuracy was 76.43%. At 10 epochs, training accuracy improved to 98.89% with validation accuracy of 80.34%. Finally, at 15 epochs, the model achieved 99.50% training accuracy and 83.95% validation accuracy. The graphs of accuracy and loss also confirmed that the model continued to learn well and gave stable results even without the ₹2000 denomination Shown in Table 3.

Table 3 **The proposed model CNN performance on dataset without 2000/- note**

Epochs	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
5	98.09	76.43	0.06	1.28
10	98.89	80.34	0.04	1.31
15	99.5	83.95	0.02	0.81

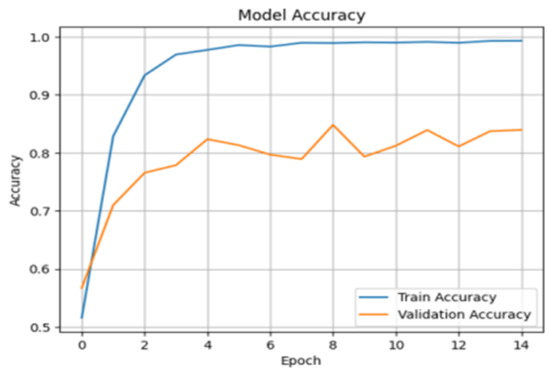

Figure 4 **The Model Performance Epoch Vs Accuracy Without 2000 Note**

Conclusion

we used a deep learning CNN model for Indian currency classification and detection. To improve accuracy, we applied data augmentation using rotation ranging from 5% to 95%. also performed data modification, where removed the ₹2000 notes considering the present situation. With ₹2000 notes, the model achieved 98.93 % training accuracy and 90.82 % validation accuracy. Without ₹2000 notes, the model achieved 99.50% training accuracy and 83.95 % validation accuracy. In the future, it can be improved by adding fake note detection and using larger datasets or advanced models for even higher accuracy.

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