Counterfeit Currency Detection Leveraging MobileNet and ResNet Models

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Abstract. Today the world economy is suffering from severe problems due to the growing fake currency notes circulation that reduces faith in monetary systems, and raises financial instability. Instant fake currency detection is being a challenging task for development of innovative solutions especially due to the diversified fake currency notes. Physical inspection is the predominant technique in traditional systems of counterfeit currency detection. Real or fake notes detection using CNN-based architectures Using CNN based technology, MobileNet achieved the highest accuracy of 96.03% and ResNet provided the lowest accuracy of 74.03%. Further, the system may recognize the circulation monetary note and currency image denomination. This can be achieved by applying image augmentation and preprocessing techniques to enhance model performance. In addition, the interface of the real-time currency detection is built on with Streamlit, providing human-friendly and convenient platform for people meeting the need of counterfeit checking on the spot by themselves.

Keywords: Counterfeit, MobileNet, ResNet, Image Processing and Streamlit.

1 Introduction

Circulation fake notes is one of the most serious global threats to financial stability and economic integrity. The adoption of fake note creation supported by digital tools and high-resolution printing to fraudulently print notes becomes more sophisticated every day, which replaces traditional methods for detection. As per the reports of Reserve Bank of India (RBI), number of counterfeit notes (especially high denomination like ₹500) have increased over the years, so detection has to be done immediately.

Traditional techniques like visual inspection or checking under a UV light are also no longer feasible in the context of quick-moving, high through-put situations. In response, there may be some promise with artificial intelligence (AI) and deep learning approaches. The popular use of Convolutional Neural Networks (CNNs) in counterfeit detection for visual pattern recognition tasks such as has high accuracy.

This research investigates the distinction between real and fake currency notes via MobileNet and ResNet CNN architectures. While MobileNet has a fast and lightweight performance that is suitable for real-time applications, ResNet is good at deep feature extraction. In our system,

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we integrate these models with pre-processing techniques and a Streamlit based interface to allow real-time public-facing verification of currency notes.

2 Related works

Automatic counterfeit banknote detection has been extensively studied in recent years. Jahan et al. [1] proposed an image-processing-based detection system that efficiently identifies fake banknotes. Similarly, Li et al. [2] developed a deep learning approach using visual saliency for counterfeit detection, demonstrating improved robustness over conventional techniques.

Amin and Khan [3] introduced a method for detecting counterfeit Euro, Dollar, and Indian currency notes, highlighting the role of feature extraction. Rehman et al. [4] extended this work by employing deep learning models for automatic detection, achieving high accuracy in real-time scenarios. Preprocessing steps for enhancing recognition accuracy in ATMs were explored by Mohan and Ramesh [5].

Datasets play a crucial role in counterfeit detection research. Dua and Graff [6] made the UCI banknote authentication dataset publicly available, which has since been widely adopted in machine learning experiments. Roy and Das [7] focused on Indian currency, using unique security features for recognition and verification. Agarwal and Jain [8] studied human factors in counterfeit detection, revealing cognitive limitations in manual identification.

Recent works also compare traditional versus deep learning methods. Khan and Rafiq [9] presented a comparative study, showing the superiority of deep learning models. Howard et al. [10] introduced MobileNets, a lightweight convolutional neural network architecture that significantly benefits mobile vision applications, including currency authentication tasks.

He et al. [11] developed the deep residual learning framework (ResNet), which remains a foundation for high-performance detection models. Singh et al. [12] proposed a hybrid approach combining deep learning with traditional image processing for real-time authentication. Gupta et al. [13] emphasized robust and accurate detection using advanced CNN models in large-scale scenarios.

Sharma et al. [14] applied machine learning methods for currency recognition and reported effective performance in diverse conditions. More recently, Patel et al. [15] introduced an ensemble-based approach, integrating multiple machine learning models for improved reliability in fake currency detection.

3 Methodology

3.1 Dataset

Datasets are very important to train a particular model. Because, the data what we had provided for the model, it is able to learn from it and generates accurate results based on training experience. For this work we also need to train our model on various Indian currency notes. We gathered currency images both fake and real one from online resources and even we captured live notes of different notes.

These images are captured at different angles under various lighting conditions with backgrounds so that they are too real. It increases the variability to our model. Non-currency notes are also added to dataset so that it able to distinguish whether it is a currency note or not.

All these images are labelled according to their denominations like ₹10, ₹20, ₹50, ₹100, ₹200, ₹500, and non-currency categories. After the collection of data, it is supposed to preprocess to reduce noise and to make it consistent. To ensure the standardization of the data, images are transformed to uniform size (224*224) to maintain the entire data consistent.

Some of the Data Augmentation techniques namely flipping, rotating, re-scaling, cropping is performed so that model variability across dataset improved which reduces training period and it generalizes easily for real time scenarios. Normalization is one such preprocessing strategy to scale the pixel values, it improves the rate of convergence of model. Later noise reduction techniques like Gaussian blur and median filtering to eliminate unwanted artifacts.

These steps help refine the dataset, making it easier for the model to extract essential features and enhance its accuracy in detecting counterfeit notes. All these helps model to reduce risk by memorizing specific patterns rather learning the features in general. This makes the model more robust to minor changes to images like scaling, rotation and orientation. Fig 1 shows the collection of currencies of various classes.

Fig. 1. Collection of currencies of various classes.

3.2 Principles

The core methodologies of this work are MobileNet and ResNet which are the best Convolutional Neural Networks. Pointwise convolutions, depth wise convolutions are used

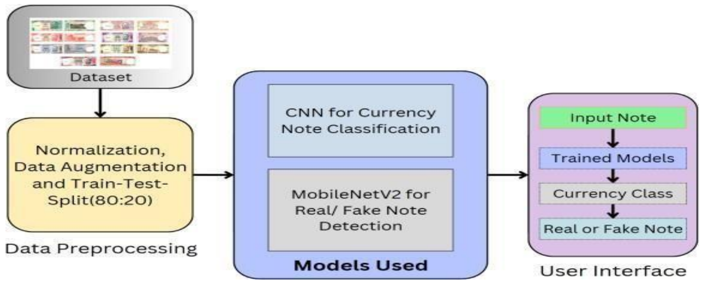

Fig. 2. Proposed Methodology of Fake Currency Identification.

instead of standard convolutions where single filters are added among all channels. Without compromise in the performance it can work with very few parameters and features and yields best outputs. Light weight architecture is key component of this MobileNet it helps for real time detections with limited resources. Fig 2 shows the Proposed Methodology of Fake Currency Identification.

Instead of learning straightly to point input to output, ResNet figures the differences among input and output and its dependencies then able to map between input and output. Model size and data overfitting often minimalized as ResNet uses global average pooling.

ResNet stabilizes the model training by normal activation functions ultimately ends up with good convergence rates. ResNet are the deep residual networks, which reduces the gradient issues. The detection mechanism we proposed is with intuitive user interface which simply allows you to input an image to the system which reports the denomination of the currency note along with its validity and to upload a currency note if it is a non-currency note. Instant currency verification is authenticated simply by streamlet interface.

3.2.1 Convolutional Neural Networks

CNNs can train spatial feature hierarchy across multiple layers they are also excellent for image recognition. These networks are very well-suited for applications such as currency note detection as minor details matter as they are designed to auto-detect patterns such as edges, textures, and shapes. Fig 3 shows the CNN architecture.

CNN contain layers convolutional layer 1, pooling layer, fully connected layers and there are many layers. CNN take input from the user and passes to the input layer and then it passes to the convolutional layer 1 for the feature extraction. We apply the filter to the inputs for the extraction of features like micro-text, shapes, variations and edges.

Then it passed to the pooling layer for the further feature extraction and as well as it removes the noisy the data from the data. It also reduces the dimensionality of the data, extracts important features and removes the unimportant features. Finally, we have the fully connected layer all the features from the pooling layer passes to the last layer. Fully connected layer determines whether the note is real or fake with the help of features that are extracted from the pooling layer.

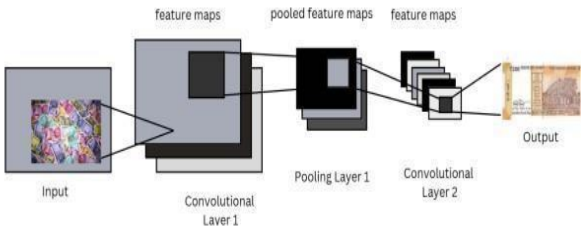

Fig. 3. CNN Architecture.

In the dataset we have training data and testing data. Training data is used for to train model. CNN was trained using training data and to check the performance of CNN model we use the testing data testing data contains both fake note and real note. CNN model compares it with the testing data and give the output whether the note is real or fake. It also gives denomination of a note by extracting features

3.2.2 MobileNet

MobileNet is used for the image classification tasks hence used in fake currency detection. MobileNet classifies whether the note is real or counterfeit by extracting the features. Fig 4 shows the mobile net architecture.

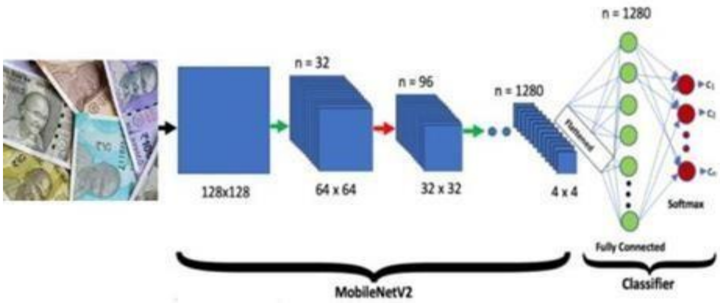

Fig. 4. MobileNet Architecture.

Compared with the convolutional neural networks MobileNet has high accuracy because it uses the depth wise convolutional neural networks. In this the inputs are passed to first layer and in the further future extraction it passes to another layer. It applies one filter to the one channel and extracts the features by applying grayscale. Each filter slides over the corresponding channel and extract the all features. In this it uses the inverted residual blocks to extract the features like edges, shapes. A linear bottleneck layer is used for extract only essential information and removes not useful information. Instead of expanding the features at beginning it starts with the low dimensional representation. Then it further expands the data at the time of processing. MobileNet provides 96.03% accuracy compared with other model it provides high accuracy as well as it is highly efficient.

3.2.3 ResNet

The term "Residual Network" (ResNet) refers to a deep learning architecture that utilizes shortcut connections to pass on residual knowledge. These shortcuts allow the network to bypass one or more layers, improving learning efficiency, particularly in very deep models. A well- known example is the ResNet-50 model, which addresses the vanishing gradient problem, a common issue in training deep networks. This feature is particularly valuable for complex image recognition tasks, such as detecting counterfeit currency, where subtle details are crucial to distinguishing genuine notes from counterfeit ones. The key to ResNet design lies in its residual blocks, which enable the network to determine when to learn residual features rather than full transformations. These blocks consist of several convolutional layers, with shortcut connections that skip certain layers. Fig 5 shows the res net architecture.

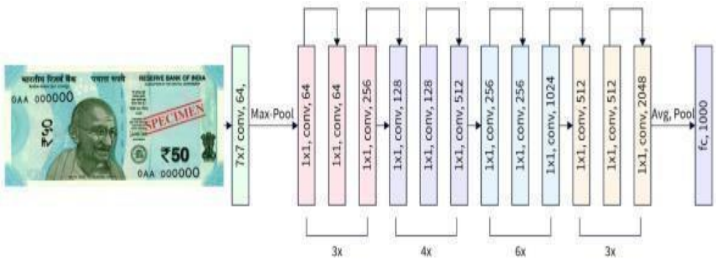

Fig. 5. ResNet Architecture.

The model captures higher features from the input photos by convoluting features throughout an array of layers, and in each of those layers a different part of the photos can be capture.

ResNet is essential to this fake currency recognition system because it takes images of the bills as input and then works to determine whether the given bill is authentic or counterfeit. ResNet introduced a new solution to solve the problem of degrading deep networks based on the traditional Convolutional Neural Network. Because you can more easily maximize weights when you stack lots of layers together a network will tend to perform poorly the deeper it becomes.

4 Results

In this study, three deep learning models CNN, MobileNet, ResNet were tested to evaluate effectiveness of counterfeit currency detection. Performance was measured using various indicators such as precision, recall, accuracy, loss curves, to assess each model's performance. CNN model, which was specifically developed for classifying currency, achieved high accuracy and proved to be a reliable tool for identifying different denominations. MobileNet model achieved the highest success rate of 96.03%, outperforming the other models in distinguishing between real and fake currency. Although ResNet is known for its strong architecture, its accuracy was lower at 74.03%. This underperformance is likely due to complexity of its deeper structure, which required more fine-tuning and larger dataset for optimal results. Fig 6 CNN accuracy and loss for currency and fig 7 ROC curve for CNN model.

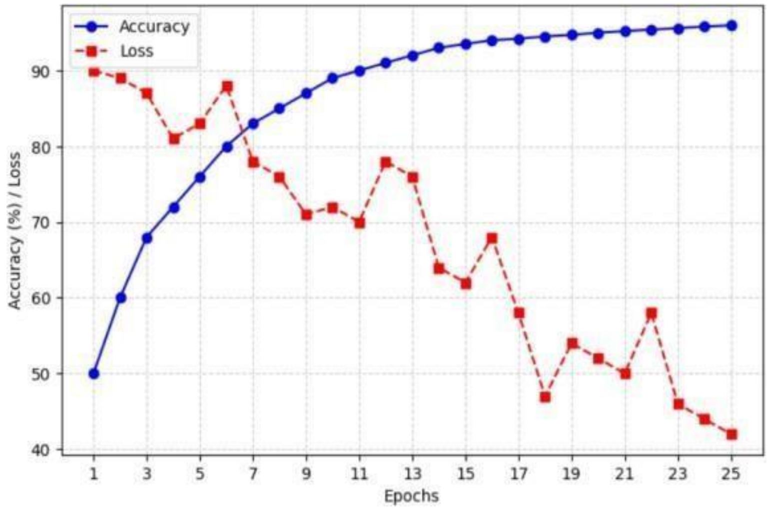

Fig. 6. CNN Accuracy and Loss for Currency.

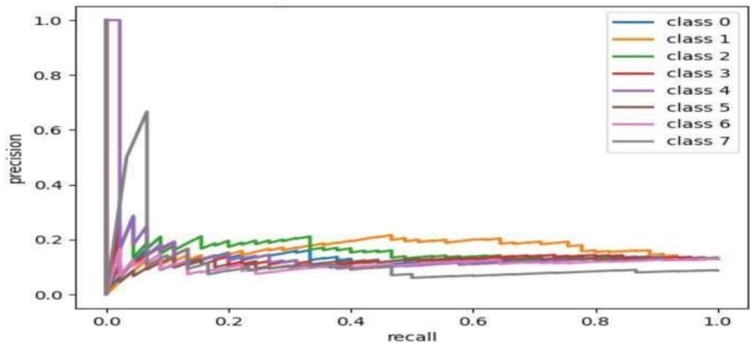

Fig. 7. ROC Curve for CNN Model**.**

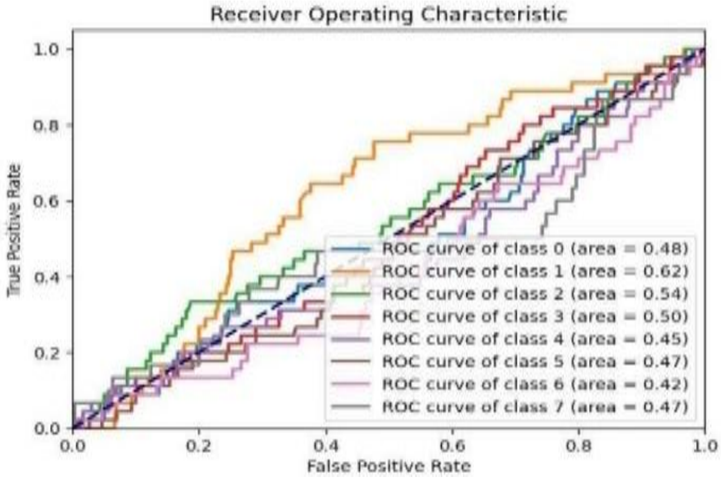

Fig. 8. Precision, Recall Curve for CNN Model.

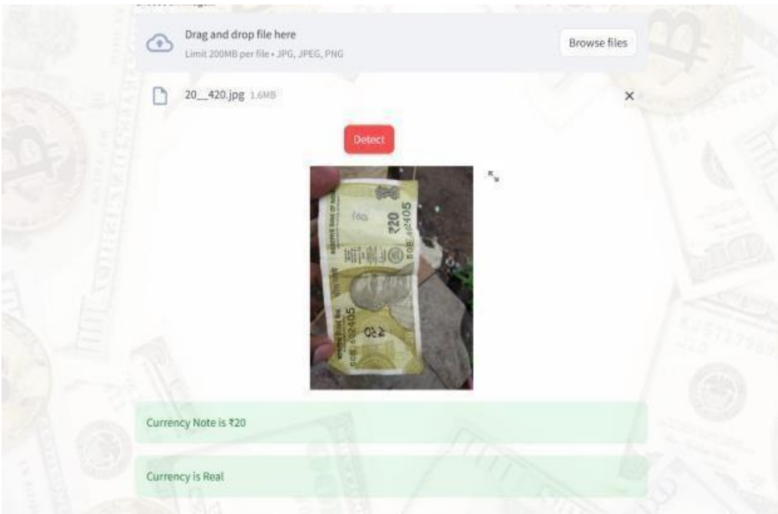

Fig. 9. User Interface.

Fig 8 Precision, Recall Curve for CNN Model. It will be possible for users to submit pictures of bills through a UI, and deep learning algorithms will inspect the pictures to determine whether they are genuine. The model displays the probability scores for each prediction when a user uploads a picture and votes on whether the note is genuine or not. Due to its high precision, we mostly used MobileNet model in real-time detection scenarios to ensure the precise and rapid classification results. Fig 9 and 10 shows the user interface and real time prediction.

Fig. 10. Real Time Prediction.

References

[1] Jahan, N., Alam, S., & Islam, M. (2014). An automatic fake banknote detection system using image processing. 2014 International Conference on Informatics, Electronics & Vision (ICIEV) (pp. 1–6). IEEE. https://doi.org/10.1109/ICIEV.2014.6850773

[2] Li, X., Zhu, C., & Lu, J. (2018). Banknote image counterfeit detection based on visual saliency and deep learning. Journal of Visual Communication and Image Representation, 55, 169–177. https://doi.org/10.1016/j.jvcir.2018.05.007

[3] Amin, M., & Khan, A. (2017). Detection of counterfeit Euro, Dollar and Indian currency notes. 2017 4th International Conference on Advanced Computing and Communication Systems (ICACCS) (pp. 1–5). IEEE. https://doi.org/10.1109/ICACCS.2017.8014603

[4] Rehman, A., Abbas, S., & Nawaz, T. (2019). Deep learning-based automatic counterfeit banknote detection system. 2019 International Conference on Computer and Information Sciences (ICCIS) (pp. 1–6). IEEE. https://doi.org/10.1109/ICCISci.2019.8716468

[5] Mohan, V., & Ramesh, K. (2018). Image preprocessing techniques for currency note recognition in ATMs. International Journal of Computer Applications, 182(3), 10–15. https://doi.org/10.5120/ijca2018917321

[6] Dua, D., & Graff, C. (2019). UCI machine learning repository: Banknote authentication dataset. University of California, Irvine. Retrieved January 5, 2022, from https://archive.ics.uci.edu/ml/datasets/banknote+authentication

[7] Roy, D., & Das, A. (2017). A novel approach for Indian currency recognition and verification using security features. International Journal of Computer Applications, 171(6), 32–37. https://doi.org/10.5120/ijca2017915112

[8] Agarwal, R., & Jain, S. (2016). Human factors in detecting counterfeit currency: A study. Journal of Economic Psychology, 53, 128–135. https://doi.org/10.1016/j.joep.2015.12.003

[9] Khan, M., & Rafiq, M. (2019). Comparative study of traditional and deep learning approaches for counterfeit currency detection. International Journal of Advanced Computer Science and Applications, 10(8), 520–526. https://doi.org/10.14569/IJACSA.2019.0100866

[10] Howard, A. G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., Andreetto, M., & Adam, H. (2017). MobileNets: Efficient convolutional neural networks for mobile vision

applications. arXiv preprint arXiv:1704.04861. https://arxiv.org/abs/1704.04861
[11] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (pp. 770–778). IEEE. https://doi.org/10.1109/CVPR.2016.90
[12] Singh, P., Kaur, G., & Sharma, V. (2019). Real-time currency note authentication using hybrid image processing and deep learning. International Journal of Engineering Research & Technology (IJERT), 8(3), 12–20. https://doi.org/10.17577/IJERTV8IS030176
[13] Gupta, A., Goel, A., & Gokaslan, A. (2019). Towards robust and accurate currency detection using deep learning. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) (pp. 1420–1428). IEEE. https://doi.org/10.1109/CVPR.2019.00152
[14] Sharma, R., Verma, K., & Yadav, P. (2020). Currency recognition using machine learning techniques. International Journal of Computer Applications, 176(32), 25–30. https://doi.org/10.5120/ijca2020920053
[15] Patel, S., Desai, M., & Shah, R. (2021). An ensemble-based machine learning approach for fake currency detection. International Journal of Intelligent Engineering and Systems, 14(6), 367–377. https://doi.org/10.22266/ijies2021.1231.32