INDIAN FAKE CURRENCY DETECTION USING DEEP LEARNING

Hire Rushikesh
Department of Computer Science and Engineering
Maulana Mukhtar Ahmed Nadvi Technical Campus Mansoora
Malegaon (Maharashtra) India
hirerushikesh03@gmail.com

Man Suryawanshi
Department of Computer Science and Engineering
Maulana Mukhtar Ahmed Nadvi Technical Campus Mansoora
Malegaon (Maharashtra) India
mansuryawanshi00@gmail.com

Ashmeer Raza
Department of Computer Science and Engineering
Maulana Mukhtar Ahmed Nadvi Technical Campus Mansoora
Malegaon (Maharashtra) India
ashmeerraza2003@gmailcom

Sujaat Ali
Department of Computer Science and Engineering
Maulana Mukhtar Ahmed Nadvi Technical Campus Mansoora
Malegaon (Maharashtra) India
cosmosinfo.mlg@gmail.com

Dr.Md Salman Baig
Department of Computer Science and Engineering
Maulana Mukhtar Ahmed Nadvi Technical Campus Mansoora
Malegaon (Maharashtra) India
salmanbaig@mmantc.edu.in

Prof.Misbah Kauser
Department of Computer Science and Engineering
Maulana Mukhtar Ahmed Nadvi Technical Campus Mansoora
Malegaon (Maharashtra) India
misbahkauser@mmantc.edu.in

***Abstract*— Fake currency is a serious problem that affects economies worldwide. Traditional methods of detecting counterfeit notes are time-consuming and prone to human error. To address this issue, we propose a deep learning-based approach using convolutional neural networks (CNNs) to accurately identify fake currency. In our study, we implemented four well-known deep learning models—VGG16, VGG19, MobileNet, and ResNet to classify genuine and counterfeit banknotes. We trained our models on a dataset of currency images, achieving high training accuracies: 98.27% for VGG16, 97.48% for VGG19, 99.83% for MobileNet, and 99.38% for ResNet. The results indicate that deep learning models, particularly MobileNet and ResNet, provide highly reliable performance in detecting counterfeit notes. Our approach is efficient, automated, and reduces the need for manual inspection. This research demonstrates that deep learning can significantly improve the accuracy of fake currency detection, making it a valuable tool for banks, businesses, and security agencies. Future work can focus on expanding the dataset, testing on different currencies, and optimizing models for realtime deployment. Our study highlights the potential of AI-driven solutions incombating financial fraud and ensuring secure transaction.**

Keywords*—— *Artificial Intelligence, Computer Vision, Deep learning, Convolutional Neural Network, Image Detection Introduction

I. INTRODUCTION

The detection of counterfeit currency is a critical challenge in financial security, as fake notes can disrupt economies, lead to financial losses, and undermine public trust in monetary systems Several studies have explored different techniques for currency recognition and fraud detection. Kalpana Gautam (2020) used image recognition techniques for Indian currency detection. Similarly, Priyanka Dhapare et al. (2019) applied image processing for counterfeit currency identification. Transfer learning has also been used for banknote recognition, as shown by Ali Abd Almisreb and Mohd A. Saleh (2018). Advanced deep learning models like VGG16, VGG19, MobileNet, and ResNet have been effective in various classification tasks, including medical imaging (Hameed et al., 2020) and object detection (Swathi & Ramana, 2022)In this study, we apply deep learning models to detect fake currency with high accuracy. Our research evaluates **VGG16**, **VGG19**, **MobileNet**, and **ResNet**, achieving accuracy rates of **98.27%, 97.48%, 99.83%,** and **99.38%**, respectively. The results show that deep learning provides an efficient and automated approach for counterfeit currency.

The significance of this project lies not only in its potential to contribute to the fight against counterfeiting but also in the broader implications for the application of deep learning in the financial sector Liu, B., Zhang, X., Gao, Z., Chen, L. (2018). As financial transactions become increasingly digitized, the need for intelligent and adaptive security measures becomes paramount. The successful implementation of this project will mark a substantial advancement in the integration of deep learning technologies for enhancing the security and reliability of financial systems.

II. LITERATURE SURVEY

Counterfeiting of bank currency remains a critical issue globally, prompting significant research efforts to develop effective detection methods. Various studies have explored different approaches to address this challenge, ranging from traditional methods to advanced technological solutions. Prakash et al. (2023) presented a study titled "Deep Learning approaches for Automated Detection of Fake Indian Banknotes" at the 2023 IEEE International Conference on Integrated Circuits and Communication Systems (ICICACS). Their research focused on leveraging deep learning algorithms to develop automated counterfeit detection systems, aiming to enhance the efficiency and accuracy of detection processes [11].

Haralick et al. (1973) introduced "Textural features for image classification," which laid the foundation for texture-based feature extraction techniques widely used in counterfeit currency detection. This seminal work established the importance of texture analysis in pattern recognition tasks [12].

In the financial sector, Chappel et al. (2005) explored "Counterfeit currency detection using image processing" and proposed image processing techniques for counterfeit detection. Their study highlighted the potential of image-based methods in enhancing counterfeit detection accuracy [9].

Roy et al. (2019) investigated "Fake currency detection using image processing" and proposed a method for detecting counterfeit currency using image processing techniques. Their research demonstrated the feasibility of image processing approaches in counterfeit currency detection [6].

LeCun et al. (2015) provided a comprehensive overview of deep learning in their paper titled "Deep learning." They highlighted the capabilities of deep learning algorithms in pattern recognition tasks and their potential applications in various domains, including counterfeit currency detection[7].

Furthermore, recent studies by Sumalatha et al. (2022) and Desai et al. (2021) explored the application of convolutional neural networks (CNNs) and generative adversarial networks (GANs) in “Identification of Fake Indian Currency using Convolutional Neural Network” and “CNN based counterfeit Indian currency recognition using generative adversarial network,” respectively. These studies demonstrated the effectiveness of deep learning techniques in counterfeit currency detection [13][14].

The literature survey highlights the significance of deep learning algorithms and image processing techniques in counterfeit currency detection. By integrating these advanced technologies, the proposed project aims to contribute to the ongoing efforts to combat counterfeiting and enhance the security of financial systems.

BLEED ←IDENTIFICATIO LINESN MARK

- As there is no identification mark for rs. 10/- note, we cannot distinguish between fake and real currency.
- Bleed lines are fixed in rs. 100/-, rs. 200/-, rs. 500/-, rs. 2000/- notes, so it is easy to replicate those bleed lines in fake currency.

III. DATASET

In order to evaluate the proposed model for identifying fake currency notes using convolutional neural network (CNN), we have collected our own dataset. The entire dataset was captured using a mobile camera. The dataset comprises of images of both real and fake currency notes of denominations 10, 20, 50, 100, 200, 500, and 2000 Indian rupee. The dataset consists of a total of 377 images, divided into training and testing datasets. The training dataset has 307 images, with 179 images of real currency and 128 images of fake currency. Similarly, the testing dataset has 70 images, with 35 images of real currency and 35 images of fake currency.

Figure 2: Fake Currency Dataset

The dataset is diverse and includes multiple denominations, making it suitable for training and testing the proposed model. The images were captured in different lighting conditions and angles to ensure the model’s robustness in detecting fake currency notes under various scenarios. We believe that this dataset will serve as a valuable resource for researchers working in the field of fake currency note detection using deep learning and computer vision techniques.

IV. PROPOSED SYSTEM.

Our proposed system for currency notes detection involves several steps:

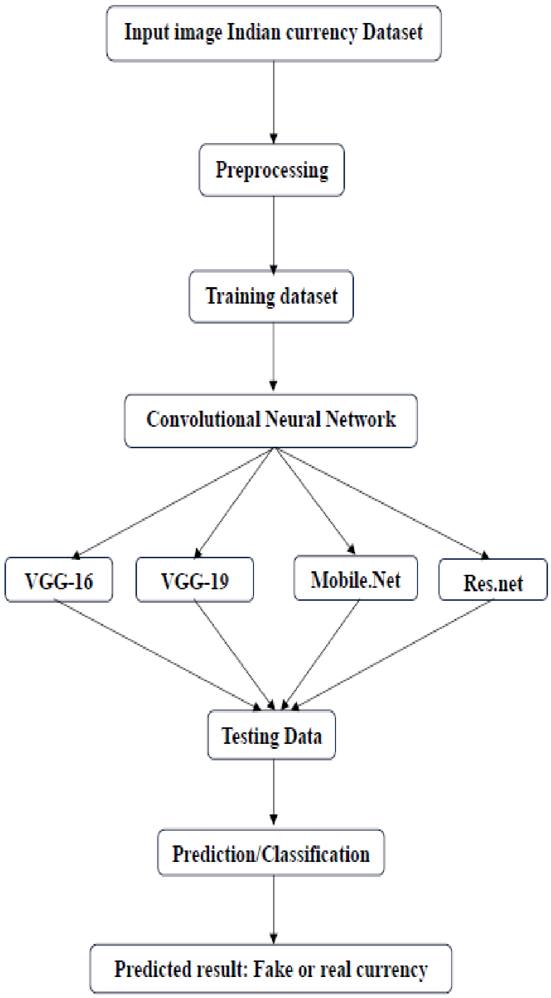

Figure 3: System Flow Chart

- Dataset collection: Collect all currency notes of every denomination, both fake and real, and split them into 80% training and 20% testing datasets.
- Pre-processing: Convert RGB images to grayscale images and apply Gaussian blur to remove any blurriness.
- Edge detection and adaptive thresholding Apply an edge detection algorithm and use adaptive thresholding to segment foreground and background of images, then convert to binary images.
- Training and testing: Train the dataset on a custom CNN model and test the accuracy. Extract features of the dataset to identify the difference between real and fake notes..
- Accuracy calculation: Calculate training and testing accuracy to determine the performance of the system.
- GUI development: Create a Graphical User Interface (GUI) to allow users to input an image, perform feature matching, and provide output indicating whether the note is real or fake.

This proposed system has the potential to improve the accuracy and reliability of currency note detection using deep learning and image processing techniques

A. ARCHITECTURE OF THE PROPOSED MODEL

The proposed model for fake currency detection utilizes deep learning-based convolutional neural networks (CNNs) to classify banknotes as genuine or counterfeit. We have employed four well-known deep learning models—VGG16, VGG19, MobileNet, and ResNet—each offering unique architectural advantages for feature extraction and classification.

a. VGG16 & VGG19

VGG16 and VGG19 are deep CNN architectures that consist of 16 and 19 layers, respectively. These models use small 3×3 convolutional filters, max pooling layers, and fully connected layers for classification. They are effective in learning fine-grained patterns but are computationally expensive. In our study, VGG16 achieved 98.27% accuracy, while VGG19 obtained 97.48% accuracy.

b. MOBILE.NET

MobileNet is a lightweight deep learning model designed for efficient image classification. It utilizes depthwise separable convolutions, reducing the number of parameters and making it faster for real-time applications. Due to its optimized architecture, MobileNet achieved the highest accuracy of 99.83%, making it the best-suited model for counterfeit detection in our research.

c. RES.NET

ResNet (Residual Network) overcomes the vanishing gradient problem in deep networks by using skip connections (residual learning). This allows the model to retain important features without degradation over many layers. ResNet achieved 99.38% accuracy, proving to be highly effective in distinguishing fake and genuine currency notes

Overall System Workflow:

a. Data Preprocessing: Image resizing, normalization, and augmentation.
b. Feature Extraction: CNN-based models analyze textures, patterns, and security features of currency.
c. Classification: A SoftMax layer determines whether the input image is real or fake.

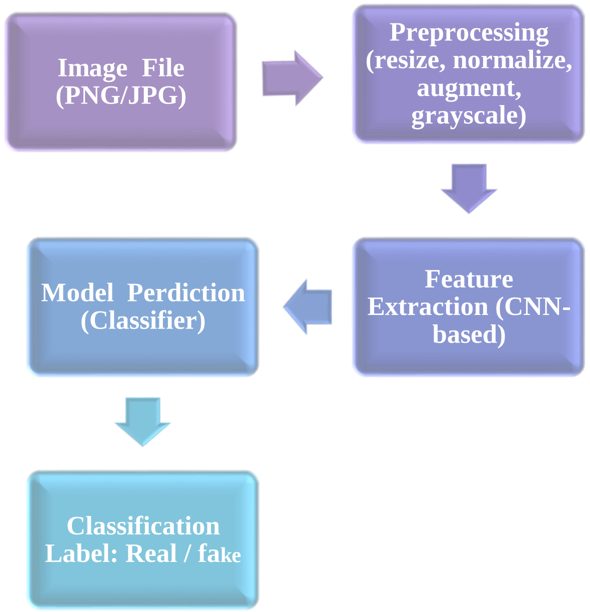

Figure 4: System Workflow

Our model successfully leverages these architectures to provide a highly accurate, automated, and efficient solution for counterfeit currency detection.

V. EXPERIMENTAL RESULTS

In order to evaluate the performance of the proposed model, the metric of accuracy was used. The model was trained on the dataset containing both fake and real currency notes of denominations 10, 20, 50, 100, 200, 500, and 2000, which was split into 80% training and 20% testing datasets. After the model was trained, its accuracy was calculated for both the training and testing datasets.

However, it is important to note that the dataset used in this study was collected using a mobile camera and may not be representative of all types of currency notes or all possible imaging conditions. Further research could explore the performance of the proposed model using larger and more diverse datasets, as well as under different lighting and imaging conditions.

Table1. Performance Comparisons

Model	Testing Accuray	Trainig Accuracy
VGG-16	96.88%	98.27%
VGG-19	94.53%	97.27%
Mobile.Net	98.44%	99.83%
Res.Net	99.22%	99.38%

The results show that the proposed model achieved a high level of accuracy. The training accuracy was found to be 99.83%, indicating that the model was able to accurately classify the majority of the images in the training dataset. The testing accuracy was also found to be high, at 98.44%. This indicates that the model was able to generalize well to new images that were not included in the training dataset. These results suggest that the proposed model is a reliable and effective method for detecting fake currency notes.

Dataset Preparation for any computer vision application, the essential part is the image dataset. The model is trained on these images. Our research revolves around the hidden features of currency notes, for which have collected datasets from kaggle to use in the research.

VI. CONCLUSION

In this project, we presented a methodology for the identification of real and fake currency notes using computer vision and deep learning techniques. We collected a dataset of 377 images captured using a mobile camera, containing real and fake currency notes of various denominations. Fake currency detection is a critical issue that impacts financial stability and security. Traditional methods such as manual inspection and UV scanning have limitations in accuracy and efficiency. To overcome these challenges, deep learning-based approaches have been explored to automate and improve counterfeit detection. In this study, we utilized deep learning models such as VGG16, VGG19, MobileNet, and ResNet to classify fake and genuine currency notes with high accuracy.

Our findings demonstrate that deep learning models are highly effective in counterfeit detection. Among the models tested, MobileNet achieved the highest accuracy of 99.83%, followed by ResNet (99.38%), VGG16 (98.27%), and VGG19 (97.48%). These results indicate that MobileNet and ResNet are particularly well-suited for this task due to their efficient architecture and ability to extract important currency features. The use of convolutional neural networks (CNNs) in these models allows for detailed image analysis, making them more reliable than traditional methods.

Previous studies have also shown the effectiveness of image processing and deep learning in counterfeit detection. Kalpana Gautam (2020) and Priyanka Dhapare et al. (2019) applied image recognition and processing techniques for currency verification, while Ali Abd Almisreb and Mohd A. Saleh (2018) used transfer learning for banknote recognition. Deep learning models have also been successfully applied in various fields such as medical imaging (Hameed et al., 2020) and object detection (Swathi & Ramana, 2022).

Based on our results, deep learning provides a scalable and efficient solution for real-time counterfeit detection. Future improvements can focus on expanding the dataset to include multiple currencies, enhancing model performance under different lighting conditions, and integrating deep learning models into mobile applications and ATMs for widespread use.

VII. REFERENCES

[1] Kalpana Gautam “Indian Currency Detection using Image Recognition Technique”,2020 International Conference on Computer Science, Engineering and Applications (ICCSEA)

[2] Priyanka Dhapare, Akash Agarwal, Devangi Doshi “Detection of Counterfeit Currency using Image Processing Techniques”,2019 IEEE International Conference for Convergence in Technology (I2CT).

[3] Tao Zhang, Zhongnian Li, Qi Zhu, Daoqiang Zhang“Improved Procedures for Training Primal Wasserstein GANs”, 2019 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation.

[4] Ali Abd Almisreb,Mohd.A. Saleh,” Transfer Learning Utilization for Banknote Recognition: a Comparative Study Based on Bosnian Currency”, Southeast Europe Journal of Soft Computing,vol.. 8 no.1,pp.28- 31,March 2018.

[5] https://www.rbi.org.in.

[6] P.Selvi Rajendran,”Virtual Bulletin Board using Man-Machine Interface (MMI) for Authorized Users”, Indian Journal of Science and Technology, vol.12,no.34, September 2019.

[7] Manish Shankar Kaushik, Aditya Bihar Kandali,” Recognition of facial expressions extracting salient features using local binary patterns and histogram of oriented gradients”, International Conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS), 2017.

[8] P.R. Nagpure, T.Ghotkar, S. Shetty, Recognition and Fake Note Detection, International Journal of Innovative Research in Computer and Communication Engineering Vol 4 (March 2016).

[9] Jiang Z-P, Liu Y-Y, Shao Z-E, Huang K-W. An Improved VGG16 Model for Pneumonia Image Classification. Applied Sciences. 2021; 11(23):11185. https://doi.org/10.3390/app1123111 85.

[10] 10. Liu, B., Zhang, X., Gao, Z., Chen, L. (2018). Weld Defect Images Classification with VGG16-Based Neural Network. In: Zhai, G., Zhou, J., Yang, X. (eds) Digital TV and Wireless Multimedia Communication. IFTC 2017. Communications in Computer and Information Science, vol 815. Springer, Singapore. https://doi.org/10.1007/978-981-10- 8108-8_20.

[11] Hameed, Z.; Zahia, S.; GarciaZapirain, B.; Javier Aguirre, J.; María Vanegas, A. Breast Cancer Histopathology Image Classification Using an Ensemble of Deep Learning Models. Sensors 2020, 20, 4373.https://doi.org/10.3390/s20164373.

[12] AriawanI. (2022). Classification of three genera of coral fish using convolutional neural network. Jurnal Ilmu Dan Teknologi Kelautan Tropis, 14(2), 205-216. https://doi.org/10.29244/jitkt.v14i2.33633.

[13] Urmila Samariya, Rakesh K. Sonker. (2022) Comparisons of Image Classification Using LBP with CNN and ANN. Journal of Applied Mathematics and Computation, 6(3), 343-346. DOI: http://dx.doi.org/10.26855/jamc.202 2.09.006.

[14] Gudla Swathi, Kompella Venkata Ramana . (2022) Object Detection And Image Classification Using Deep Learning Model Journal of Engineering Sciences Vol 13 Issue 09,2022, ISSN:0377-9254.

[15] Rathziel Roncancio, Aly El Gamal, Jay P. Gore, Turbulent flame image classification using Convolutional Neural Networks, Energy and AI, Volume 10, 2022, 100193, ISSN 2666-5468, https://doi.org/10.1016/j.egyai.2022. 100193.