A Deep Learning Approach for Enhanced Counterfeit Currency Detection and Classification

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Abstract. Counterfeit currency poses a significant threat to financial systems around the world. In this study, an innovative approach to counterfeit currency detection and classification is proposed leveraging the power of deep learning. The proposed system integrates deep learning models, each trained to identify intricate patterns and features inherent in genuine and counterfeit currency notes. These networks are trained on a comprehensive dataset comprising authentic and counterfeit currency images, allowing the system to learn and distinguish subtle visuals that are challenging for traditional methods. The deep learning approach further refines the detection process, providing a robust and adaptable solution capable of handling various counterfeiting techniques. The pro- posed deep learning approach represents a significant advancement in counterfeit currency detection, combining the strengths of deep neural networks.

Keywords: Counterfeit detection, Deep Convolution Neural Network (Deep CNN), fake currency, deep learning.

1 Introduction

1.1 Background

Counterfeit currency detection is a critical task in maintaining the integrity of financial systems worldwide. With the increasing sophistication of counterfeiters, traditional methods for detecting fake currency notes have become less effective [10]. This approach presents an innovative deep learning approach to significantly enhance the accuracy and reliability of counterfeit currency de- tection and classification. Counterfeit currency has posed an ongoing threat to financial systems, leading to the continual evolution of detection methods. Tra- ditional approaches, based on rule-based systems and simple image processing techniques [9], often fail to identify intricately forged notes. As counterfeiters em- ploy advanced technologies, there is a pressing need for more sophisticated and adaptable detection systems. Previous research has shown the efficiency of deep learning in various image-related tasks, prompting exploration of its potential in counterfeit

N. Bhat et al. (eds.), *Proceedings of the International Conference on Materials, Energy, Environment Manufacturing Sciences Computational Intelligence and Smart Communication (MEEMS-CISC 2024)*, Advances in Engineering Research 269,
https://doi.org/10.2991/978-94-6463-762-5_2

currency detection. By adopting a deep learning approach using the VGG16 model, the challenges of counterfeit currency detection and classification are effectively mitigated. The deep convolutional layers of the VGG16 architec- ture helps to extract intricate features that are important for telling apart real and fake bills.

The paper discusses challenges in detecting counterfeit currency, including the need for versatility in detecting different denominations and currencies, time- consuming manual inspection processes, and evolving counterfeiting techniques with advanced technologies. Conventional procedures struggle to effectively han- dle these issues, necessitating an innovative solution. This paper aims to solve this gap by introducing a deep learning technique that significantly improves the accuracy of counterfeit currency detection and classification.

Currency authentication apps serve multiple sectors: banking and finance, retail, law enforcement, tourism, and currency exchange. They verify currency notes, reducing the risk of counterfeit money acceptance in banking and retail. Law enforcement agencies use them in investigations, while tourist areas bene- fit from preventing counterfeit currency circulation. Currency exchange offices also rely on these apps to authenticate foreign currencies, ensuring transaction security.

2 Literature Survey

The literature survey on counterfeit currency detection and classification serves as a comprehensive exploration of existing research and advancements in the field. This examination delves into various methodologies, technologies, and models employed to address the critical challenge of identifying and distinguishing genuine currency from counterfeit counter parts. Scholars and researchers have extensively contributed to this domain, utilizing a spectrum of techniques ranging from traditional methods to cutting-edge technologies such as machine learning and deep learning. In this proposed paper [4] author aims to address the challenge of banknote recognition for visually impaired individuals through a proposed system leveraging deep learning. Their approach involves VGG16, a pretrained convolutional neural network, to directly process banknotes with various orientations, extracting deep features. It highlights the advantages of VGG16 in extracting deep features accurately compared to the existing system that uses AlexNet. The survey concludes that the proposed method achieves a high accuracy of 99% in recognizing Indian currencies, making it beneficial to visually impaired individuals.

Here [6] author investigated a solution using K-Nearest Neighbors (KNN) and image processing to swiftly detect counterfeit currency in electronic de vices. With a focus on addressing the rising cases of counterfeit currency in India, the research aims to enhance the accuracy using the KNN algorithm for effec- tive classification. The approach integrates traditional methods with advanced computational techniques, offering a streamlined solution to combat fraudulent activities related to counterfeit currency consistently outperforms, achieved an accuracy of 99.2%, with 80% of the results being 100% accurate. GBC closely follows KNN with 99.4% ac curacy, while SVC lags behind with 97.5%. Notably, all three algorithms maintain impressive accuracy levels above 97%.

Fake currency directly effects the economic condition of the country [3]. so here the article, proposed solution which involves Deep Learning, specifically a Convolution Neural Network (CNN) model, to identify counterfeit notes using images captured by smartphone cameras. The model, trained and tested on a self-generated dataset, achieves an accuracy of approximately 85.6%. Despite the success, there is room for further research and improvements in the Deep CNN model architecture [2]. The issue is crucial as counterfeit currency poses a significant challenge, even with the security features implemented by the Reserve Bank of India (RBI). The proposed deep learning model aims to address this challenge by automating the detection process through image classification.

The research on fake Currency Detection Using Machine Learning [7] gave technological advancements in printing and scanning has exacerbated the issue of counterfeiting, impacting economies. Traditional methods based on hardware and image processing are inefficient and time consuming. To address this, article

[7] proposed an approach which uses transfer learning, where a pre-trained CNN model is fine-tuned on a dataset of 2000 images of real and counterfeit Indian currency notes to learn the feature maps. Once trained, the CNN model can iden- tify fake currency in real-time by examining input currency images, eliminating the need for manual feature extraction used in traditional methods. The pro- posed CNN-based approach aims to provide an efficient, accurate solution with less time consumption compared to traditional methods. It can assist common people in identifying counterfeit notes. Future work includes exploring different CNN architectures to improve accuracy and increasing the dataset size.

The research [5] describes a proposed web application for detecting fake Indian currency notes using image processing and deep learning techniques. The motivation behind this application is to provide a solution for common people to identify counterfeit currency notes easily. It proposes a mechanism for detecting fake currency notes by leveraging image processing and deep learn- ing techniques like CNN. It discusses the motivation, features extracted, and a high-level system architecture. The study [1] presents a method for detecting counterfeit Indian currency notes using machine learning techniques. The paper proposes an effective machine learning based approach utilizing image features and logistic regression for accurate detection of counterfeit Indian currency notes compared to conventional methods. The model achieves an accuracy of 98.36% in correctly identifying genuine and counterfeit banknotes on the test data.

The Proposed manuscript [8] gives a method for real-time detection of counterfeit Indian currency notes (denominations of 50, 200, 500 and 2000) using deep learning techniques, specifically a transfer learning approach with the AlexNet convolutional neural network (CNN). The AlexNet CNN model pre-trained on a large dataset is used. During real-time detection, an input currency image is captured, and the fine-tuned AlexNet model extracts the learned features to compare with the genuine currency features and predict if the note is real or counterfeit. The proposed method achieved an average accuracy of 81.5% in detecting genuine notes and 75% in detecting counterfeit notes across the four denominations tested.

The articles reviewed collectively underscore the significant challenge posed by counterfeit currency detection. Numerous studies emphasize the effective- ness of Convolutional Neural Networks (CNNs) and transfer learning, reporting impressive accuracy rates, including 99 with the VGG16 model and 85.6 with alternative models. Additionally, machine learning methods such as K-Nearest Neighbors (KNN) and Logistic Regression exhibit robust performance, achieving accuracy levels above 98. Traditional image processing methods concentrate on feature extraction, leveraging security features like watermarks, latent images, and ultraviolet lines. Proposed applications encompass mobile applications de- signed for visually impaired individuals, web-based platforms accessible to the public, and real-time detection systems aimed at high-value currency denominations.

There is notable drawback in the existing literature, including an over reliance on restricted datasets that hinder generalizability and a lack of emphasis on the integration of real-world applications, such as banking systems. The vari- ability in accuracy underscores the necessity for the optimization of deep learning models, while the concentration on Indian currency restricts the applicability to multiple currencies. The practical implementation of accessible and user-friendly solutions, as well as the issue of counterfeiting in lower denominations, has not been sufficiently examined. By addressing these deficiencies, the efficacy of coun- terfeit detection systems can be significantly improved.

3 System Design

3.1 Architectural diagram

The system architecture shown in the Fig 1 makes use of a number of interconnected parts to make the identification and categorization of counterfeit currency easier. The dataset assembly, which contains pictures of real and fake banknotes, is its central component. The machine learning model is trained and evaluated using this dataset. After ingesting data, various data sources such image files or databases are combined and preprocessed like resizing, normalization, noise reduction, and feature extraction to get ready for the next step of training the model. The architecture and implementation of the counterfeit cash detection model, which is usually based on Convolutional Neural Networks (CNNs) and optimized for image classification tasks, are most likely contained in the model.py Python script file. Using preprocessed pictures from the dataset, trained CNN models go through a rigorous training process where they iteratively refine parameters to enhance performance and reduce over fitting. When training results are adequate, the model is serialized and saved for later use.

The test dataset is different from the training dataset and is used to evaluate the generalization skills of the model. The trained model is then provided with captured images of money notes for real-time classification, which makes authenticity prediction possible. 'Predict Fake or Real' is the last stage, when the CNN model is used to assess input photos and produce classifications that show whether the money notes are genuine or not.

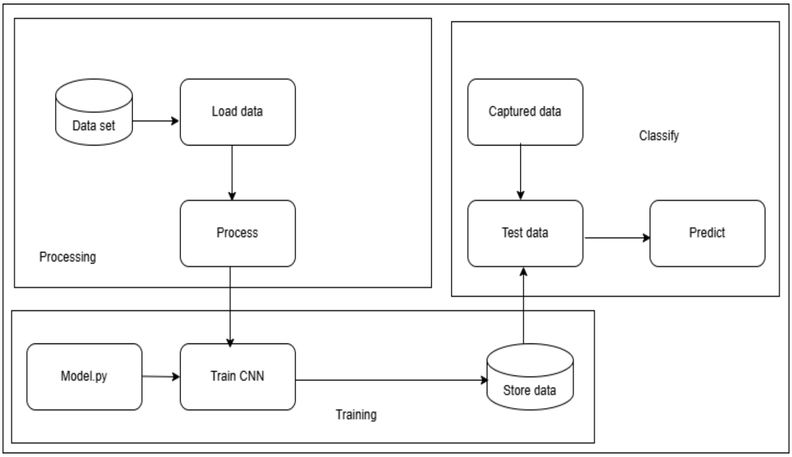

Fig. 1. Architectural Diagram

4 Implementation

4.1 Dataset Description

The dataset was gathered from diverse sources, including publicly available images from Google and mobile phone pictures captured specifically for this proposal. This combination ensured a comprehensive dataset comprising various perspectives and scenarios, enhancing the model's robustness and generalization capabilities. Fig2 refer to a sample in the dataset of fake and real currency.

4.2 Design Of Models

Image Preprocessing. This stage involves converting the image to a tensor format compatible with Tensor Flow operations. This process includes selecting the RGB channels, expanding dimensions to add a batch dimension for batch processing, resizing the image to a standardized size of 224x224 pixels, and normalizing the pixel values to a range between 0 and 1. These preprocessing steps ensure that the input images are properly formatted and scaled for effective training of the machine learning model. Preprocessing involves augmenting the dataset with operations like rotation or flipping to enhance its diversity and robustness.

Fig. 2. Dataset Screenshot of fake and real currency

Model Construction. The VGG16 architecture was selected as the model because it has a track record of success in image classification tasks, which makes it a good fit for applications like counterfeit currency detection. With 16 layers total 13 convolutional and 3 fully connected—the VGG16 deep convolutional neural network is well-known for its robust performance and ease of use.

Training and Testing. The dataset is partitioned into 80% training and 20% for validation sets for model development. Training progresses while moni- toring and adjusting hyper parameters to optimize performance. Techniques like gradient descent are employed to update model parameters, minimizing the loss between predicted and ground truth change masks during training. The testing process ensures that the model trains correctly on the provided data.

4.3 Algorithm Design

– **VGG16 Model Architecture.** The architecture of VGG16 comprises a comprehensive arrangement of convolutional layers, pooling layers, and fully connected layers meticulously de- signed to extract intricate features from input images, enabling robust pat- tern recognition and classification tasks. It takes in images as input, usually 224 by 224 pixels with three RGB color channels. There are thirteen convolutional layers in the network, and an activation function called a Rectified Linear Unit (ReLU) comes after each one. From the input images, these convolutional layers are in charge of extracting distinct information at various degrees of abstraction. These layers are added after a few convolutional lay- ers in order to decrease the feature maps' spatial dimensions. This process essentially down samples the features while keeping the most pertinent data. The final three layers of the network are fully connected layers, and they use the features from the convolutional layers before them to conduct classification. Each of the initial two completely connected layers contains 4096 neurons, followed by a final output layer with 1000 neurons, corresponding to the 1000 classes in the ImageNet dataset for which VGG16 was originally trained. The output layer typically employs a SoftMax activation function to convert the raw output scores into probabilities, representing the likelihood.

5 Results and Discussion

In this study on counterfeit currency detection using a deep learning ap- proach, a dataset comprising a total of 500 banknotes, with 20% reserved for validation was utilized. The proposed model achieved a remarkable F1 score of 95.83%, indicating its robust performance in balancing precision and recall.

5.1 Results

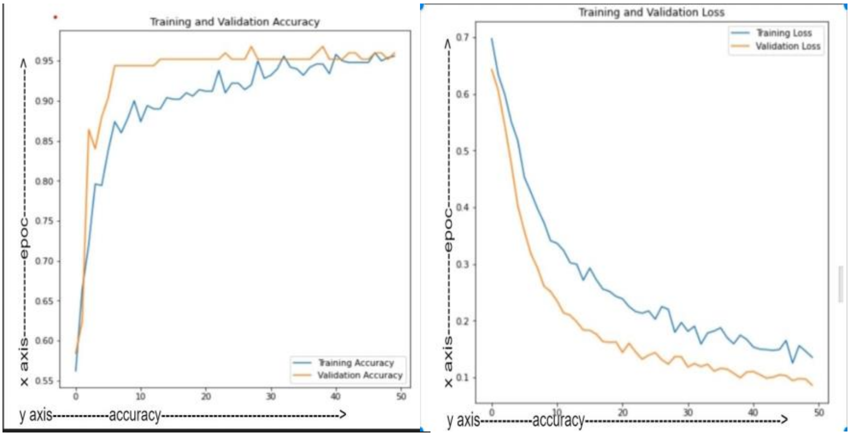

Fig. 3. Accuracy and Loss graph of VGG16 Model

The accuracy graph and the loss graph shown in Fig. 3 for a VGG16 model depict its performance during training and validation. The accuracy graph illustrates how well the model classifies data over iterations, with the blue line representing training accuracy and the red line indicating validation accuracy. An upward trend in both lines indicates improved performance, while a plateau or decline in validation accuracy relative to training accuracy may indicate over-fitting. In contrast, the loss graph illustrates the error rate of the model, with lower values indicating better performance. The blue line represents training loss, which should decrease over iterations as the model learns.

The confusion matrix serves as a visual representation of the performance of a classification model, offering a comprehensive breakdown of its predictive capabilities. Each cell within the matrix delineates the classification outcomes, with the diagonal cells representing correct classifications (true positives and true negatives) and the off-diagonal cells indicating misclassifi- cations (false positives and false negatives). This matrix facilitates a nuanced understanding of the model's strengths and weaknesses, guiding efforts to refine its accuracy and effectiveness in distinguishing between genuine and fake currency. Fig 4 shows the matrix out of the total instances examined, there were 70 true positives, indicating that the model correctly identified 70 instances of fake currency. This suggests the effectiveness of the model in accurately flagging counterfeit currency.

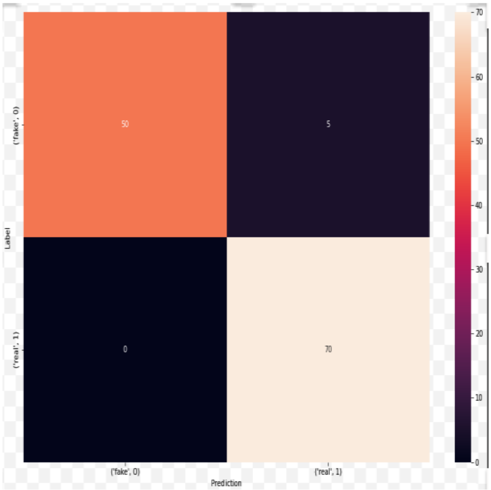

Fig. 4. Confusion Matrix

6 Conclusion and Future work

In conclusion, the comprehensive exploration conducted in this study demonstrates the effectiveness of utilizing deep learning techniques for fake currency detection. The proposed approach achieves high precision in identifying counterfeit bills. Moving forward, the focus will be on integrating all security features of currency into a robust foundational framework, accompanied by thorough preparatory data. Through rigorous experimentation, the proposed model was successfully implemented and tested various strategies outlined in this study. Notably, Convolutional Neural Networks (CNN) emerged as the optimal feature for the proposed approach, showcasing remarkable performance in model classification with a 95% accuracy rate. In future iterations of this work, a key focus will be on broadening the scope of the dataset by incorporating varied datasets encompassing different currency types, denominations, and appearances, one could aim to enhance the model's adaptability and accuracy across global contexts.

Disclosure of Interests. The authors have no competing interests.

References

1. Beigh, T. M., Arivazagan, J., Venkatesan, V. P. *Counterfeit Currency Detection using Machine Learning*. Journal of Emerging Technologies and Innovative Research, 10(3), 356–358, 2023.
2. Gaikwad, Mayadevi A., Vaijinath V. Bhosle, and Vaibhav D. Patil. *Au- tomatic Indian New Fake Currency Detection Technique*. International Journal of Engineering Research & Technology (IJERT), 6(11), 2017. DOI:10.17577/IJERTV6IS110028
3. K. Kamble, A. Bhansali, P. Satalgaonkar, and S. Alagundgi, *Counterfeit Currency Detection using Deep Convolutional Neural Network*. 2019 IEEE Pune Section International Conference (PuneCon), Dec. 2019, DOI: 10.1109/punecon46936.2019.9105683.
4. Raj N, Dr. Nijil and Ram, Anandu S and Joseph, Aneeta Binoo and S, Shabna, *Deep Learning Based Indian Currency Detection for Visually Challenged using VGG16* International Journal of Recent Technology and Engineering (IJRTE), vol. 9, no. 2, pp. 969–972, Jul. 2020, DOI: 10.35940/ijrte. b3955.079220.
5. Gaikwad, A., Dudka, S., Shah, D. G., Mitkar, S., and Kumbhar, P. *Fake Cur- rency Detection Web Application*. International Research Journal of Modern- ization in Engineering Technology and Science, May 2023, DOI: 10.56726/irjmets39409.
6. Bhatia, A., Kedia, V., Shroff, A., Kumar, M., Shah, B. K. *Fake currency detection with machine learning algorithm and image processing*. 5th international conference on intelligent comput- ing and control systems (ICICCS). IEEE, 2021. DOI: 10.1109/ICICCS51141.2021.9432274
7. Lakshmi, B. Naga, and G. Sarath Kumar. *Fake Currency Detection Using Machine Learning*. Journal of Engineering Sciences 13.12 (2022).
8. M. Laavanya, V. Vijayaraghavan. *Real Time Fake Currency Note Detection using Deep Learning* . International Journal of Engineering and Advanced Technology (IJEAT),, vol. 9, no. 1S5, pp. 95–98, Dec. 2019, DOI: 10.35940/ijeat.a1007.1291s52019.
9. Nagendra Kumar, Naseem Ahmad, Amit Mittal and Akhilesh Singh. *Detection of Fake Currency Notes Using Image Processing Technique*. International Conference on Emerging Research Areas DOI:10.1109/AICERA/ICIS59538.2023.10420367.
10. Pummi Dhiman *A Scientometric Analysis of Deep Learning Approaches for Detecting Fake News*.vol. 12, no. 4, p. 948, Feb. 2023, doi: 10.3390/electron- ics12040948.