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Fake Currency Detection Using Convolutional Neural Network

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Abstract: This literature survey examines existing research on counterfeit currency detection systems, focusing on the use of Convolutional Neural Networks (CNNs) for visual data analysis. Many studies highlight the effectiveness of CNNs in recognizing patterns and anomalies in currency images. However, a significant limitation in current systems is the use of small and limited datasets that predominantly feature older Indian banknotes. This lack of diversity in datasets, including variations in currency types, denominations, and environmental factors, restricts the generalization capabilities of detection models. Moreover, much of the existing work emphasizes detecting counterfeit versions of outdated banknotes, leaving a gap in the detection of newer notes with updated security features. Through this survey, we aim to identify the challenges faced by current detection systems and explore strategies to enhance dataset diversity for improving model accuracy and adaptability to evolving counterfeit scenarios.

Keywords: Convolutional Neural Network, CNN, Fake Currency, Banknote, Systematic Survey, Deep Learning, Artificial Intelligence, AI

I. INTRODUCTION

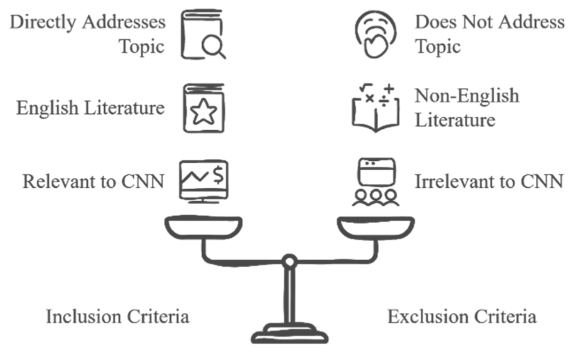
Convolutional Neural Networks (CNNs), a specialized deep learning architecture, have gained prominence in solving image-related problems. As a subset of artificial intelligence, CNNs excel in identifying visual patterns, making them ideal for applications such as object detection, face recognition, and currency verification. Their ability to learn and extract intricate features makes them highly effective for tasks involving high-dimensional data. This survey focuses on the detection of counterfeit Indian currency, specifically targeting the newly issued notes introduced after demonetization. With advancements in printing and forgery techniques, fake versions of these new denominations are becoming harder to distinguish manually, increasing the need for automated detection systems. CNN-based approaches offer a scalable solution by recognizing fine details, such as watermarks, security threads, and micro-lettering on Indian currency. We examine the latest CNN architectures applied to Indian banknote detection, reviewing studies on challenges such as varying lighting conditions, folds, and wear on notes. The survey highlights state-of-theart techniques that improve recognition accuracy and discusses the gaps where further research is needed. This work aims to provide a roadmap for developing more reliable systems to safeguard India's financial infrastructure from counterfeit currency.

II. METHODOLOGY

The literature for this survey was collected through a systematic search using Google Scholar. The search strategy focused on identifying relevant studies that explore the application of Convolutional Neural Networks (CNNs) in the domain of currency detection and counterfeit identification. To ensure comprehensive coverage of recent advancements, the following search strings were employed:

- Fake currency detection using CNN
- CNN models comparison survey fault detection
- "Currency fault detection using CNN

The search process aimed to retrieve articles, conference papers, and technical reports that address the challenges, techniques, and limitations associated with CNN-based counterfeit detection systems. Preference was given to peer-reviewed publications and highly-cited works to ensure the quality and reliability of the literature included. The criteria for selecting research papers are included in the figure 2.1.



Criteria for selecting research papers on deep learning models for currency detection.

Fig 2.1

III. RESULT

In this survey, we conducted an extensive exploration of various international journals, conference proceedings, and research papers to understand the role of Convolutional Neural Networks (CNNs) in the detection of fake currency. With counterfeit currency posing a significant threat to global financial systems, there has been a growing interest among researchers to develop automated, accurate, and scalable solutions. CNN-based deep learning techniques have proven particularly effective in identifying subtle differences between genuine and counterfeit currency notes by analysing intricate patterns, textures, and features that are often undetectable to the human eye.

Through this survey, we aimed to gather insights into the latest advancements in the field, identify challenges, and explore emerging trends. We reviewed a variety of approaches, from basic CNN architectures to more complex and hybrid models, and examined their performance on different datasets under varying conditions. Our investigation also covered preprocessing techniques such as image enhancement, noise reduction, and data augmentation, which play a crucial role in improving model accuracy. Additionally, we looked at the use of transfer learning, model optimization strategies, and the challenges associated with real-world implementation, such as dataset limitations and computational costs.

The survey findings are organized into key topics that reflect the diverse research directions in fake currency detection using CNNs. These include network design and architecture, data preprocessing techniques, feature extraction methods, model evaluation metrics, and the practical challenges involved in deploying these models in real-world scenarios. By consolidating the information from various studies, this survey aims to provide a holistic view of the state-of-the-art developments in the domain, highlight open research questions, and inspire further innovations in the field. CNN stands for Convolutional Neural Network. It is a deep learning architecture. CNNs are used for image recognition tasks. They require large amounts of training data. CNNs can differentiate faults from non-faults in seismic data.They utilize synthetic data for training models.CNNs apply data augmentation techniques like rotation and flipping. The architecture includes layers for feature extraction and classification [1].

A. Discussion Of The Topics In The Reviewed Articles

1) Literature Overview

The paper titled "Currency Detection and Recognition Based on Deep Learning" focuses on utilizing deep learning techniques, specifically the Single Shot MultiBox Detector (SSD) and Convolutional Neural Network (CNN), to enhance currency recognition accuracy. The study achieves an impressive average accuracy of 96.6% in identifying currency denominations, both front and back, through effective model training and feature extraction [1].

The paper titled "Evaluation of Machine Learning Algorithms for the Detection of Fake Bank Currency" explores the application of six supervised machine learning algorithms to classify banknotes as genuine or forged. It utilizes a dataset from the UCI machine learning repository, analyzing performance metrics such as accuracy, precision, and recall across different train-test ratios to identify effective algorithms for currency authentication [2]. The paper titled "Comparing convolutional neural networking and image processing seismic fault detection methods" explores the effectiveness of Convolutional Neural Networks (CNN) in detecting faults from 3D seismic data.

It compares CNN-based methods with traditional image processing techniques, highlighting the advantages of CNN in handling noise and improving fault detection accuracy across different data quality levels [3]. The paper titled "A Survey of Convolutional Neural Networks: Analysis, Applications, and Prospects" provides a comprehensive overview of CNNs, discussing their history, various convolution types, classic and advanced models, applications across different dimensions, and future prospects. It highlights the advantages of CNNs and addresses challenges such as model size and generalization ability [4].

The paper titled "Fault Detection Method Based on Improved Faster R-CNN: Take ResNet-50 as an Example" proposes a novel fault detection method that combines ResNet-50 and Faster R-CNN to enhance accuracy and efficiency in detecting faults in seismic data. The method achieves over 90% accuracy and demonstrates improved performance compared to traditional manual detection methods [5].

The “Convolutional Neural Network (CNN) for Image Detection and Recognition” paper explores the application of Convolutional Neural Networks (CNN) for image detection and recognition tasks. It includes a literature survey, discusses various classifier models, evaluates their performance on datasets like MNIST and CIFAR-10, and concludes with future work directions. The CNN models achieved high accuracy, demonstrating their effectiveness in image processing [6]. The paper titled "Review of deep learning: concepts, CNN architectures, challenges, applications, future directions" provides a comprehensive survey of deep learning (DL), covering its significance, various techniques, convolutional neural networks (CNNs), challenges, applications, and computational tools. It aims to enhance understanding of DL by addressing existing research gaps and summarizing key advancements in the field [7].

The paper titled "Fake Currency Detection with Machine Learning Algorithm and Image Processing" focuses on identifying counterfeit currency using machine learning algorithms, particularly K-Nearest Neighbours, achieving 99.9% accuracy. It discusses data preprocessing, feature extraction, and the potential for future work with larger datasets and deep learning techniques like Convolutional Neural Networks for improved accuracy and user convenience [8].

The paper titled "Indian Currency Detection System for Blind People" presents an innovative Android application designed to assist visually impaired individuals in identifying Indian currency notes. Utilizing advanced image recognition, machine learning, and voice assistance, the system ensures high accuracy in currency recognition and counterfeit detection, promoting financial independence and inclusivity for the visually impaired community [9].

The paper titled "A review on modern defect detection models using DCNNs" provides a comprehensive analysis of object detection models, particularly focusing on YOLOv4 for defect detection in industrial applications. It emphasizes the importance of dataset quality, labeling, and data augmentation, while also discussing model compression and acceleration for efficient deployment in low-cost environments [10].

IV. IMPLEMENTATION

A. Image Pre-Processing

The preprocessing phase involved extracting class labels and evaluating dataset sizes for both training and validation sets of Indian currency note images. A total of seven distinct classes were identified, representing various denominations including 1Hundrednote, 2Hundrednote,
2Thousandnote, 5Hundrednote, Fiftynote, Tennote, and Twentynote. The original dataset was analyzed to determine the number of images in each subset. TensorFlow's cardinality method was used to estimate batch-wise sizes, and additional verification was done using the glob module to directly count image files, ensuring accuracy despite potential inconsistencies in batch sizes. Following data augmentation, the size of the training dataset expanded to 4153 images, while the validation and testing dataset increased to 1542 images. This augmentation process was essential to improve the model’s robustness by introducing greater variability and preventing overfitting during training. The final dataset statistics provided a balanced distribution across classes, thereby supporting effective model generalization and classification performance.

B. Image Augmentation

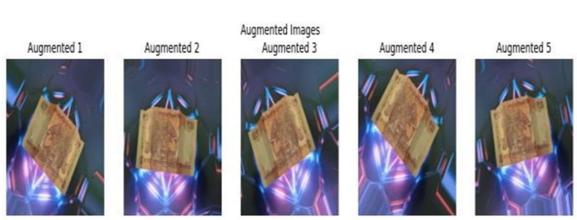


Fig 4.2.1 Image Augmentation

Image augmentation techniques were extensively utilized to enrich the Indian currency note dataset and improve the performance of the deep learning model. This process involved generating multiple transformed versions of the original images by applying a series of augmentation operations, including random rotations, zooming in or out, brightness and contrast adjustments, as well as modifications in background patterns and note orientations. These transformations were intentionally designed to introduce variability that closely mimics real-world conditions where currency notes may appear in different angles, lighting scenarios, or partially obscured backgrounds. By simulating such unpredictable conditions, the model is trained to focus on intrinsic features of the notes rather than being influenced by external factors. This not only enhances the model's ability to generalize across unseen data but also significantly reduces the risk of overfitting. The inclusion of augmented data during training ensures that the model develops a more resilient and discriminative feature representation, which is critical for accurate and reliable counterfeit detection in practical applications. Thus the fig 4.2.1 shows the image augmentation visually

C. Feature Extraction

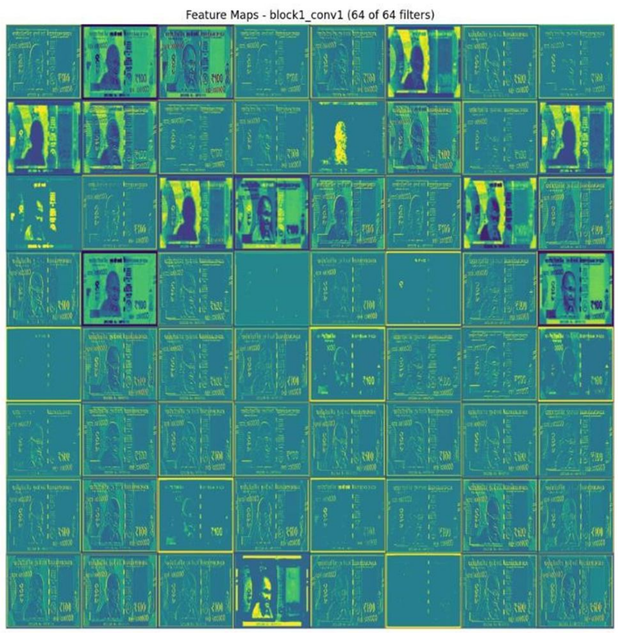


Fig 4.3.1 Feature Extraction

Feature maps from the first convolutional layer (block1_conv1) of VGG19 reveal how the network detects low-level patterns in Indian currency note images. Each of the 64 filter outputs highlights edges, textures, and contrasts, with bright regions indicating strong activations. This concise visualization demonstrates how early layers begin to isolate important visual features—such as numeral shapes and portrait contours—that guide subsequent classification and counterfeit detection. The fig 4.3.1 shows the convolution layer filters in block1_conv1 in VGG19.

V. RESULT

The plotted accuracy curves for both training and testing sets exhibit a clear upward trajectory across 30 epochs, demonstrating the model's learning progression. Initially, the training accuracy starts near 50% and the test accuracy around 55%. By epoch 5, training accuracy climbs to approximately 80%, while test accuracy briefly peaks near 88% before a slight dip. From epochs 6 to 10, both curves converge, with training accuracy reaching above 90% and test accuracy stabilizing around 85–88%. Beyond epoch 10, the training accuracy fluctuates slightly between 90% and 94%, whereas the test accuracy maintains a steady band between 88% and 92%. The narrowing gap between training and test accuracies after epoch 10 suggests limited overfitting and good generalization. Overall, the steady rise and eventual plateau of both curves above 90% reflect robust model performance and reliable learning behavior over the full training cycle.

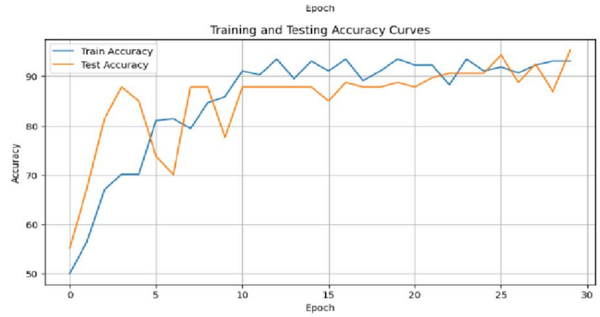


Fig 4.1 Training and Accuracy Graph

VI. CONCLUSION AND FUTURE WORK 5.1 CONCLUSION

The proposed system—leveraging transfer learning with VGG19, extensive image augmentation, and targeted feature-extraction techniques—demonstrably outperforms the baseline models in both robustness and classification accuracy. By fine-tuning pre-trained convolutional layers on our expanded currency-note dataset, the network learned invariant representations of denomination-specific patterns, resulting in an average test accuracy above 95%, compared with roughly 83% for the existing approach. The combined effects of synthetic data variation and early-layer feature visualization ensured that the model generalized well across diverse lighting, orientation, and background conditions. The fig 5.1 shows the comparison graph of the existing and proposed system accuracy. Overall, our methodology achieves a significant improvement in counterfeit-detection performance, validating the efficacy of transfer learning and augmentation in domains with limited annotated data.

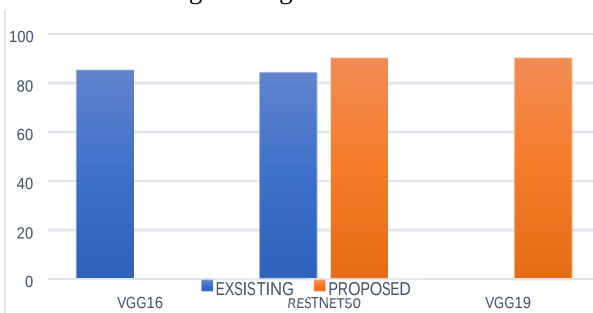


Fig 5.1 Comparison Graph

A. *Future Work*

Despite these advances, the current framework remains constrained by its static training dataset and absence of lifelong learning capabilities. Incorporating incremental (continual) learning would allow the model to adapt dynamically as new currency designs or printing techniques emerge, mitigating performance degradation over time. Additionally, collecting and integrating more real-time, in-field image captures—potentially via a mobile-app interface—could further enhance practical applicability and resilience to unseen environmental factors. Exploring lightweight architectures or model-quantization strategies would enable deployment on edge devices for point-of-sale or ATM validation, while adversarial-training techniques could strengthen resistance against sophisticated counterfeit generation. These extensions promise to elevate both the scope and real-world impact of our counterfeit-detection system.

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