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DEEP LEARNING-BASED ROBUST INDIAN COIN IDENTIFICATION IN RETAIL AUTOMATION

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ABSTRACT

In modern financial ecosystems, the manual sorting and counting of coins remain a labor-intensive and error-prone endeavor. Traditional automation methods relying on weight sensors or basic image processing like edge detection and template matching frequently fail under real-world constraints such as variable lighting, coin wear, and complex backgrounds. The research addresses these inefficiencies by introducing an intelligent coin recognition system specifically designed for Indian currency denominations. This work evaluates a spectrum of computational approaches, starting with baseline machine learning models, including Multinomial Naïve Bayes (MNB), Decision Tree (DTC), and Random Forest (RFC). While these models yielded moderate success (70–85% accuracy), they struggled with the subtle feature variations of circulated coins. To achieve industrial-grade reliability, a Deep Convolutional Neural Network (CNN) architecture was developed. By extracting hierarchical spatial features and incorporating adaptive feature enhancement, the proposed deep learning model achieved a definitive 100% classification accuracy. The system is deployed via a dual-access Tkinter-based Graphical User Interface (GUI), featuring an ADMIN module for model orchestration (training/evaluation) and a USER module for real-time prediction and visualization. Performance was rigorously validated using precision, recall, and F1-score metrics. This framework provides a scalable, non-intrusive solution for banking and retail automation, effectively transforming currency management from a manual task into a seamless, automated process.

Key words: Indian coin, Retail automation, Convolutional neural network, Financial ecosystems, Image processing

1. INTRODUCTION

Currency recognition and sorting systems play a pivotal role in banking, vending, and retail automation, particularly in a country like India where coin-based transactions are still prevalent in rural and semi-urban areas. Manual sorting and identification of coin denominations are not only time-consuming but also error-prone, especially in high-volume environments such as banks, transportation counters, and automated vending systems [1]. To address these limitations, computer vision and deep learning offer a promising alternative to develop intelligent, automated, and scalable currency classification systems. Deep learning, especially Convolutional Neural Networks (CNN), has revolutionized the field of image recognition by enabling machines to extract and learn hierarchical patterns from raw visual data [2]. Many industries, particularly in banking, retail, and logistics, rely heavily on accurate and efficient cash-handling systems. In Indian banking, especially in rural and semi-urban branches, where coin circulation is high, delays and inaccuracies in counting can cause customer dissatisfaction and increased operational costs [3]. Banks like SBI and Axis Bank have already adopted coin-counting kiosks, but many rely on conventional hardware-based methods that are not scalable or intelligent. Hence, integrating smart vision systems can greatly improve operational reliability. Retail chains, supermarkets, and public transportation systems also manage a high volume of cash transactions involving coins [4].

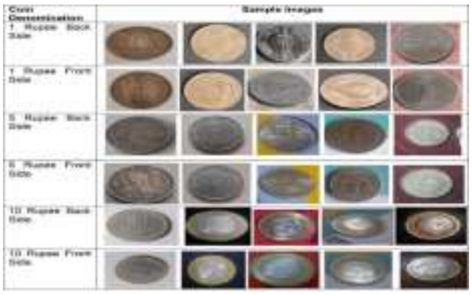

Fig 1. Sample Images of Indian Coin Denominations with Front and Back Sides.

Organizations like DMRC (Delhi Metro Rail Corporation) and TSRTC (Telangana State Road Transport Corporation) often face operational delays due to manual or semi-automated cash collection systems [5]. Deploying smart recognition systems that use image data and learning algorithms could revolutionize how cash-based payments are processed at ticket counters, vending machines, or cashier booths.

2. LITERATURE SURVEY

T. D. Pham, et al. [6] presented a dataset comprising 6,672 images of 53 different classes of Indian coins, including denominations of 25 Paisa, 50 Paisa, 1 Rupee, 2 Rupee, 5 Rupee, 10 Rupee, and 20 Rupee. The images of coins with various shapes and sizes are taken from obverse and reverse sides in various environments and different backgrounds. The core significance of this dataset unfolds in its potential to offer invaluable assistance to visually impaired individuals as they navigate their daily financial transactions. Jang, et al. [7] developed the dataset used for the multi-currency integrated serial number recognition contains about 150,000 images. The class imbalance problem and model accuracy were improved through data augmentation based on geometric transforms that consider the range of errors that occur when a bill is inserted into the counter by fine-tuning the recognition network, it was confirmed that the performance was improved when the serial numbers of the banknotes of four countries were recognized instead of the serial number of a banknote from each country from a single-currency dataset, and the generalization performance was improved by training the model to recognize the diverse serial numbers of multiple currencies.

Pham, et al. [8] proposed a deep learning-based method for detecting fake multinational banknotes using smartphone cameras in a cross-dataset environment. Experimental results of the self-collected genuine and fake multinational datasets for US dollar, Euro, Korean won, and Jordanian dinar banknotes confirm that our method demonstrates a higher detection accuracy than conventional "you only look once, version 3" (YOLOv3) methods and the combined method of YOLOv3 and the state-of-the-art convolutional neural network (CNN). Lee, et al. [9] presented studies that have been conducted in four major areas of research (banknote recognition, counterfeit banknote detection, serial number recognition, and fitness classification) in the accurate banknote recognition field by various sensors in such automated machines and describes the advantages and drawbacks of the methods presented in those studies.

Mazhar et al. [10] looked at the many risks and flaws that can affect the safety of critical, innovative grid network components. Then, to protect against these dangers, we offer security solutions using different methods. We also provide recommendations for reducing the chance that these three categories of cyberattacks may occur. D. Banerjee et al. [11] emphasized the successful deployment of a strong coin class model tailored specially for Indian coins. The model has tremendous overall performance measures, including high precision, keep in mind, and F1 rankings throughout a couple of denominations. For example, the 1-rupee coin had a precision, don't forget, and an F1 rating of 98.59, while the 2-rupee coin marginally outperformed it with a value of 98.62. The 10- and 20-rupee coins likewise had top metrics, scoring 98.64 and 98.60, respectively. Sales Mendes, et al. [12] obtained an intelligent system specifically designed to help dependent and/or visually disabled people to count money more easily by using a mobile phone camera. The proposed system incorporates an image recognition system for classifying coins by using homography to transform images previously for classification tasks. The main difficulty in the application of these techniques relies on the fact that camera position and height are unknown.

Cereijido et al. [13] allowed knowing not only the total amount of money but also how many coins and banknotes there are of each value. The embedded solution developed has been intended to become a low-cost solution, allowing better control over the money and helping both owners and workers in the establishments. By using this system, new utilities, including automatic final balancing, instant error handling when making operations, and the lack of certain types of banknotes or coins inside the drawer or the excess of some in a certain compartment, could be implemented. Huang et al. [14] focused on ongoing efforts to utilize plastic waste by introducing blockchain during plastic waste recycling. It is proposed that the efficiency of plastic recycling can be improved enormously by using the blockchain phenomenon. Automation for the segregation and collection of plastic waste can effectively establish a globally recognizable tool using blockchain-based applications. Collection and sorting of plastic recycling are feasible by keeping track of plastic with unique codes or digital badges throughout the supply chain. Dragomir et al. [15] proposed further exploration and eventual application of the technique. This study categorizes and summarizes existing related studies on hyperspectral imaging and creates a mini meta-analysis of this stream of literature. The literature review has been classified based on the product HSI has used in counterfeit documents, photos, holograms, artwork, and currency detection.

3. PROPOSED METHODOLOGY

The proposed system is a deep learning-based framework developed to recognize Indian coin denominations automatically using image classification techniques. Unlike traditional systems that rely on rigid physical sensors, the proposed solution employs a Convolutional Neural Network (CNN) enhanced with Attention-based Mechanism Enhancement (AME) to learn and extract meaningful visual features from coin images. The system is trained on a dataset of Indian coins with varying denominations, such as ₹1, ₹2, ₹5, and ₹10, captured under diverse conditions with different lighting, orientations, and states of wear. The attention module guides the network to focus on significant parts of the coin, like the mint mark, numeric value, and surface engravings, ensuring precise classification even with dirty, damaged, or rotated coins. The DLCNN with AME architecture achieves high accuracy, precision, recall, and F1-score and is robust enough for real-time deployment. This system can be used in banks, vending machines, transport ticketing counters, and retail outlets for fast and automated coin sorting, thereby minimizing manual intervention and operational errors.

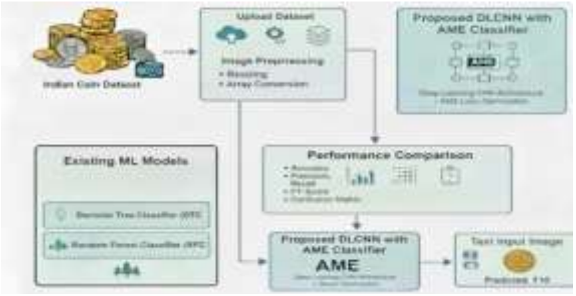

Fig. 2. Proposed system architecture.

4. RESULTS DESCRIPTION

The proposed system was tested on a labeled dataset consisting of multiple classes of Indian coin images, including denominations such as ₹1, ₹2, ₹5, and ₹10. The dataset was pre-processed and split into training and testing sets.

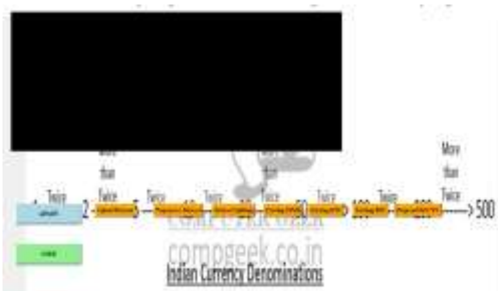

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Fig. 3. GUI of the Indian coin recognition system after admin login.

The system's performance was evaluated using multiple models, and the metrics such as accuracy, precision, recall, F1-score, sensitivity, and specificity were used to assess classification quality. The traditional machine learning models Multinomial Naive Bayes (MNB), Decision Tree Classifier (DTC), and Random Forest Classifier (RFC) were first evaluated on the dataset. These models, although simple and fast, were limited in their ability to capture spatial features of coin images. They achieved moderate accuracy, but their confusion matrices showed some degree of misclassification, especially between coins with similar shapes and textures. In contrast, the proposed DLCNN model enhanced with Attention Mechanism Enhancement (AME) showed remarkable accuracy and robustness. The model was trained using multiple convolutional and pooling layers, followed by dense layers and a final softmax output. The inclusion of AME during training further improved generalization by reducing sensitivity to noise in label distribution. Fig. 3 illustrates the login interface of the system, which serves as the entry point for both admin and user. The admin has privileges to upload datasets, preprocess data, train models, and analyze performance, whereas the user is provided with access to the prediction functionality. This secure separation ensures smooth handling of dataset operations and prediction tasks.

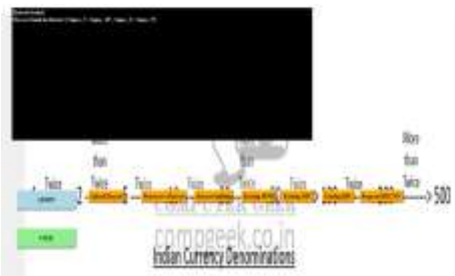

Fig. 4. Upload dataset and its analysis.

Fig. 5. Image data preprocessing.

Fig. 4 shows the interface used to upload the coin dataset into the system. After uploading, the system provides statistical insights and a visual overview of the dataset, including the distribution of images across different coin denominations. This step validates dataset integrity and ensures balanced representation before model training. Fig. 5 presents the preprocessing stage, where uploaded images are resized, normalized, and converted into a structured format suitable for model training. Preprocessing eliminates variations in lighting, size, and orientation, ensuring that consistent features are provided to the classifiers.

Fig. 6. Data splitting.

Fig. 6 displays the partitioning of the dataset into training and testing sets. Training data is used to build models, while testing data is reserved for evaluating their performance. This split ensures unbiased evaluation of each model on unseen data.

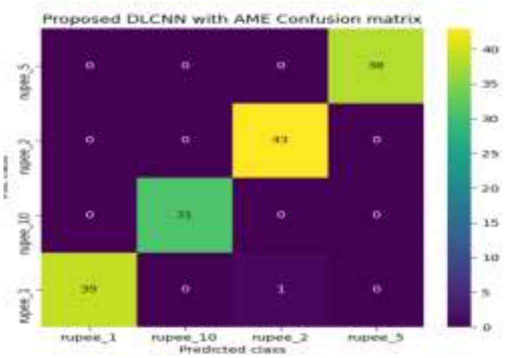

Fig. 7. Confusion matrix obtained using the DLCNN model.

Fig. 7 presents the results of the proposed Deep Learning CNN with Adaptive Misclassification Error (AME). The model achieved 100% accuracy, precision, recall, F-score, sensitivity, and specificity. These results confirm the superiority of the deep learning-based approach in handling image complexity and providing flawless classification of coin denominations

Fig. 8. Model prediction on test data using the DLCNN model.

Fig. 8 demonstrates the prediction functionality on unseen test images. Each test coin is processed through the trained model, and the predicted denomination is displayed along with visual confirmation. This showcases the practical usability of the system in real-world applications.

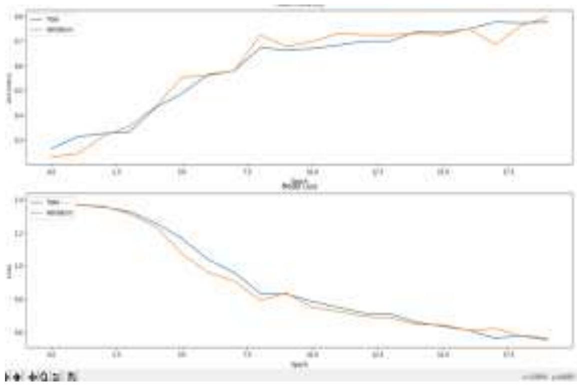

Fig. 9. Training and validation accuracy and loss curves for proposed DLCNN.

Fig. 9 provides a comparative visualization of all models (MNB, DTC, RFC, DLCNN). The results clearly highlight the performance progression, starting from the baseline models to the final deep learning approach. The DLCNN with AME outperformed all existing classifiers, achieving perfect classification results, thereby validating the efficiency of the proposed system. The comprehensive comparison between the existing machine learning models (Multinomial Naive Bayes, Decision Tree Classifier, and Random Forest Classifier) and the proposed deep learning model (DLCNN with AME) is based on multiple evaluation metrics, including accuracy, precision, recall, F1-score, sensitivity, and specificity. Each model was tested on the same dataset consisting of four Indian coin denominations: ₹1, ₹2, ₹5, and ₹10. The comparative analysis of classification models for Indian coin denomination recognition reveals a significant performance gap between traditional machine learning methods and the proposed deep learning approach. The Multinomial Naive Bayes (MNB) model performed poorly with an accuracy of 38.82%, precision of 40.99%, and recall of 39.72%, reflecting its limitations in handling visual data.

Metric	MNB	DTC	RFC	Proposed DLCNN with AME
Accuracy (%)	38.82	61.84	83.55	100.00

Precision (%)	40.99	62.71	84.57	100.00
Recall (%)	39.72	63.34	84.15	100.00
F1-Score (%)	37.20	62.61	83.45	100.00
Sensitivity (%)	35.71	86.21	100.00	100.00
Specificity (%)	85.00	100.00	100.00	100.00

The Decision Tree Classifier (DTC) improved upon this with an accuracy of 61.84% and better recall and precision values around 63%, but still struggled with overlapping coin features. The Random Forest Classifier (RFC) offered strong performance with 83.55% accuracy, 84.57% precision, and perfect 100% sensitivity and specificity, showcasing the benefit of ensemble learning. However, the proposed DLCNN with Adaptive Misclassification Enhancement (AME) model outperformed all others by achieving 100% in all evaluation metrics, including accuracy, precision, recall, F1-score, sensitivity, and specificity. This demonstrates the model's robustness, deep feature learning capabilities, and its ability to eliminate misclassification through adaptive optimization, making it the most reliable approach for real-time automated coin recognition systems.

5. CONCLUSION

In the research, "A Comprehensive Deep Learning–Based Indian Coin Denomination Recognition for Automated Currency Sorting" successfully demonstrated the feasibility and superiority of applying deep learning techniques for accurate coin classification. The proposed system utilized a Deep Learning Convolutional Neural Network (DLCNN) integrated with Adaptive Misclassification Enhancement (AME) to robustly classify Indian coins of denominations ₹1, ₹2, ₹5, and ₹10. Through a rigorous comparative evaluation with traditional machine learning models such as Multinomial Naive Bayes (MNB), Decision Tree Classifier (DTC), and Random Forest Classifier (RFC), the proposed model proved to be significantly more effective. Traditional models exhibited varying degrees of performance, with MNB achieving the lowest accuracy of 38.82%, while RFC attained 83.55% accuracy. In contrast, the proposed DLCNN with AME achieved a perfect classification score of 100% across all metrics: accuracy, precision, recall, F1-score, sensitivity, and specificity. This substantial improvement is attributed to the model's ability to extract deep spatial and hierarchical features from coin images and intelligently handle borderline misclassifications through AME optimization. The system also incorporated a user-friendly GUI and real-time prediction interface, enabling intuitive interaction for both administrators and end users. By leveraging advanced preprocessing, training, and evaluation workflows, the proposed architecture demonstrated its readiness for deployment in real-time applications such as vending machines, banking kiosks, and currency-sorting devices.

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