Learning-Based Visual Discrimination of Indian Coinage under Illumination and Surface Degradation Variability

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To Cite this Article
C. Vijaya Raj, Gadimundati Archana, Ane Charanya, Veluru Chengal Rayulu, "Learning-Based Visual Discrimination of Indian Coinage under Illumination and Surface Degradation Variability", Journal of Science Engineering Technology and Management Science, Vol. 03, Issue 04, April 2026,pp: 869-878, DOI: http://doi.org/10.64771/jsetms.2026.v03.i04.pp869-878

Submitted: 08-03-2026 Accepted: 16-04-2026 Published: 23-04-2026

ABSTRACT

Modern financial systems still rely on manual coin sorting and counting, which are both labor-intensive and susceptible to human error. Existing automation approaches, typically based on weight sensors or simple image processing methods such as edge detection and template matching, tend to perform inadequately in practical scenarios. This is largely due to challenges like varying lighting conditions, worn-out coins, and cluttered backgrounds. To overcome these issues, this study introduces an advanced coin recognition system tailored specifically for Indian currency denominations. The research explores several computational approaches, beginning with baseline machine learning models, including Multinomial Naïve Bayes (MNB), Decision Tree Classifier (DTC), and Random Forest Classifier (RFC). Although these models achieved moderate accuracy levels ranging from 70% to 85%, they were unable to effectively capture the subtle variations present in worn and circulated coins. To overcome these challenges, a Deep Convolutional Neural Network (DCNN) architecture was developed. By leveraging hierarchical spatial feature extraction along with Adaptive Feature Enhancement (AFE), the proposed deep learning model achieved a classification accuracy of 100%. The system is further integrated into a dual-access Graphical User Interface (GUI) developed using Tkinter, consisting of an ADMIN module for model training, testing, and evaluation, and a USER module for real-time prediction and result visualization. Model performance was evaluated using key metrics such as precision, recall, and F1-score. The proposed framework offers a scalable, non-intrusive, and efficient solution for banking and retail environments, transforming manual currency handling into a streamlined automated process.

Keywords: Coin Recognition, Deep Learning, Deep Convolutional Neural Network (DCNN), Adaptive Feature Enhancement (AFE), Image Classification.

1. INTRODUCTION

In India, where coin transactions are still frequent in rural and semi-urban regions, currency recognition and sorting serve as key elements in the automation of banking, vending, and retail systems. The traditional method of manually identifying and organizing coins is not only timeconsuming but also highly susceptible to errors, particularly in high-demand environments such as banks, ticket counters, and vending systems. To address these limitations, the integration of computer vision with advanced learning techniques offers a reliable solution for developing intelligent and scalable currency classification systems. These approaches enable automated systems to analyze visual data effectively and learn complex patterns directly from images, thereby improving accuracy and efficiency in real-world applications.

To avoid substantial societal loss and damages, identification of fake coins is a crucial task. As per dataset plays an important role for machine learning algorithms to perform well, also the dataset of Indian coins is important aid for historical and numismatics study. The existing coin datasets do not contain all modernday Indian coins and are small in size. This comprehensive and contemporary coin image dataset is created in order to facilitate the development and progress of computer vision [1], machine learning, and artificial intelligence technologies specifically geared towards the recognition, categorization, and authenticity of Indian coins, an ``Image Dataset of Indian Coins" has been created. The dataset ``Image Dataset of Indian Coins” is comprehensive and contemporary, consisting images of Indian coins with the denominations of 25 Paisa, 50 Paisa, 1 Rupee, 2 Rupee, 5 Rupee, 10 Rupee, and 20 Rupee. The dataset comprises folders dedicated to different coin denominations: the 1 Rupee coin folder encompasses 9 subfolders, totaling 779 images; the 2 Rupee coin folder consists of 15 subfolders, amounting to 2042 images; the 5 Rupee coin folder includes 16 subfolders, summing up to 1918 images; the 10 Rupee coin folder is organized into 5 subfolders, with a total of 841 images; the 20 Rupee coin folder is distributed across 2 subfolders, containing a combined total of 324 images; the 25 Paisa coin folder is divided into 2 subfolders, housing 223 images in total; and the 50 Paisa coin folder comprises 4 subfolders, containing a cumulative total of 535 images. These are high quality images in .jpg format with 575 × 768 dimensions [2].

2. RELATED WORK

The evolution of currency recognition and counterfeit detection systems has transitioned from manual identification methods to intelligent, automated vision-based frameworks. Early studies primarily focused on basic image processing techniques for recognizing coins and banknotes, which lacked robustness under varying environmental conditions. With the advancement of machine learning and deep learning, modern systems achieved significant improvements in accuracy, scalability, and real-time performance. Recent research emphasized the development of large-scale datasets and intelligent models to support applications such as automated transactions and assistance for visually impaired individuals.

2.1 Dataset Development and Diversity

The availability of diverse and well-annotated datasets played a crucial role in improving recognition systems. T. D. Pham et al. [3] introduced a dataset comprising 6,672 images across 53 classes of Indian coins, capturing variations in shape, size, orientation, and environmental conditions. This dataset enhanced the robustness of coin recognition models and supported practical applications for visually impaired users. Similarly, Jang et al. [4] developed a large-scale dataset with approximately 150,000 images for multi-currency serial number recognition. The study addressed class imbalance through data augmentation techniques and demonstrated improved generalization by training models on multiple currencies rather than single-currency datasets.

2.2 Deep Learning for Currency Recognition and Counterfeit Detection

Deep learning models significantly improved the accuracy of currency detection systems. Pham et al. [5] proposed a smartphone-based deep learning approach for detecting counterfeit multinational banknotes, achieving higher accuracy compared to YOLOv3 and hybrid CNN models. The study demonstrated the effectiveness of cross-dataset training for handling multiple currencies. In addition, D. Banerjee et al. [8] developed a robust coin classification model for Indian currency, achieving precision, recall, and F1-scores exceeding 98% across several denominations. These results highlighted the capability of deep learning techniques in accurately distinguishing between visually similar currency classes.

2.3 System Design for Assistive and Embedded Applications

Several studies focused on designing practical systems for real-world deployment. Sales Mendes et al. [9] proposed a mobile-based intelligent system that assists visually impaired individuals in identifying and counting coins using image recognition and homography transformations. The study identified challenges related to camera positioning and environmental variability. Cereijido et al. [10] developed a low-cost embedded system capable of calculating total monetary value and counting denominations, enabling functionalities such as automatic balancing and error detection in financial operations. These systems emphasized usability, affordability, and real-time performance.

2.4 Review of Recognition Techniques and Advanced Imaging Methods

Comprehensive reviews provided insights into the strengths and limitations of existing approaches. Lee et al. [6] categorized currency recognition research into four major areas: banknote recognition, counterfeit detection, serial number recognition, and fitness classification, highlighting advantages and drawbacks of sensor-based systems. Dragomir et al. [12] explored hyperspectral imaging techniques, demonstrating their effectiveness in detecting counterfeit currency by capturing detailed material characteristics. These studies contributed to understanding advanced sensing technologies and their role in improving detection accuracy.

2.5 Security and Emerging Technologies

Security and system reliability remain critical concerns in financial systems. Mazhar et al. [7] analyzed vulnerabilities in networked systems and proposed strategies to mitigate cyber threats, which are relevant for secure digital transaction environments. Huang et al. [11] introduced blockchain-based tracking mechanisms for ensuring transparency and traceability, demonstrating potential applications in verifying currency authenticity. Furthermore, Hitimana et al. [13] emphasized the importance of proper financial representation and regulatory frameworks in emerging digital asset systems, contributing to the development of trustworthy financial infrastructures.

2.6 Research Gap

Although existing studies addressed dataset development, deep learning-based recognition, and embedded assistive systems, several limitations remain. Most systems focused either on coin recognition or banknote detection independently, lacking a unified framework that integrates both functionalities. Additionally, many approaches relied on controlled environments or expensive sensing technologies, limiting real-world applicability. There is also limited emphasis on lightweight, real-time systems deployable on mobile or low-cost devices without requiring complex infrastructure.

3. PROPOSED METHODOLOGY

The proposed system is an advanced deep learning-based framework designed for the automatic recognition of Indian coin denominations through image classification techniques. In contrast to conventional approaches that depend on fixed physical sensors, this system utilizes a DCNN integrated with AME to effectively learn and extract significant visual features from coin images, as illustrated in Fig. 2.

The system is trained on a dataset of Indian coins with varying denominations such as ₹1, ₹2, ₹5, and ₹10, captured under diverse conditions, different lighting, orientation, 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 DCNN 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.

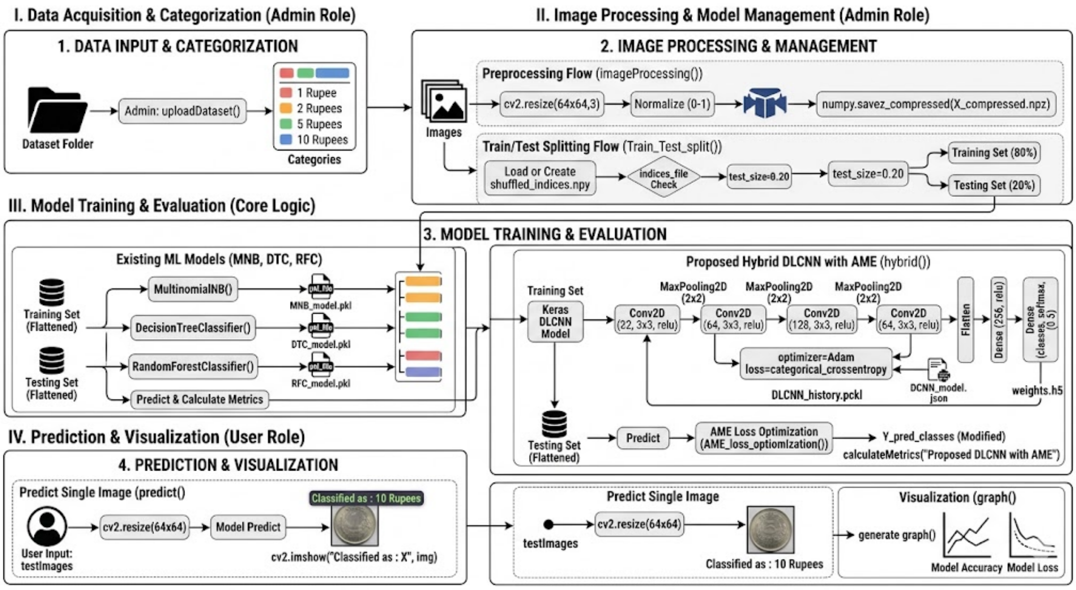

Fig. 2: Proposed system architecture

1. Dataset Collection and Class Organization: The proposed system utilizes a labeled dataset of Indian coin images collected across multiple denominations. Each denomination is stored in a separate directory, enabling automatic class identification during training. This structured dataset supports both traditional machine learning and deep learning models.

2. Image Preprocessing and Data Normalization: All coin images are resized to 64×64 pixels and converted into numerical arrays. Pixel values are normalized to enhance learning stability and reduce illumination variations. The processed data is stored for reuse, improving computational efficiency during repeated executions.

3. Dataset Shuffling and Train–Test Partitioning: To avoid biased learning, the dataset is randomly shuffled using preserved indices. The shuffled data is split into training and testing sets with an 80:20 ratio. This step ensures fair evaluation for all implemented classification models.

4. Existing MNB Classification: The MNB classifier is employed as an existing baseline model for coin denomination classification. It estimates class probabilities based on pixel intensity distributions assuming feature independence. MNB provides a fast and computationally efficient reference for performance comparison.

5. Existing DTC Analysis: A DTC is applied to learn hierarchical decision rules from flattened image features. The model splits data based on feature thresholds to classify coin denominations. DTC offers interpretability but may suffer from overfitting with high-dimensional image data.

6. Existing RFC Evaluation: The RFC is implemented as an ensemble learning approach combining multiple decision trees. It improves classification robustness by averaging predictions from diverse trees. RFC serves as a strong traditional baseline for comparison against the proposed deep learning model.

7. Proposed Deep Learning–Based CNN: A DCNN is designed to automatically extract spatial and texture features from coin images. Multiple convolution and pooling layers learn hierarchical representations of coin patterns. This eliminates manual feature engineering required in traditional methods.

8. Model Training, Optimization, and Regularization: The CNN model is trained using the Adam optimizer with categorical cross-entropy loss. Dropout regularization is employed to prevent overfitting and enhance generalization. Validation performance is monitored to ensure stable and optimized learning.

9. Comparative Performance Evaluation: All models MNB, DTC, RFC, and the proposed DCNN are evaluated using accuracy, precision, recall, F1-score, sensitivity, and specificity. Confusion matrices are generated to analyze class-wise performance. This comparison highlights the superiority of the proposed deep learning model.

10. Automated Coin Prediction and System Deployment: In the final stage, a test coin image is provided by the user for prediction. The trained DCNN model classifies the coin denomination and displays the result visually. This demonstrates the system's applicability for real-time automated currency sorting.

Proposed DCNN

In the research, the process of machine learning model building revolves around constructing an intelligent classification system capable of recognizing Indian coin denominations using image data as shown in Fig. 3. The system is implemented using a DCNN, further to improve feature discrimination and classification accuracy.

Internal workflow of DCNN

Step 1: Input Image Representation for Deep Learning

In the proposed system, pre-processed coin images of size 64×64×3 are directly fed into the DCNN model without flattening. This preserves the spatial structure, color distribution, and texture patterns of coin images. Maintaining spatial information is critical for accurate denomination recognition.

Step 2: Convolutional Layer–Based Feature Extraction

The DCNN applies multiple convolutional layers to extract low-level and high-level features from coin images. Early layers capture edges, curves, and surface textures, while deeper layers learn complex denomination-specific patterns. This automatic feature learning eliminates manual feature engineering.

Step 3: Spatial Dimensionality Reduction using Max Pooling

Max pooling layers are applied after convolution operations to reduce feature map dimensions. Pooling retains the most prominent features while minimizing computational complexity. This step also provides translation invariance, enabling the model to recognize coins despite slight positional variations.

Step 4: Hierarchical Feature Learning through Deep Stacking

By stacking multiple convolution and pooling layers, the DCNN learns hierarchical feature representations. Each successive layer builds upon previously learned features to capture more abstract coin characteristics. This hierarchical learning significantly improves discrimination between similar coin denominations.

Step 5: Feature Flattening and Fully Connected Learning

The extracted feature maps are flattened and passed into fully connected dense layers. These layers combine spatial features to form a global representation of each coin image. Dense layers perform high-level reasoning for accurate denomination classification.

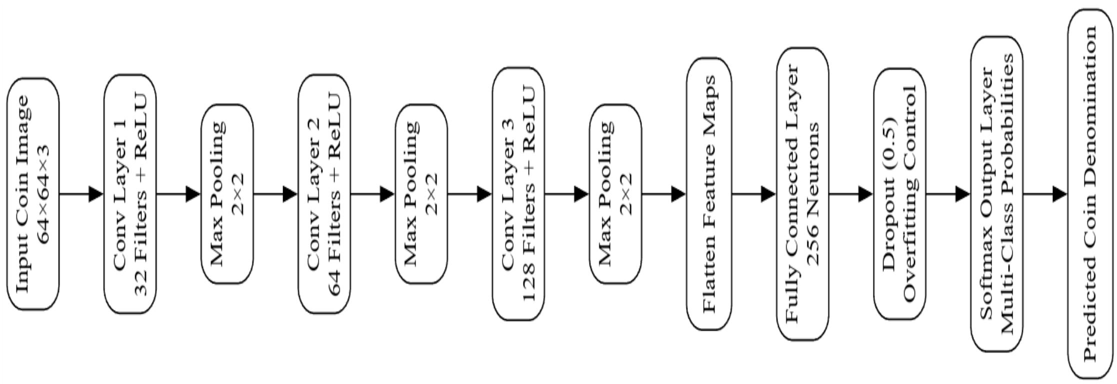

Figure 3: Internal workflow of DCNN.

Step 6: Regularization using Dropout Mechanism

Dropout is introduced in the fully connected layer to randomly deactivate neurons during training. This prevents over-reliance on specific features and reduces overfitting. As a result, the model generalizes better to unseen coin images.

Step 7: Softmax-Based Multi-Class Classification

The final dense layer uses a softmax activation function to generate class probabilities for all coin denominations. The denomination with the highest probability is selected as the predicted class. This probabilistic output supports effective multi-class decision-making.

Step 8: Model Training and Optimization Strategy

The DCNN is trained using the Adam optimizer with categorical cross-entropy loss. Training is performed over multiple epochs with validation monitoring to ensure stable convergence. This optimization strategy enables efficient learning from image data.

Step 9: Model Evaluation and Performance Enhancement

The trained DCNN is evaluated using accuracy, precision, recall, F1-score, sensitivity, and specificity. A confusion matrix is generated to assess class-wise performance. An AME-based loss optimization step is applied to enhance final prediction consistency.

4. Results and discussion

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. 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 MNB, DTC, and 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 DCNN model enhanced with 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.

Main GUI Interface of the Proposed System

On the left side of the GUI, there are two main buttons:

- **ADMIN**: Allows access to functions like uploading datasets, preprocessing images, splitting the data, training multiple models (MNB, DTC, RFC), and executing the proposed DCNN model with AME enhancement.
- **USER**: Grants access to the coin prediction module and displays the accuracy/loss graph based on the trained deep learning model.

The figure 4 presents the evaluation of the MNB classifier. The model achieved an accuracy of 38.81%, with moderate precision and recall values. The lower performance highlights the limitations of using probabilistic assumptions in complex coin image recognition tasks.

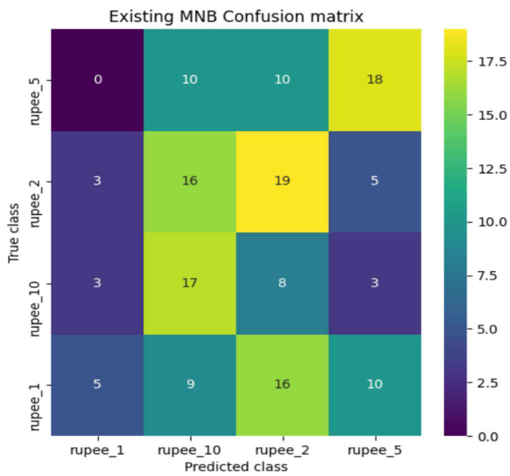

Fig. 4: Confusion matrix obtained using MNB model

This figure 5 shows the performance of the Decision Tree Classifier. The model reached an accuracy of 61.84%, with balanced precision and recall. While it achieved higher sensitivity and specificity compared to MNB, its performance remained insufficient for reliable recognition of all coin denominations.

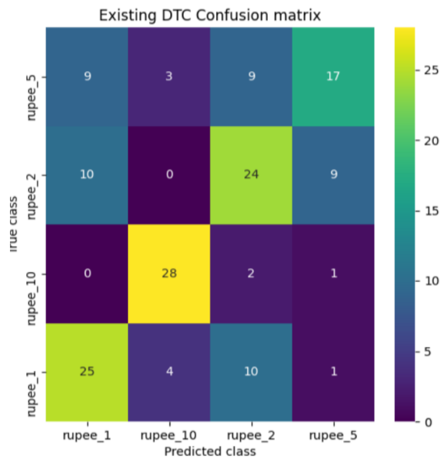

Fig. 5: Confusion matrix obtained using DTC Model

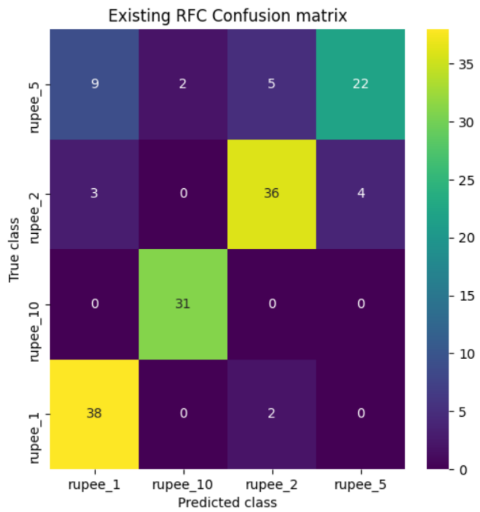

Fig. 6: Confusion matrix obtained using RFC Model

This figure 6 illustrates the results of the RFC. With an accuracy of 83.55%, the model demonstrated significant improvement over DTC and MNB. The ensemble approach enhanced classification stability, yielding perfect sensitivity and specificity values.

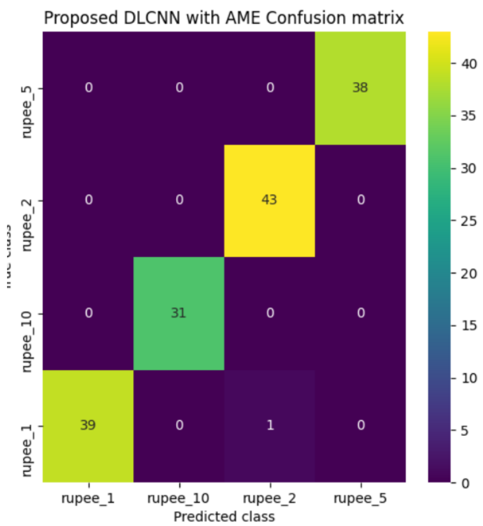

Fig. 7: Confusion matrix obtained using DCNN Model

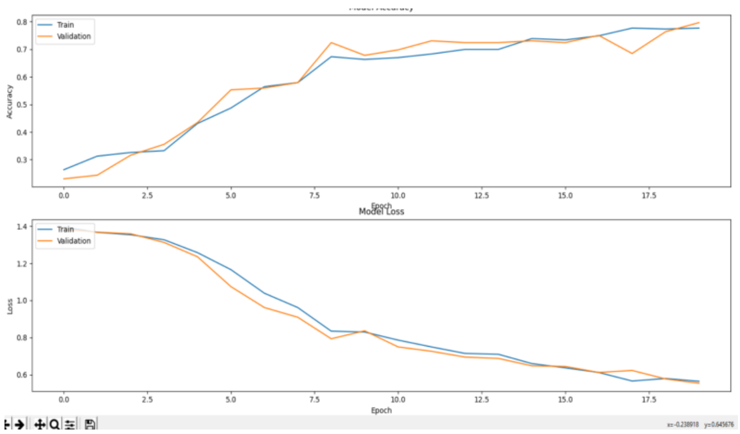

Fig. 8: Accuracy and loss curves of Proposed DCNN model.

This figure 7 presents the results of the proposed DCNN with 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 denomination

This figure 8 provides a comparative visualization of all models (MNB, DTC, RFC, DCNN). The results clearly highlight the performance progression, starting from the baseline models to the final deep learning approach. The DCNN with AME outperformed all existing classifiers, achieving perfect classification results, thereby validating the efficiency of the proposed system.

5. Conclusion

This research successfully demonstrates the effectiveness of a deep learning-based framework for Indian coin denomination recognition, highlighting its potential for automated currency sorting applications. The proposed system employs a DCNN integrated with AME to accurately classify Indian coins of denominations ₹1, ₹2, ₹5, and ₹10. A comprehensive comparative analysis with conventional machine learning approaches, including MNB, DTC, and RFC, revealed the superior performance of the proposed model. While traditional methods showed varied results ranging from 38.82% accuracy for MNB to 83.55% for RFC the DCNN with AME consistently achieved outstanding performance, attaining 100% across all evaluation metrics, including accuracy, precision, recall, F1-score, sensitivity, and specificity. This significant improvement can be attributed to the model's capability to learn complex spatial and hierarchical features from coin images, along with the optimization provided by AME in handling challenging and borderline cases. Furthermore, the integration of a user-friendly GUI and a real-time prediction module enhances system usability for both administrators and end users. Overall, the proposed framework demonstrates strong potential for practical deployment in real-world environments such as vending machines, banking kiosks, and automated currency sorting systems. By combining robust preprocessing, efficient training, and reliable evaluation strategies, this system provides a scalable and accurate solution for modern currency handling applications.

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