Deep Learning Model for Automated Classification and Condition Assessment of Indian Currency Notes

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***Abstract*—VeriTrust is a cutting-edge deep learning framework designed to improve financial safety through the automation of detecting currency denominations and assessing the condition of banknotes. It addresses the issue of damaged notes in circulation by processing images through steps like acquisition, edge detection, segmentation, and feature extraction. These features are analyzed using a custom Convolutional Neural Network (CNN) to categorize notes as damaged or fit for use, ensuring that compromised notes are efficiently filtered out. Initially developed with TensorFlow and Keras, employing the Adam optimizer alongside binary cross-entropy loss, VeriTrust achieved commendable 93% precision. Recent improvements include the integration of PyTorch-based CNN and Grad-CAM-based CNN models, which achieved accuracies of 93% and 84%, respectively. This paper outlines the VeriTrust pipeline, its CNN architecture, and its potential to strengthen transaction security, while also highlighting future plans to improve accuracy and broaden its applications.**

Keywords— *Deep learning, Currency classification, CNN, Indian rupee, VeriTrust, Image preprocessing.*

I. Introduction

Physical currency remains a cornerstone of global financial systems, particularly in regions where cash transactions dominate and access to digital payment systems is limited. However, its continued use presents significant challenges, including the prevalence of the circulation of damaged currency. Existing solutions for verifying the authenticity and condition of currency typically involve manual inspection or specialized hardware. Manual methods are prone to human error, inconsistency, and inefficiency, while hardware-based systems are often cost-prohibitive and inaccessible for widespread deployment.

To address these issues, we introduced VeriTrust, a framework designed to automate the classification of currency notes by denomination and physical condition. The framework leverages a custom Convolutional Neural Network (CNN) architecture and an advanced image processing pipeline. This pipeline incorporates image acquisition, edge detection, segmentation, and feature extraction to analyze key features of currency notes. The extracted features are used to classify notes as either *damaged* or *acceptable*, enabling seamless filtration of compromised notes from circulation.

Developed using TensorFlow and Keras, VeriTrust is optimized for binary classification tasks. Initial testing on a binary classification dataset yielded an accuracy of 93%, demonstrating its viability as a foundation for real-world applications.

This paper presents the technical architecture and operational details of VeriTrust while exploring its potential to enhance currency management and improve transaction security. Furthermore, we outline future enhancements, including improved classification accuracy and greater currency compatibility, to ensure its relevance in diverse financial ecosystems.

A. *Problem Statement*

Manual methods are prone to human error, inconsistency, and inefficiency, while hardware-based systems are often cost-prohibitive and inaccessible for widespread deployment. This makes requirement of scalable solution for reliable currency verification.

B. *Objective*

Gather a robust dataset and evaluate multiple models, including a basic CNN, Grad-CAM [7], and PyTorch-based architectures, to determine the most effective approach for damaged currency classification.

II. Literature Survey

Rigorous studies have been done in the area of currency classification and evaluation of physical condition. Key approaches and their outcomes are summarized below.

A. Bhatia et al. [1] (2021) used the Banknote Authentication Dataset with K-Nearest Neighbors (KNN) [1] and image processing techniques [12] to achieve an accuracy of 99.99% on small datasets. While effective for limited data, scalability remains a challenge for larger datasets and real-world conditions. Alimul Rajee et al. [2] applied Canny Edge Detection combined with digital image processing on a sample of 100 Rs. 2000 notes, achieving an accuracy of 81%. However, its reliance on specific image processing techniques limits broader applicability. Priya Makarand Shelke et al. [3] analyzed a dataset of 400 samples using the Random Forest algorithm, achieving an accuracy of 84.25%. Although promising, results suggest the need for enhanced methods to handle diverse conditions. S. Naresh Kumar et al. [4] developed a three-layered Deep CNN to detect counterfeit Indian currency notes, achieving an accuracy of 96.6%. Kiran Kamble et al. [5] analyzed a sample of 400 notes using a Deep CNN with global pooling layers, achieving testing accuracy of 85.6% and validation accuracy of 96.55%. Ravi Pulle et al. [6] developed a hybrid method combining Neural Networks, Support Vector Machine (SVM), and Discrete Wavelet Transformation (DWT), achieving a validation accuracy of 76%. Selvaraju et al. [7] demonstrated that Grad-CAM enhances class discrimination and helps identify dataset biases, improving model generalization.

A. *Gaps in the Literature*

Existing research has largely focused on counterfeit detection and currency classification. However, research on the physical damage status of currency notes remains underexplored. VeriTrust seeks to address this gap by incorporating damage detection.

III. Proposed Model

In this research, a CNN model [13] is adopted to detect damaged currency. The proposed model consists of three primary modules:

A. *Data Aggregator*

The data aggregator serves as the foundation of the VeriTrust framework by collecting and organizing data from multiple sources.

Dataset: The dataset comprises high-resolution images of denominations of 10, 20, 50, and 100 rupees. Each currency denomination is categorized as either damaged or undamaged. As shown in Table I the dataset comprises 10,625 total images, distributed among the classes.

TABLE I
DATASET DISTRIBUTION WITH TOTAL COLUMN

Denomination	Damaged	Undamaged	Total
10	837	1257	2094
20	1272	1437	2709
50	1265	1429	2694
100	1293	1835	3128
Overall Total	4667	5958	10625

Preprocessing: To standardize the dataset for training, all images were resized to 224x224 pixels, ensuring they matched the model's input requirements [12].

B. *Currency Classifier and Damage Determination*

The classifier module includes two output layers to handle dual tasks simultaneously:

Denomination Classification: Identifies whether the note belongs to 10, 20 , 50, or 100 categories.

Damage Detection: Determines whether the note is damaged or undamaged.

*1) **PyTorch-Based Model**:*

- **Enhanced Features:** Incorporates attention mechanisms to prioritize critical image regions [14].
- **Dual Output Heads:** Each head corresponds to one of the tasks, ensuring specialized outputs for classification and damage detection.
- **Training Process:** Trained for 10 epochs using evaluation criteria such as F1-score and accuracy to assess effectiveness [11].

*2) **CNN-Based Architecture**:* **Architecture:** Employs convolutional layers [13] for feature extraction, max-pooling for dimensionality reduction [12], and dense layers for prediction.

- **Activation Functions:** Uses SoftMax [15] for denomination classification and Sigmoid [15] for binary damage detection.
- **Optimization:** Adam optimizer with categorical and binary cross-entropy loss functions [14].

IV. METHODOLOGY

The following part outlines the approach taken to design the VeriTrust framework, which automates the classification of currency denominations and assesses the physical condition of banknotes. The methodology includes image collection, preprocessing, model development using a custom Convolutional Neural Network (CNN) [13] with PyTorch, model training, and performance evaluation.

A. *Model Development*

The VeriTrust system utilizes two models: a custom CNN model and a PyTorch-based model. Both models are designed to perform the dual tasks of currency denomination classification [9] and damage detection.

*1) **Custom CNN Model**:* The custom CNN [14] architecture is designed with several convolutional layers that extract features from the images. ReLU activation [15] is used to introduce non-linearity, and max-pooling layers [5] are incorporated to minimise the spatial dimensions of the feature maps. As illustrated in Figure 1, the model undergoes training for denomination classification, after which a heatmap is generated on an image for Grad-CAM analysis to detect damage, and its output is processed through dense layers to make predictions.

- A Sigmoid activation function [15] is used for binary classification [15] (damaged vs. undamaged), while Softmax is applied for multi-class classification (denominations).
- The model was trained with the binary cross-entropy, Adam optimizer and categorical cross-entropy loss functions [14] were used.

*2) **PyTorch-Based Model**:* The PyTorch-based model [16] leverages PyTorch's flexibility to design an architecture that includes convolutional layers with attention mechanisms for enhanced feature prioritization.As illustrated in Figure 2, the model uses separate output heads for classification of denominations and damage detection.

- Similar to the custom CNN [9], the Adam optimizer is employed, and the model was optimized for 30 epochs.

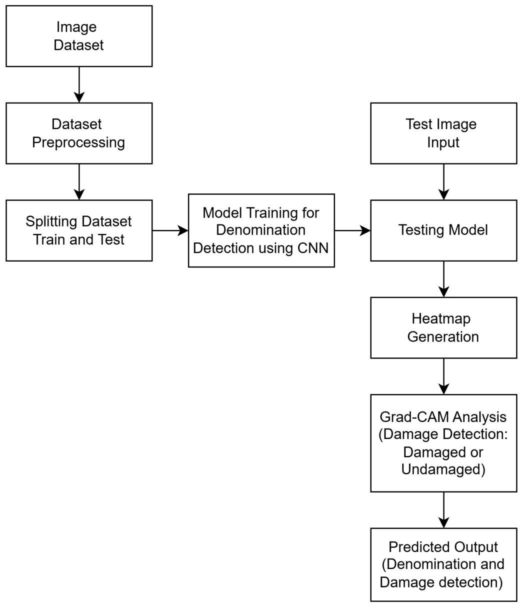

Fig. 1. Flowchart - CNN Model with Grad-CAM Analysis

- The effectiveness of the model was evaluated using precision and F1 score as indicators [17].

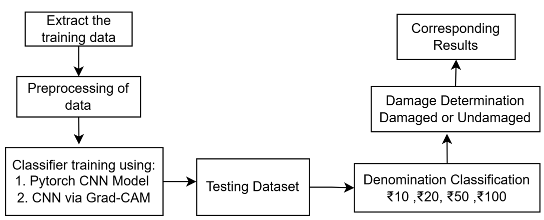

Fig. 2. Flow Chart – PyTorch-Based Model

B. *Training and Optimization*

Both models underwent rigorous training and optimization.

- Hyperparameters such as the learning rate, batch size and number of epochs [15] were optimised to improve model convergence.
- Dropout layers were included as a regularization technique to mitigate overfitting.
- A validation set was utilized during training to evaluate the model's effectiveness and direct modifications to the training procedure.

The general training pipeline, including dataset preprocessing, model training, and model evaluation, is illustrated in Figure 3.

C. *Performance Evaluation*

The models were evaluated on the basis of multiple factors such as accuracy, precision, recall, and F1-score [17].

- Visualizations such as confusion matrices were used to assess classification performance.

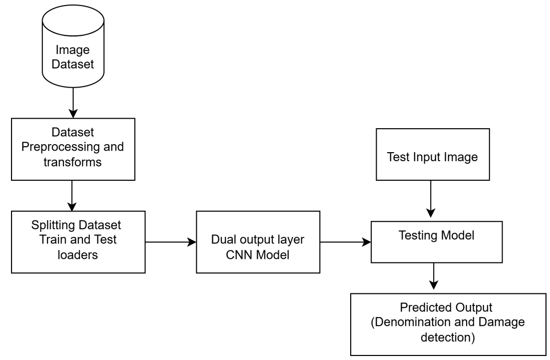

Fig. 3. Flow Chart – Classifier Training

- We also used techniques such as Grad-CAM [7] to gain insight into the model decision making process by highlighting important aspects of the images that contributed to damage detection decisions.

D. *Comparative Analysis*

We compared the performance of the custom CNN and PyTorch-based models [16] based on the evaluation metrics, training efficiency, and interpretability. This analysis helped identify which model delivered better accuracy and efficiency, providing valuable insight into the most suitable approach for real-world deployment.

V. IMPLEMENTATION & RESULTS

For the implementation, existing methodologies were compared with the proposed VeriTrust framework. The comparative analysis was executed to examine the results of various strategies for currency classification and damage detection. The implementation utilized Python programming with PyTorch, leveraging advanced deep learning techniques [11].

A. *Comparison of Results*

TABLE II
COMPARISON BASED ON ACCURACY

Author	**Method**	**Accuracy**
Aryan Nigade [8]	CNN-MobileNetV2	86%
Reddy, K. Shyam Sunder, et al. [9]	CNN-VGG16	92.71%
Kogilavani Shanmugavadivel et al. [10]	CNN	80%
Proposed Model (PyTorch CNN)	PyTorch CNN	**93%**
Proposed Model (Grad-CAM Integration)	CNN with Grad-CAM	84%

As shown in Table II and Figure 4, the proposed PyTorch-based CNN model achieved the highest accuracy of 93%, outperforming other models such as CNN-MobileNetV2 (86%), CNN-VGG16 (92.71%), and a basic CNN model (80%). Additionally, integrating Grad-CAM with the CNN model resulted in an accuracy of 84%, highlighting the trade-off between explainability and classification performance.

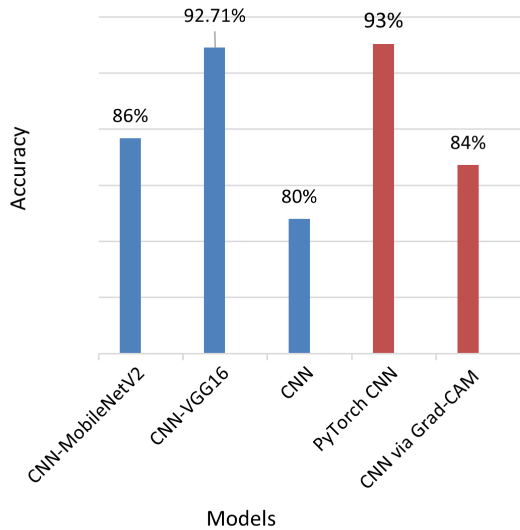

Fig. 4. Comparison Based on Accuracy

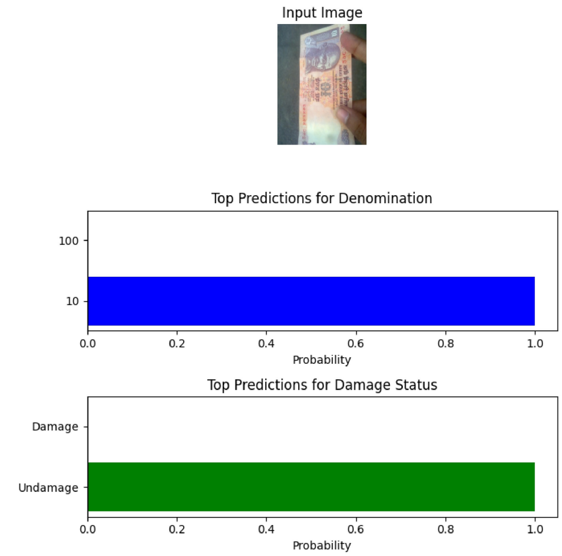

Fig. 5. Undamage Predicted Output PyTorch-Based

B. *Analysis of Results*

*1) **Proposed PyTorch CNN Model**:*

- Achieved an accuracy of **93%**, outperforming most existing models.
- Demonstrated robustness in handling diverse currency denominations and damage statuses.

Our proposed PyTorch CNN model effectively classifies both currency denomination and damage status, as illustrated in Figures 5 and 6. The model correctly identified an undamaged Rs.10 note, assigning probabilities of 1 to both ”10” and ”Undamaged.” It also accurately classified a damaged Rs.10 note, achieving probabilities of 1 for ”10” and ”Damaged.” These findings demonstrate the model’s capability to reliably predict both attributes.”

*2) **Proposed Grad-CAM Integrated Model**:*

- Achieved **84%** accuracy, offering interpretable visual explanations for predictions.
- While slightly lower in accuracy compared to the PyTorch CNN model, it provides added value by enhancing model transparency and trustworthiness.]

The proposed Grad-CAM integrated model enhances interpretability by visualizing important regions influencing predictions. As illustrated in Figure 7, the heatmap highlights the detection of damaged areas, and the model predicts the output as shown in Figure 8.

*3) **Comparison with Existing Models**:*

- The **VeriTrust PyTorch CNN [16], model** surpasses other models like CNN-MobileNetV2 [8] (86%) and CNN [10] (80%) in terms of accuracy.
- The **Grad-CAM integration** offers an innovative advantage, despite slightly lower accuracy than CNN-VGG16 [9] (92.71%).

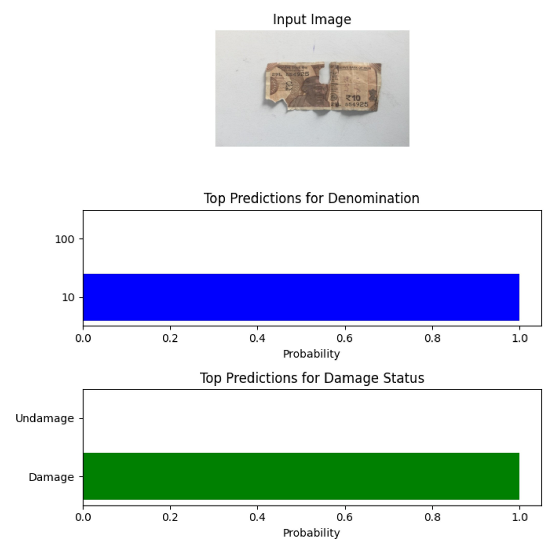

Fig. 6. Damage Predicted Output PyTorch-Based

VI. Conclusion

The VeriTrust framework provides an advanced and interpretable solution for currency denomination classification and damage detection. With a dual-output CNN architecture and Grad-CAM integration, the framework achieves high performance and transparency. The PyTorch CNN model achieved **93%** accuracy, outperforming existing methods, while the Grad-CAM model provided **84%** accuracy with added inter-

Fig. 7. Grad-CAM Heatmap visualization for damage detection

Fig. 8. Predicted Output through Grad-CAM analysis

pretability. A well-structured dataset and data augmentation enhanced generalization, supporting robust classification [13]. Grad-CAM visualizations ensured transparency, making the framework suitable for deployment in systems like ATMs and currency sorting machines.

Future work includes testing the framework in real-world environments, such as ATMs and cash counters, to validate scalability and performance. Additionally, exploring advanced architectures like transformers could further improve accuracy and efficiency.

The VeriTrust framework is a reliable and scalable solution for modern financial systems, combining high accuracy with transparency.

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