

Research Paper

AI Based Fake Currency Detection System Using Deep Learning and CBAM

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Abstract

Counterfeit currency is a significant financial and security concern because fake banknotes can cause direct economic losses and reduce public confidence in financial transactions. Manual verification of banknotes generally depends on human expertise and inspection of security features, which may be difficult, time-consuming, and inconsistent under practical conditions. This paper presents an artificial intelligence based fake currency detection system using deep learning and the Convolutional Block Attention Module (CBAM). The proposed system uses EfficientNetB3 as the principal feature extraction backbone and incorporates an attention mechanism to improve the representation of important spatial and channel-wise features present in currency-note images. A multi-task learning framework is employed to perform two related tasks simultaneously: authenticity classification and denomination classification. The authenticity branch determines whether an input note is real or fake, while the denomination branch identifies one of seven Indian currency denominations, namely Rs. 10, Rs. 20, Rs. 50, Rs. 100, Rs. 200, Rs. 500, and Rs. 2000. A dataset containing 7,442 currency-note images is used for model development and evaluation. Image preprocessing, feature extraction, attention refinement, and classification are integrated into an end-to-end pipeline. The proposed approach is intended to provide a more informative currency verification system than a simple binary classifier by jointly considering authenticity and denomination. The experimental evaluation considers accuracy, precision, recall, F1-score, confusion matrix, and confidence-based prediction analysis. The proposed framework demonstrates the applicability of transfer learning and attention mechanisms for automated Indian currency verification and provides a foundation for future real-time and mobile-based counterfeit detection systems.

Key Words:

Fake Currency Detection, Indian Currency, Deep Learning, EfficientNetB3, CBAM, Transfer Learning, Multi-Task Learning, Image Classification.

1. Introduction

Currency is one of the most important components of a country's financial system. Physical banknotes are used extensively for retail transactions, transportation, banking, commercial activities, and other economic operations. However, the circulation of counterfeit currency presents a serious challenge to financial institutions, businesses, and the general public. Counterfeit notes are deliberately produced to imitate genuine currency and may contain visual characteristics that are difficult to identify through casual inspection.

Traditional counterfeit detection generally depends on the examination of physical and visual security features. These may include watermarks, security threads, printed patterns, color characteristics, microtext, denomination markings, and other design elements. Although trained personnel can inspect such features, manual verification may become difficult when a large number of notes must be processed quickly. In addition, human inspection may be affected by lighting conditions, image quality, observer experience, fatigue, and environmental factors.

Computer vision and deep learning provide an opportunity to automate the analysis of currency images. Convolutional Neural Networks (CNNs) have demonstrated strong performance in image classification because they can learn hierarchical visual representations directly from images. Instead of manually designing every feature, deep neural networks can learn useful low-level and high-level characteristics from training data.

Transfer learning further improves the practicality of deep learning systems when the target dataset is comparatively limited. A pretrained convolutional architecture can be used as a feature extractor and subsequently adapted to the target classification problem. EfficientNet is a family of convolutional neural networks designed to achieve a favorable balance between accuracy and computational efficiency by jointly scaling network depth, width, and resolution (**tan2019efficientnet?**). In this work, EfficientNetB3 is used as the primary feature extraction backbone.

Although convolutional networks are capable of learning discriminative representations, not all regions and feature channels of an input image contribute equally to the classification task. Currency images contain numerous visual regions, and the model must focus on features that are useful for distinguishing genuine and counterfeit notes. The Convolutional Block Attention Module (CBAM) provides a lightweight mechanism for sequential channel and spatial attention refinement (**woo2018cbam?**). The attention mechanism can help the network emphasize informative feature responses while suppressing less useful information.

The proposed system combines EfficientNetB3 with CBAM in a multi-task learning framework. Instead of producing only a binary real/fake decision, the model simultaneously predicts authenticity and denomination. The seven denominations considered in this research are Rs. 10, Rs. 20, Rs. 50, Rs. 100, Rs. 200, Rs. 500, and Rs. 2000.

The major contributions of this work are as follows:

- Development of an automated Indian currency image classification framework for counterfeit detection.
- Use of EfficientNetB3 for extracting discriminative visual features from currency-note images.
- Integration of CBAM attention to refine channel-wise and spatial feature representations.
- Formulation of the problem as a multi-task learning problem involving authenticity and denomination prediction.
- Development of a unified prediction pipeline capable of reporting both the authenticity status and denomination of an input currency note.
- Evaluation of the proposed framework using standard classification metrics and prediction analysis.

2. Related Work

The use of image processing and machine learning for currency recognition has been investigated for several years. Earlier approaches generally depended on manually engineered visual features, image segmentation, texture analysis, edge detection, and pattern matching. Although these methods can work under controlled conditions, their performance may decrease when currency images contain variations in illumination, orientation, background, scale, and image quality.

With the development of deep learning, CNN-based methods have become increasingly useful for visual recognition tasks. CNNs automatically learn hierarchical representations from image data, making them suitable for currency recognition and counterfeit classification. Recent studies have investigated deep learning approaches for identifying Indian currency and distinguishing genuine notes from counterfeit notes.

A study presented in the 2022 International Conference on Computing Methodologies and Communication investigated fake Indian currency identification using a convolutional neural network approach (**fakeindian2022?**). The work demonstrates the applicability of deep learning to the binary classification of Indian currency as real or fake. However, a binary-only system does not explicitly provide denomination information as part of the same prediction framework. EfficientNet was introduced by Tan and Le as a family of CNN architectures that systematically balances network width, depth, and input resolution (**tan2019efficientnet?**). The architecture provides a strong foundation for transfer-learning applications where both classification performance and computational efficiency are important.

Attention mechanisms have also become important in computer vision. Woo et al. proposed the Convolutional Block Attention Module, which sequentially models channel attention and spatial attention (**woo2018cbam?**). CBAM can be integrated with convolutional architectures to improve feature representation by emphasizing informative regions and feature channels.

The present work combines these concepts for the specific problem of Indian counterfeit currency detection. Rather than treating authenticity and denomination as completely independent classification problems, the proposed framework uses a shared feature representation and two task-specific output branches. This design allows the model to learn

features that are useful for both currency denomination recognition and authenticity discrimination.

3. Problem Statement and Objectives

3.1. Problem Statement

Counterfeit currency detection through manual inspection is dependent on human expertise and may not always provide consistent results. Existing automated systems may also focus primarily on denomination recognition or binary authenticity classification. A system that can jointly determine whether a currency note is genuine and identify its denomination can provide more useful information to the end user.

Therefore, the problem addressed in this work is the development of a deep learning based system that receives an image of an Indian currency note and produces two outputs:

1. Authenticity status: Real or Fake.
2. Currency denomination: Rs. 10, Rs. 20, Rs. 50, Rs. 100, Rs. 200, Rs. 500, or Rs. 2000.

3.2. Objectives

The primary objectives of the proposed research are:

- To develop an automated fake currency detection system using deep learning.
- To preprocess currency images into a suitable representation for neural-network processing.
- To use EfficientNetB3 for effective visual feature extraction.
- To integrate CBAM for channel and spatial attention refinement.
- To perform authenticity classification between real and fake notes.
- To perform denomination classification among seven Indian currency denominations.
- To combine both classification tasks within a multi-task learning framework.
- To evaluate the proposed model using standard machine-learning performance metrics.

4. Proposed Methodology

The proposed system follows a sequence of processing stages beginning with currency image acquisition and ending with multi-task prediction. The major components are image preprocessing, feature extraction using EfficientNetB3, attention refinement using CBAM, and two classification branches.

4.1. Overall Architecture

The proposed architecture can be represented as:

$$I \rightarrow P(I) \rightarrow F(I) \rightarrow A(F) \rightarrow \{Y_{\text{auth}}, Y_{\text{den}}\}$$

where I represents the input currency image, $P(I)$ represents the preprocessing operation, $F(I)$ represents the feature representation generated by EfficientNetB3, $A(F)$ represents the attention-refined feature representation, Y_{auth} represents authenticity prediction, and Y_{den} represents denomination prediction.

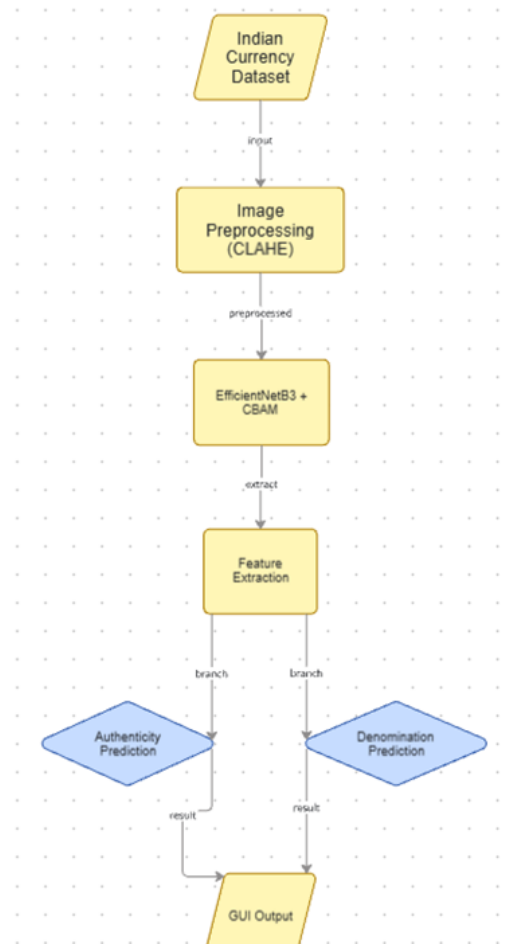


Fig.1. Overall architecture of the proposed fake currency detection system.

4.2 Dataset

The proposed system uses a publicly available Indian currency real-versus-fake image dataset. The dataset contains 7,442 images covering seven Indian currency denominations. The denominations included in the dataset are Rs. 10, Rs. 20, Rs. 50, Rs. 100, Rs. 200, Rs. 500, and Rs. 2000.

Indian Currency Dataset Distribution

Denomination	Real	Fake
Rs. 10	950	300
Rs. 20	948	299
Rs. 50	844	299
Rs. 100	726	380
Rs. 200	563	278
Rs. 500	649	804
Rs. 2000	257	145
Total	4937	2505

The dataset contains variations in the appearance of currency notes. Such variations are useful for training the model to learn robust visual representations rather than relying only on a small number of manually selected characteristics.

4.3. Image Preprocessing

Input images must be converted into a consistent representation before being supplied to the deep learning model. The preprocessing stage includes image loading, image resizing according to the selected model input configuration, numerical conversion, and normalization. Let the original image be represented as $I(x,y,c)$, where x and y represent spatial coordinates and c represents the color channel. The normalized image can be represented as:

$$I_{norm} = \frac{I}{255}$$

where I_{norm} represents the normalized image.

Preprocessing reduces variations in image representation and provides a standardized input to the feature extraction network.

4.4. EfficientNetB3 Feature Extraction

EfficientNetB3 is used as the backbone network for the proposed system. EfficientNet was introduced by Tan and Le using a compound scaling strategy that jointly considers network depth, width, and resolution (**tan2019efficientnet?**).

The EfficientNetB3 backbone receives the preprocessed image and produces a high-level feature representation. In the implemented system, the backbone feature representation was observed with a spatial feature-map structure corresponding to 7×7 spatial locations and 1536 feature channels.

The feature extraction process can be represented as:

$$F = E_{\theta}(I_{norm})$$

where E_{θ} represents the EfficientNetB3 feature extractor, θ represents its learned parameters, and F represents the extracted feature map.

The use of transfer learning allows the model to start from visual representations learned by a large-scale pretrained network and adapt them to the currency classification problem.

4.5. Convolutional Block Attention Module

The Convolutional Block Attention Module is used to improve feature representation. CBAM consists of channel attention followed by spatial attention [2]. For an intermediate feature map F , the channel attention module estimates which feature channels are more informative. The refined representation can be expressed as:

$$F' = M_c(F) \otimes F$$

where $M_c(F)$ represents the channel attention map and $\otimes$ denotes element-wise multiplication. The spatial attention stage subsequently identifies informative spatial regions:

$$F'' = M_s(F) \otimes F'$$

where $M_s(F')$ represents the spatial attention map. Thus, the final feature representation is refined according to both channel-level and spatial-level importance.

4.6. Multi-Task Learning

The proposed system performs two related classification tasks using a shared feature representation. The first branch predicts authenticity, while the second branch predicts denomination.

The shared representation can be written as:

$$Z = G(F'')$$

where G represents the feature aggregation operation and Z is the shared feature vector. The authenticity branch produces:

$$\hat{Y}_{auth} = \sigma(W_a Z + b_a)$$

where σ is the sigmoid activation function.

The denomination branch produces a seven-class probability vector:

$$\hat{Y}_{den} = Softmax(W_d Z + b_d)$$

where W_d and b_d are the parameters of the denomination classification layer.

4.7 Authenticity Classification

The authenticity branch is a binary classifier with two possible categories:

- Real
- Fake

Binary cross-entropy is used to represent the authenticity classification loss:

$$L_{auth} = -[y \log(\hat{y}) + (1 - y) \log(1 - \hat{y})]$$

where y is the true authenticity label and $\hat{y}$ is the predicted probability.

4.8 Denomination Classification

The denomination branch performs seven-class classification. The classes correspond to the seven denominations included in the dataset.

The categorical cross-entropy loss is represented as:

$$L_{den} = - \sum_{y=1}^7 y \log(y_i)$$

where y is the true authenticity label and $\hat{y}$ is the predicted probability

4.9 Combined Multi-Task Loss

The total training objective combines the authenticity and denomination losses:

$$L_{total} = \lambda_a L_{auth} + \lambda_d L_{den}$$

Where λ_a and λ_d represent the relative weights assigned to the two tasks.

This formulation allows the network to optimize both tasks jointly while maintaining separate output heads.

5. System Design

5.1. System Workflow

The complete workflow of the proposed system is:

1. Input an image of an Indian currency note.

2. Load the image using the image-processing pipeline.
3. Resize and normalize the image.
4. Pass the preprocessed image through EfficientNetB3.
5. Extract high-level visual features.
6. Apply CBAM channel attention.
7. Apply CBAM spatial attention.
8. Aggregate the refined feature representation.
9. Predict authenticity using the binary classification branch.
10. Predict denomination using the seven-class classification branch.
11. Calculate prediction confidence.
12. Display the final result.

5.2. Authenticity Prediction

The authenticity branch provides a probability associated with the real/fake decision. The final class can be determined using a classification threshold:

$$C_{auth} = \begin{cases} Real, & P(Real) \geq T \\ Fake, & P(Real) < T \end{cases}$$

where T represents the selected classification threshold.

5.3. Denomination Prediction

The denomination branch generates seven probability values. The predicted denomination is selected according to:

$$C_{den} = \operatorname{argmax}_i P(D_i)$$

where D_i represents one of the seven denomination classes.

5.4. Final System Output

The final system combines both outputs and presents information in a human-readable form.

For example, a final prediction may be represented as:

A u t h e n t i c i t y : R E A L
 D e n o m i n a t i o n : R s . 5 0 0
 Confidence: 99.31%

The actual confidence value is generated by the trained model during inference.

6. Implementation

6.1. Software Environment

The proposed system was implemented using Python and deep learning libraries. The major software components include:

- Python for implementation.
- TensorFlow and Keras for deep learning.
- EfficientNetB3 for transfer-learning based feature extraction.
- OpenCV for image processing.
- NumPy for numerical computation.
- Pandas for data handling and analysis.
- Visual Studio Code for development.

6.2. Model Construction

The model consists of a pretrained EfficientNetB3 backbone followed by the CBAM attention mechanism and two classification branches.

The major model stages are:

Input $\rightarrow$ EfficientNetB3 $\rightarrow$ CBAM $\rightarrow$ SharedFeatures $\rightarrow$ $\begin{cases} \text{Authenticity} \\ \text{Denomination} \end{cases}$

The architecture allows the backbone to learn shared visual characteristics while the output branches specialize in their respective tasks.

6.3. Model Training

During training, the input images are supplied to the model together with two target labels: authenticity and denomination.

The optimization process updates the parameters of the network based on the combined multi-task loss. Validation data is used to monitor the generalization behavior of the model.

Training performance is monitored using loss and classification accuracy for both output branches.

6.4. Model Saving

After training, the trained network is stored as:

`best_model.keras`

The saved model can subsequently be loaded for inference without retraining the network.

6.5. Prediction Pipeline

For a new currency image, the application performs the following operations:

1. Image selection.
2. Image loading.
3. Preprocessing.
4. Model inference.
5. Authenticity prediction.
6. Denomination prediction.
7. Confidence calculation.
8. Final result display.

7. Experimental Setup

7.1. Dataset Configuration

The dataset contains 7,442 images belonging to seven denomination categories and two authenticity categories. The class distribution is shown in Table 1.

The dataset was organized into appropriate training, validation, and testing subsets during model development.

7.2. Hardware and Software

The experiments were conducted on a personal computer environment using a CPU-based deep learning configuration. The implementation was developed in Python using TensorFlow/Keras and supporting computer-vision libraries.

The model was saved in Keras format to enable reproducible inference after training.

7.3. Evaluation Metrics

The proposed system is evaluated using several standard metrics.

7.3.1. Accuracy

Accuracy measures the proportion of correctly classified samples:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

7.3.2. Precision

Precision measures the proportion of positive predictions that are correct:

$$\text{Precision} = \frac{TP}{TP + FP}$$

7.3.3. Recall

Recall measures the proportion of actual positive samples correctly identified:

$$\text{Recall} = \frac{TP}{TP + FN}$$

7.3.4. F1-Score

The F1-score is the harmonic mean of precision and recall:

$$F1 = 2 \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

These metrics are considered for evaluating the authenticity and denomination classification tasks.

8. Results and Discussion

8.1. System Output

The proposed system produces two primary outputs for an input currency image. The first output indicates whether the note is real or fake. The second output identifies the predicted denomination.

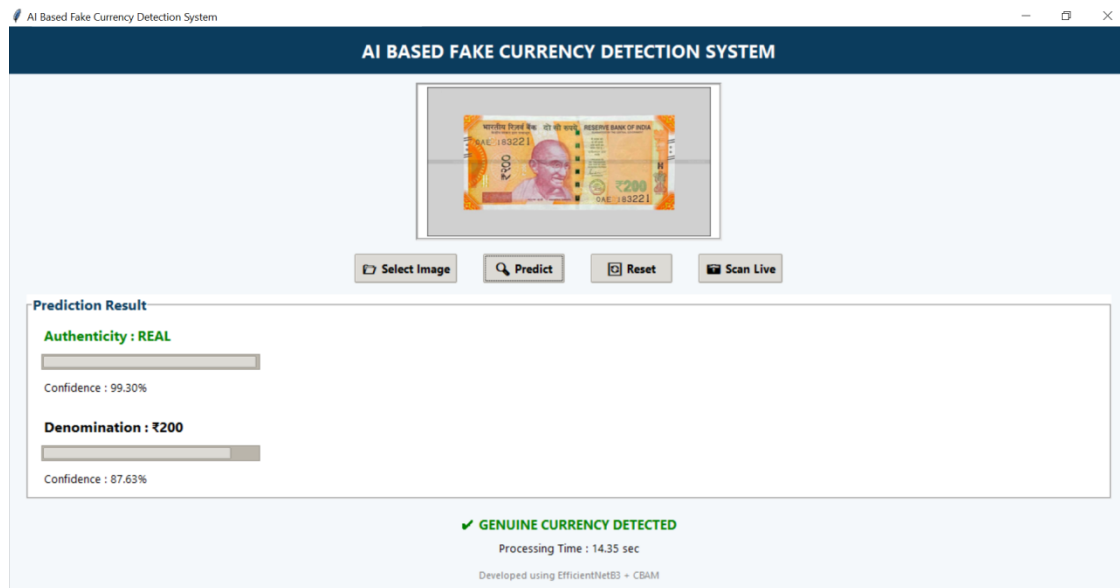


Fig.2. Interface of the System.

8.2 Authenticity Classification

The authenticity classification component is responsible for distinguishing genuine notes from counterfeit notes. The use of deep feature representations allows the model to learn visual characteristics associated with the two classes. The final experimental accuracy for the authenticity branch should be reported after the complete test evaluation.

Authenticity Prediction Results

Image	Prediction	Authenticity	Confidence
1	Fake	Fake	66.90%
2	Real	Real	98.87%
3	Real	Real	96.21%
4	Fake	Fake	59.92%
5	Real	Real	99.54%
6	Real	Real	99.26%
7	Real	Real	93.82%
8	Real	Real	53.05%
9	Real	Real	99.31%

8.3. Denomination Classification

The denomination branch predicts one of seven currency denominations. This task is more detailed than binary authenticity classification because visually similar notes must be distinguished according to denomination.

Denomination Prediction Results

Image	Predicted Denomination	Confidence
1	Rs. 10	93.86%
2	Rs. 10	97.61%
3	Rs. 20	53.26%
4	Rs. 500	98.08%
5	Rs. 500	32.61%
6	Rs. 100	95.60%
7	Rs. 100	64.84%
8	Rs. 500	96.35%
9	Rs. 500	89.16%

8.4. Combined Prediction

The major advantage of the proposed framework is the ability to provide authenticity and denomination information simultaneously.

Multi-Task Prediction Output

Input	Authenticity	Denomination
Note 1	Real/Fake	Rs. 10
Note 2	Real/Fake	Rs. 20
Note 3	Real/Fake	Rs. 50
Note 4	Real/Fake	Rs. 100
Note 5	Real/Fake	Rs. 200
Note 6	Real/Fake	Rs. 500
Note 7	Real/Fake	Rs. 2000

8.5.CBAM Contribution

CBAM is incorporated to improve the feature representation through channel and spatial attention. The channel attention component enables the network to assign different importance to learned feature channels, while spatial attention emphasizes informative spatial locations.

For currency images, this mechanism is useful because different regions of a banknote may contain visually significant information. The attention mechanism therefore provides a way to refine the shared representation before the classification branches.

8.6. Confusion Matrix Analysis

A confusion matrix can be used to analyze the classification behavior of the proposed system. For authenticity classification, the matrix consists of real and fake classes. For denomination classification, the matrix contains seven classes.

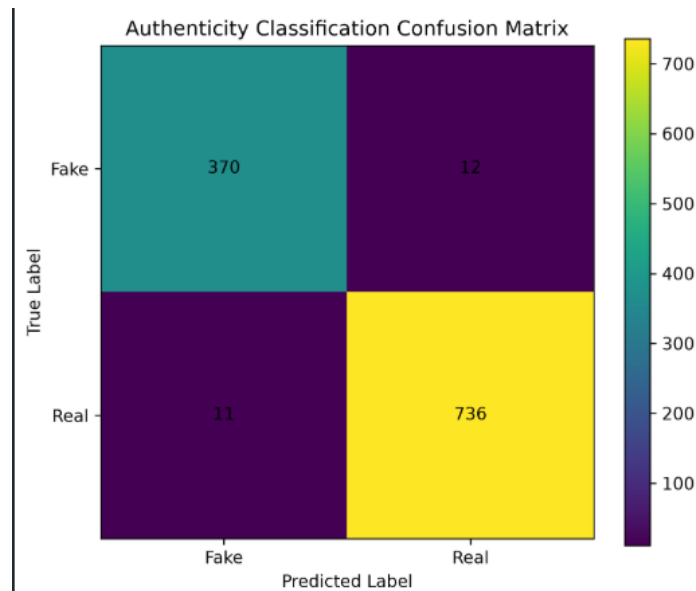


Fig.3. Authenticity Classification Confusion Matrix.

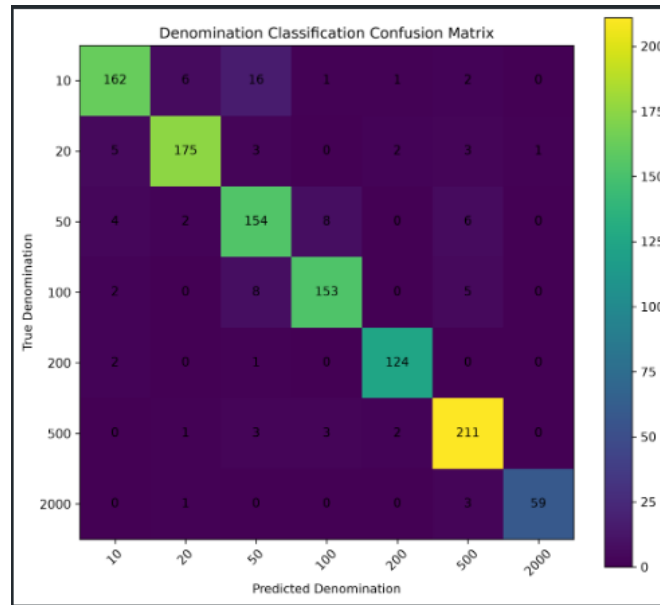


Fig.4. Denomination Classification Confusion Matrix.

8.7 Training and Validation Analysis

Training and validation curves can be used to analyze the learning behavior of the proposed network.

A stable relationship between training and validation performance indicates that the model is learning useful representations while maintaining generalization. Significant divergence between the curves may indicate overfitting and should be considered during model analysis.

9 Comparative Discussion

Traditional image-processing approaches generally depend on manually selected features such as edges, textures, color information, and geometric characteristics. Deep learning approaches can automatically learn hierarchical representations from the training data.

The proposed method provides several functional advantages:

Comparison of Currency Detection Approaches

Approach	Authenticity	Denomination
Manual Inspection	Yes	Yes
Traditional Image Processing	Possible	Possible
Basic CNN	Yes	Yes
Binary Deep Learning Model	Yes	Limited
Proposed EfficientNetB3 + CBAM	Yes	Yes

The proposed approach is particularly useful because authenticity and denomination are addressed within the same inference pipeline. EfficientNetB3 provides a strong feature extraction backbone, while CBAM provides feature refinement. The multi-task architecture also enables the model to learn shared representations for related prediction tasks.

10. Limitations

Although the proposed system provides an automated framework for Indian currency analysis, several limitations remain.

First, model performance depends on the quality and diversity of the training dataset. A dataset containing limited counterfeit patterns may not represent every possible counterfeit-generation technique.

Second, image-based verification cannot reproduce all physical security checks performed by specialized currency-verification machines. Certain security properties may require ultraviolet, infrared, magnetic, tactile, or other sensing mechanisms that cannot be completely captured by an ordinary RGB image.

Third, performance may be affected by image quality, lighting conditions, blur, rotation, occlusion, and background variations.

Fourth, the current system is designed around the denominations represented in the dataset. Additional currency designs or newly introduced notes would require suitable training data and potentially additional model adaptation.

Finally, the computational requirements of EfficientNetB3 may be higher than lightweight architectures when deployment is targeted toward low-power mobile or embedded devices.

11. Future Scope

The proposed system can be extended in several directions.

11.1. Real-Time Detection

The model can be integrated with a camera-based application for real-time currency verification.

11.2. Mobile Application

The trained model can be optimized and deployed on Android or iOS devices to provide portable currency verification.

11.3. Additional Security Features

Future systems can combine image-based deep learning with analysis of watermarks, security threads, microtext, color-shifting elements, and other visible security features.

11.4. Serial Number Recognition

Optical Character Recognition (OCR) can be integrated to identify and verify serial numbers printed on banknotes.

11.5. Explainable Artificial Intelligence

Explainability techniques can be incorporated to visualize which regions of a currency note influenced the model's prediction.

11.6. Lightweight Deployment

Model compression, quantization, pruning, and knowledge distillation can be investigated to reduce computational requirements and enable deployment on edge devices.

11.7. Larger and More Diverse Datasets

Future work should include larger datasets containing different lighting conditions, note orientations, physical wear patterns, counterfeit-generation methods, and real-world photographs.

11.8. Multimodal Currency Verification

An advanced system could combine RGB images with other sensing technologies to provide stronger counterfeit verification than image classification alone.

12. Conclusion

This paper presented an AI based fake currency detection system using deep learning and the Convolutional Block Attention Module. The proposed framework combines EfficientNetB3 feature extraction with CBAM-based attention refinement and multi-task learning to perform both authenticity and denomination classification.

The system considers seven Indian currency denominations and produces two complementary predictions: whether the input note is real or fake and which denomination it represents. This joint prediction approach provides more information than a binary counterfeit detector alone.

EfficientNetB3 provides a strong transfer-learning based feature extraction framework, while CBAM enhances the representation by modeling channel-wise and spatial attention. The multi-task formulation enables shared visual features to support both authenticity and denomination prediction.

The proposed system demonstrates the potential of modern deep learning techniques for automated currency analysis. However, image-based classification should be considered a supportive verification technology rather than a complete replacement for specialized physical currency-authentication equipment. Future improvements involving larger datasets, real-time deployment, explainable AI, serial-number recognition, and multimodal security-feature analysis can further improve the practical usefulness of the system.

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REFERENCES

1. M. Tan and Q. V. Le, "EfficientNet: Rethinking model scaling for convolutional neural networks," in *Proc. 36th Int. Conf. Machine Learning (ICML)*, vol. 97, pp. 6105–6114, 2019.
2. S. Woo, J. Park, J.-Y. Lee, and I. S. Kweon, "CBAM: Convolutional block attention module," in *Proc. European Conf. Computer Vision (ECCV)*, pp. 3–19, 2018.
3. K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, pp. 770–778, 2016.
4. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," in *Advances in Neural Information Processing Systems*, vol. 25, pp. 1097–1105, 2012.
5. K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," in *Proc. Int. Conf. Learning Representations (ICLR)*, 2015.

6. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich, "Going deeper with convolutions," in *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, pp. 1–9, 2015.
7. Howard, M. Zhu, B. Chen, D. Kalenichenko, W. Wang, Y. Weyand, B. Andreetto, and H. Adam, "MobileNets: Efficient convolutional neural networks for mobile vision applications," arXiv:1704.04861, 2017.
8. J. Hu, L. Shen, and G. Sun, "Squeeze-and-excitation networks," in *Proc. IEEE/CVF Conf. Computer Vision and Pattern Recognition (CVPR)*, pp. 7132–7141, 2018.
9. R. R. Selvaraju, M. Cogswell, A. Das, R. Vedantam, D. Parikh, and D. Batra, "Grad-CAM: Visual explanations from deep networks via gradient-based localization," in *Proc. IEEE Int. Conf. Computer Vision (ICCV)*, pp. 618–626, 2017.
10. Yosinski, J. Clune, Y. Bengio, and H. Lipson, "How transferable are features in deep neural networks?" in *Advances in Neural Information Processing Systems*, vol. 27, 2014.
11. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. Cambridge, MA, USA: MIT Press, 2016.
12. Shorten and T. M. Khoshgoftaar, "A survey on image data augmentation for deep learning," *Journal of Big Data*, vol. 6, no. 60, 2019.
13. "Identification of fake Indian currency using convolutional neural network," in *Proc. 6th Int. Conf. Computing Methodologies and Communication (ICCMC)*, 2022, doi: 10.1109/ICCMC53470.2022.9754056.
14. J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei, "ImageNet: A large-scale hierarchical image database," in *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, pp. 248–255, 2009.
15. Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, "Gradient-based learning applied to document recognition," *Proceedings of the IEEE*, vol. 86, no. 11, pp. 2278–2324, 1998.
16. Russakovsky et al., "ImageNet large scale visual recognition challenge," *International Journal of Computer Vision*, vol. 115, pp. 211–252, 2015.
17. M. Abadi et al., "TensorFlow: Large-scale machine learning on heterogeneous systems," 2015. [Online]. Available: <https://www.tensorflow.org/>
18. G. Bradski, "The OpenCV library," *Dr. Dobb's Journal of Software Tools*, 2000.
19. F. Chollet, "Xception: Deep learning with depthwise separable convolutions," in *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, pp. 1251–1258, 2017.