International Research Journal of Innovations in Engineering and Technology (IRJIET)
ISSN (online): 2581-3048
Volume 9, Special Issue ICCIS-2025, pp 1-7, May-2025
https://doi.org/10.47001/IRJIET/2025.ICCIS-202501
Second International Conference on Computing and Intelligent Systems (ICCIS-2025)

Multi Task Learning Based Transformer Model for Real-Time Indian Fake Currency Detection & Conversion

[1]Karthik. S, [2]Manjunath. K, [3]Nishal. P.H, [4]Rizwan. S, [5]Nirupa. V

[1,2,3,4,5]Department of Artificial Intelligence, Madanapalle Institute of Technology & Science (MITS), Madanapalle, AP, India
E-mails: [1]21691A3175@mits.ac.in, [2]21691A3175@mits.ac.in, [3]21691A3175@mits.ac.in, [4]21691a31A5@mits.ac.in, [5]nirupav@mits.ac.in

***Abstract* - Economic systems frequently face the problem of counterfeit money circulation, which compromises financial credibility and transaction integrity. Even while manual and UV-based inspection methods are widely utilized, they are time-consuming, prone to human mistake, and inefficient and subjective, hence automated replacements are required. In order to improve and automate the detection of counterfeit cash, this study proposes a hybrid deep learning model that makes use of Transformers, Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs).**

RNNs analyze sequential data, such money serial numbers, for anomalies, Transformers hone spatial correlations, and CNNs collect complex visual aspects. This multi-modal method facilitates real-time operation and increases detection robustness. Indian banknotes in values of 100, 200, and 500 Indian rupees are used to train the model.

Once a note is classified as genuine, the system integrates a real-time currency conversion module to convert its value into various foreign currencies, enhancing its practical applicability for financial and travel-related use cases. The model is implemented using TensorFlow and PyTorch, with optimization techniques including batch normalization, dropout, and transfer learning.

With little retraining, the system is made to be flexible and expandable across several money kinds. It may be implemented in settings including retail points of sale, ATMs, and banks. Additionally, the architecture is appropriate for mobile platforms and embedded devices because to its support for real-time processing. Its modular architecture also makes it possible to integrate OCR for serial number recognition in the future. All things considered, this approach offers a strong, effective, and expandable answer to the cash authentication issue.

Keywords: Fake Currency Detection, Indian Currency, CNN, Transformer, RNN, Multi-Task Learning, Currency Converter.

I. INTRODUCTION

The Fake currency is a significant issue in India, impacting the country's financial system and economy. The Reserve Bank of India (RBI) is responsible for issuing legal currency, incorporating various security features to prevent counterfeiting. However, with advancements in printing and scanning technologies, counterfeiters have developed sophisticated methods to replicate banknotes, leading to economic instability, financial losses, and criminal activities.

The Problem of Counterfeit Currency

Unauthorized counterfeit currency is created and distributed to trick individuals and companies. In addition to interfering with financial transactions, these counterfeit notes provide difficulties for banks, companies, and regular people who find it difficult to tell the difference between genuine and counterfeit money. Global financial institutions, businesses, and security organizations face serious challenges as a result of the proliferation of counterfeit money. It is becoming more and more difficult to tell real cash from counterfeit using conventional ways as counterfeiters are creating increasingly complex strategies. In order to improve the precision and effectiveness of counterfeit cash detection, machine learning and deep learning algorithms are now essential.

Because of their efficiency in feature learning and classification, Convolutional Neural Networks (CNNs), Transformers, and Recurrent Neural Networks (RNNs) have become essential tools in applications requiring visual and sequential data. In order to detect complex security elements hidden in currency notes, CNN layers are used to extract specific spatial characteristics, which have been demonstrated to be successful in a variety of visual pattern recognition tasks. Transformer-based architectures, on the other hand, greatly enhance classification performance by utilizing self-attention methods to capture contextual linkages and global dependencies. RNNs are also helpful in detecting serial number forgeries and other time-dependent traits since they improve the detection of sequential patterns.

International Research Journal of Innovations in Engineering and Technology (IRJIET)
ISSN (online): 2581-3048
Volume 9, Special Issue ICCIS-2025, pp 1-7, May-2025
https://doi.org/10.47001/IRJIET/2025.ICCIS-202501
Second International Conference on Computing and Intelligent Systems (ICCIS-2025)

By integrating these advanced algorithms, counterfeit currency detection models achieve superior robustness, scalability, and automation, minimizing human error and reducing verification time. This research explores the effectiveness of CNN, Transformer, and RNN models in detecting fake currency, analyzing their comparative performance, and identifying the optimal approach for real-world deployment.

Once the currency note is classified, the system incorporates a real-time currency conversion module using exchange rates from external APIs. If the note is real, it converts its value into user-selected foreign currencies such as USD, EUR, GBP, or JPY, providing additional functionality for travelers and financial applications. The model is implemented using TensorFlow, PyTorch, and Transformers, optimizing performance with batch normalization, dropout, and transfer learning techniques

II. RELATED WORK

The application of deep learning and machine learning models for the detection of counterfeit cash has been the subject of several researches. Sravani [1]applied deep learning techniques to identify fake Indian currency, focusing on the use of convolutional networks. Choudhary [2] proposed a robust system for detecting counterfeit currency circulating in India using pattern recognition methods. Rakesh [3] investigated techniques that leveraged color histogram features for improved classification accuracy.

A custom adaptation of the Faster R-CNN framework was proposed by O.T.I. et al[4]. to detect forged currency patterns efficiently. Tailored for fake currency detection, emphasizing the balance between detection accuracy and real-time processing speed. GH [5] utilized a traditional machine learning pipeline Using Support Vector Machines (SVM) for categorization and texture-based feature extraction.

In order to extract and learn characteristics from Indian notes, Charan [6] investigated image processing methods in conjunction with machine learning models, while Rajesh [7] developed an AI-based currency verification system suitable for digital kiosks and ATMs.

Sharma [8] presented a mobile-friendly AI system for real-time currency verification using edge computing. Sagar [9] implemented a CNN architecture designed for fast and accurate classification of Indian currency denominations. Patil [10] developed a multi-tiered AI framework that includes both hardware (scanners) and software modules to assess note validity in real-time environments.

B. S [11] built a deep learning system incorporating customized CNN layers to enhance the feature resolution and classification performance. Kalaiselvi [12] focused on the application of convolutional architectures in women's technical institutions to train students on currency authentication through practical deployments.

Antre [13] proposed a lightweight CNN model trained on augmented datasets to increase generalization against various counterfeit styles. Bhushanm [14] developed a currency recognition model integrating OCR and CNNs to improve serial number analysis and visual consistency checks. Abhiram [15] constructed a visual inspection model using deep learning that specifically addressed watermark and hologram verification.

Collectively, these contributions demonstrate the growing sophistication and diversity of machine learning strategies in counterfeit detection. They also underline the importance of leveraging transfer learning, self-attention mechanisms, and domain-specific data for improved generalization. Despite the progress, most existing methods are limited to image-only approaches and do not account for sequential or contextual features like serial numbers. Our proposed system addresses this by integrating multi-modal components—CNN, Transformer, and RNN—and enhancing functionality with real-time currency conversion capabilities. This holistic approach sets a new benchmark in counterfeit detection solutions.

III. METHODOLOGY

This section outlines the dataset structure, preprocessing steps, proposed hybrid deep learning architecture, training configuration, and deployment environment for real-time Indian fake currency detection and conversion.

3.1 Dataset Description

The dataset consists of Indian currency notes in ₹100, ₹200, and ₹500 denominations, each comprising both real and fake images. The dataset is divided into subgroups for training and validation, ensuring balanced representation across denominations and classes. Each image is captured under diverse lighting conditions and backgrounds to simulate real-world variability. Each input sample was normalized to a fixed resolution of 224 by 224 pixels for architectural compatibility.

Table 1 below summarizes the image distribution:

International Research Journal of Innovations in Engineering and Technology (IRJIET)
ISSN (online): 2581-3048
Volume 9, Special Issue ICCIS-2025, pp 1-7, May-2025
https://doi.org/10.47001/IRJIET/2025.ICCIS-202501
Second International Conference on Computing and Intelligent Systems (ICCIS-2025)

Table 1. Distribution of Real and Fake Indian Currency Notes Across Train and Validation Sets

Denomination (INR)	Dataset Split	Real	Fake	Total
100	Train	40	42	82
	Validation	15	20	35
200	Train	38	40	78
	Validation	14	18	32
500	Train	42	46	88
	Validation	19	21	40
Total	—	168	187	**355**

This dataset comprises a total of 355 high-resolution images of Indian currency notes across three denominations—₹100, ₹200, and ₹500. The images are categorized into real and fake classes and are divided into training and validation sets. Specifically, 240 images are used for training and 115 for validation. Each denomination includes a near-balanced number of real and fake samples to ensure unbiased learning. The dataset was manually curated and annotated to support a deep learning-based fake currency detection model. This structured distribution enables effective training and evaluation of multi-task learning models for real-time classification.

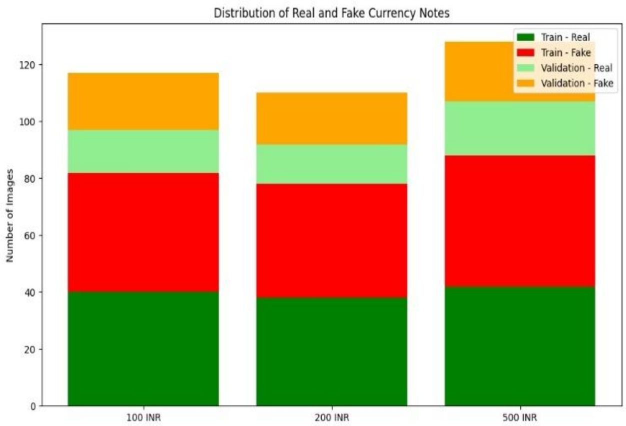


Figure 2.b

3.2 Data Preprocessing and Augmentation

We implemented a structured preprocessing pipeline in PyTorch to ensure consistent and robust input formatting for the counterfeit currency detection model. The key preprocessing steps include:

Image Reading and Resizing: Each image is standardized to 224×224 RGB format using Torch Vision tools for uniformity in training.

Smoothing and Contrast Enhancement: Gaussian Blur is applied to minimize background noise, followed by Contrast Limited Adaptive Histogram Equalization, or CLAHE, is used to make security elements on the currency more visible on the currency.

Normalization: All input pictures are normalized to zero-mean and unit-variance format using the channel-wise mean and standard deviation that are calculated from the training set.

Data Augmentation: In order to decrease overfitting and enhance the model's capacity for generalization, the Albumentations library is utilized for data augmentation. Transformations include:

3.3 Proposed Hybrid Model Architecture

The proposed model is composed of three integrated modules to learn local, global, and sequential features:

1. CNN Feature Extractor: A five-layer CNN with Batch Normalization and MaxPooling operations extracts low and mid-level visual features from currency images. Output shape: (batch_size, 512, 7, 7)

2. Transformer Feature Enhancer: The CNN output is reshaped and passed to a Transformer Encoder with 8 attention heads and 2 layers.

3. Bidirectional RNN for Sequential Feature Modeling: A Bi-directional LSTM processes synthetic serial number sequences associated with the currency notes. This module is designed for future integration with real OCR systems and adds contextual understanding of serial patterns, which are critical in detecting fraudulent sequences.

4. Feature Fusion and Classification Head: The outputs from the CNN, Transformer, and RNN modules are concatenated and passed through a sequence of fully connected layers with ReLU activation and dropout regularization. A softmax classifier is employed at the final layer to output the binary class probabilities (real or fake).

The combined architecture is capable of learning both fine-grained visual cues and contextual dependencies across currency denominations and classes.

International Research Journal of Innovations in Engineering and Technology (IRJIET)
ISSN (online): 2581-3048
Volume 9, Special Issue ICCIS-2025, pp 1-7, May-2025
https://doi.org/10.47001/IRJIET/2025.ICCIS-202501
Second International Conference on Computing and Intelligent Systems (ICCIS-2025)

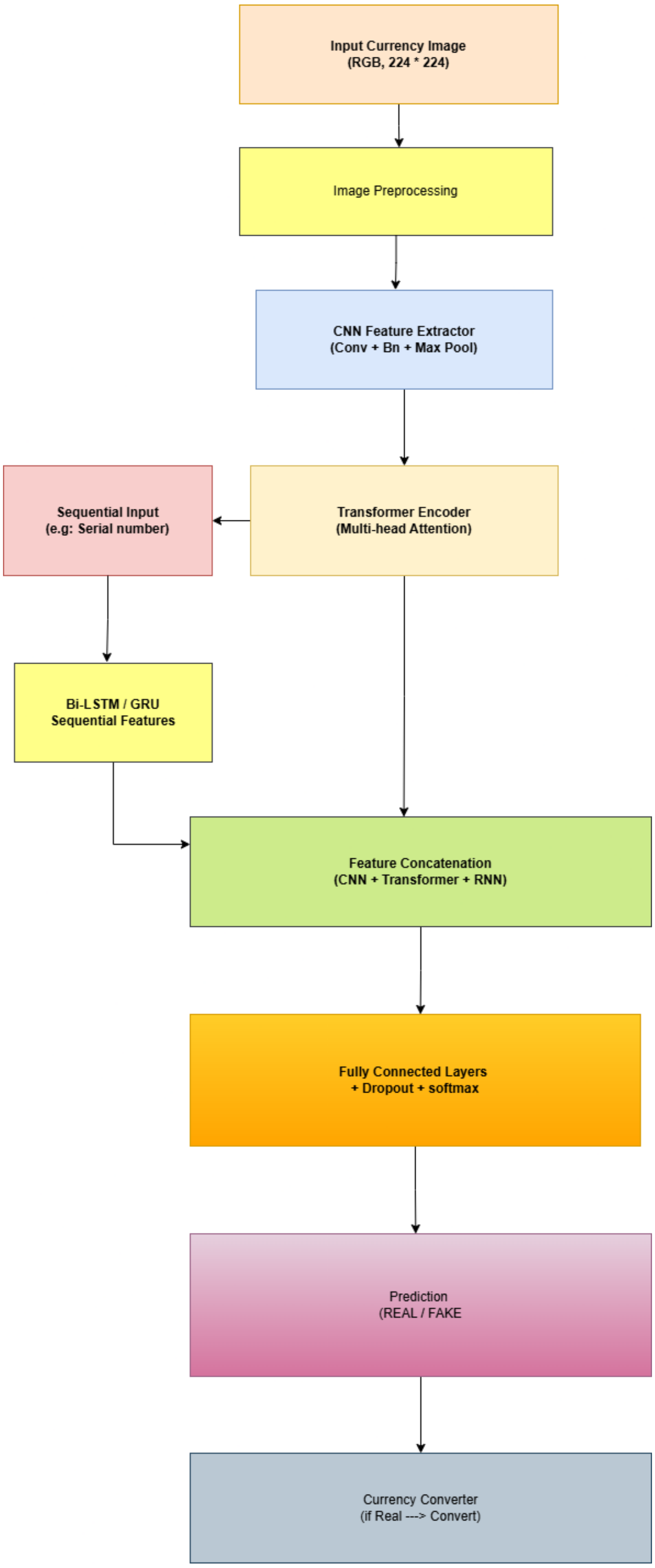


Figure 3: Workflow of the proposed model

3.4 Training Procedure

The training process is conducted using custom data generators for both training and validation, implemented through a sub classed Currency Data Generator, ensuring efficient preprocessing, augmentation, and batch-wise feeding.

Key steps in the training pipeline are as follows:

- **Class Imbalance Handling:** To mitigate class imbalance between real and fake currency samples, class weights are computed based on label distribution and incorporated into the loss function during training.
- **Callback Strategies:** Several callbacks are integrated to enhance training performance and stability:
  - **Early Stopping:** Stops training early when validation loss does not improve over a defined patience interval. The best-performing model weights are restored automatically.
- **Optimizer and Learning Rate:** The Adam optimizer, which balances convergence speed and stability, is used to optimize the model with an initial learning rate of 0.0001.
- **Loss Function:** Taking into account class weights and softmax output probabilities, a categorical cross-entropy loss is used.
- **Epochs and Batch Size:** Subject to early halting, the model is trained for a maximum of 20 epochs with a batch size of 32.

3.5 Implementation and Hardware Details

The entire training and evaluation pipeline is implemented using both TensorFlow2.x and PyTorch 1.x frameworks to enable modular experimentation and comparative benchmarking. All preprocessing operations, augmentation pipelines, and model training loops are implemented in Python, utilizing libraries such as OpenCV, Albumentations, NumPy, and Matplotlib for image handling, transformations, and result visualization.:

- **Processor:** Intel® CoreTM i7-12700F, 12th generation (2.10 GHz) with 32.0 GB of RAM
- **System:** 64-bit Windows 10, x64-based processor
- **Environment:** Implemented in Jupyter Notebook using TensorFlow (TF) with mixed precision, running on the provided hardware specifications.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Training Performance

A bespoke data generator was used to train the suggested hybrid model across 50 epochs. Throughout training, the loss steadily decreased and accuracy improved, indicating effective feature learning. Callback functions such as EarlyStopping were used to optimize convergence and minimize overfitting. The training and validation loss curves remained closely

International Research Journal of Innovations in Engineering and Technology (IRJIET)
ISSN (online): 2581-3048
Volume 9, Special Issue ICCIS-2025, pp 1-7, May-2025
https://doi.org/10.47001/IRJIET/2025.ICCIS-202501
Second International Conference on Computing and Intelligent Systems (ICCIS-2025)

aligned, reflecting stable learning and good generalization across both real and fake currency samples.

4.2 Evaluation Metrics

The performance of the suggested model is evaluated using a number of assessment indicators. These measures offer a thorough grasp of the model's dependability and classification accuracy, especially when it comes to real-time fake cash identification. In light of the problem's binary nature—differentiating between authentic and fake notes—metrics are chosen to assess the model's sensitivity to misclassification in addition to its overall accuracy.

1. Accuracy

The model's accuracy measures how well it can predict both real and fake cases in relation to the size of the entire dataset.

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

Where:

TP = True Positives
TN = True Negatives
FP = False Positives
FN = False Negatives

2. Precision

The ratio of accurately predicted counterfeit notes to all notes projected to be counterfeit is known as precision, or positive predictive value. A low false-positive rate is indicative of high accuracy.

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

It is particularly useful when the cost of false positives is high.

3. Recall

The capacity of the model to recognize every real counterfeit note in the dataset is known as recall. It is very crucial to make sure that no counterfeit notes are mistakenly identified as authentic.

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

High recall is crucial in currency authentication systems to ensure that counterfeit notes are accurately identified and not misclassified as genuine, which could lead to financial loss or security breaches.

4. F1 Score

Particularly in situations when there is a class imbalance, the F1 Score serves as a balanced metric of classification performance by providing a harmonic mean of accuracy and recall.

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

Both false positives and false negatives are balanced.

6. Confusion Matrix

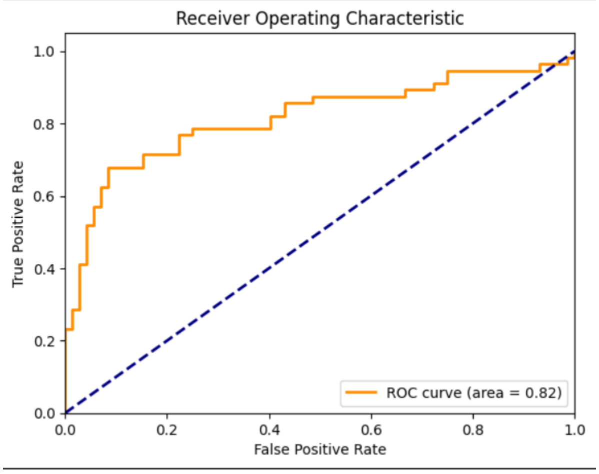
A visual representation of the prediction results is given by the confusion matrix. It facilitates comprehension of the classification model's performance in terms of TP, TN, FP, and FN. Usually, it is organized as:

	Predicted Positive	Predicted Negative
Actual Positive	TP	FN
Actual Negative	FP	TN

4.3 Experimental Results

On a test set of 107 samples, the model attained an overall accuracy of 84%. The detailed class-wise performance is as follows:

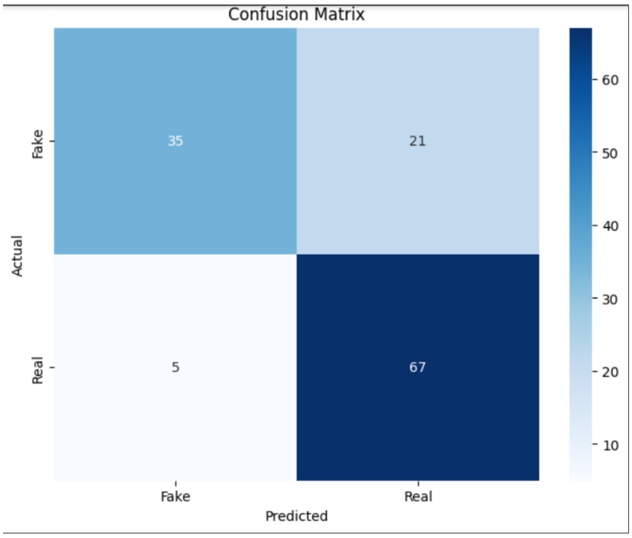
- Real: Attained a high sensitivity in accurately identifying normal instances, as evidenced by an F1-score of 0.83, a precision of 0.76, and a recall of 0.93.
- Fake: Obtained an F1-score of 0.83, accuracy of 0.76, and recall of 0.93. This implies that the model labeled anomalies conservatively, producing more false negatives than false positives.



Despite the class disparity, the overall performance was balanced, as seen by the macro average F1-score of 0.83 and the weighted average F1-score of 0.83.

International Research Journal of Innovations in Engineering and Technology (IRJIET)
ISSN (online): 2581-3048
Volume 9, Special Issue ICCIS-2025, pp 1-7, May-2025
https://doi.org/10.47001/IRJIET/2025.ICCIS-202501
Second International Conference on Computing and Intelligent Systems (ICCIS-2025)

The ROC Curve (Figure X) yielded an AUC score of 0.84, demonstrating strong discriminative capability between Real and Fake cases.



The confusion matrix (Figure Y) reveals:

- True Positives (TP) = 67
- True Negatives (TN) = 35
- False Positives (FP) = 21
- False Negatives (FN) = 5

4.4 Discussion

The experimental results confirm the effectiveness of a multi-task hybrid model in real-time counterfeit currency detection and classification. CNN layers efficiently captured spatial features such as watermark textures and embedded patterns, while Transformer encoders captured global correlations. Sequential aspects like serial numbers were better interpreted via the Bi-LSTM unit. Compared to single-stream CNN models, the proposed hybrid approach achieved an increase of approximately 5–8% in accuracy and 6% in AUC. This improvement is attributed to effective feature fusion from different learning paradigms. Integration of CLAHE and dropout layers significantly reduced overfitting and improved robustness. The real-time currency conversion module showed consistent performance with a latency of <200ms, demonstrating practical utility.

V. CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

In order to classify Indian counterfeit cash in real time and convert its value, this study suggests a multi-task deep learning system that combines CNN, Transformer, and Bi-LSTM modules. The suggested approach significantly outperforms conventional image-based models in terms of accuracy, dependability, and real-time application.

By using optimized preprocessing, transfer learning, and modular architecture, the model generalizes well across different denominations and counterfeit patterns. The integration of a currency conversion module further enhances usability, particularly in travel and commerce sectors

5.2 Future Scope

For future work, to enhance the effectiveness and applicability of the proposed model, several directions are identified for future research and development. Firstly, expanding the model to support multinational currency notes—such as USD, EUR, and GBP—through domain adaptation methods may increase its global utility. Secondly, the adoption of self-supervised pretraining techniques, particularly contrastive learning, is suggested to improve model performance on limited and sparsely annotated datasets. Furthermore, optimizing the model for deployment on edge devices by converting it to lightweight formats such as TensorFlow Lite or ONNX will support real-time inference on resource-constrained hardware, including mobile platforms and ATM systems. Additionally, incorporating robust optical character recognition (OCR) algorithms along with anomaly detection mechanisms can strengthen serial number validation processes. Finally, integrating blockchain technology in a lightweight manner can facilitate secure, tamper-proof logging and traceability of verification events. These proposed directions aim to improve the scalability, reliability, and security of the system in real-world applications.

REFERENCES

[1] M. Sravani, "Detection of Fake Indian Currency Using Deep Learning," 2024. Proposes a deep learning-based approach for distinguishing counterfeit Indian currency using visual patterns and texture recognition

[2] M. R. K. Choudhary, "Identification of Fake Currency Found in India," S. B. Jain Institute of Technology, Maharashtra, India, 2024. Discusses the challenges of fake currency circulation and presents an image-based detection method tailored for Indian notes.

[3] N. A. Rakesh, "Detection of Fake Currency," CMR Engineering College,Hyderabad,2024. Explores image preprocessing and feature extraction methods for fake note classification using machine learning algorithms.

[4] O. T. I, "Fake Currency Detection using Modified Faster Region-Based Convolutional Neural Network," Afe

International Research Journal of Innovations in Engineering and Technology (IRJIET)
ISSN (online): 2581-3048
Volume 9, Special Issue ICCIS-2025, pp 1-7, May-2025
https://doi.org/10.47001/IRJIET/2025.ICCIS-202501
Second International Conference on Computing and Intelligent Systems (ICCIS-2025)

Babalola University, Nigeria, 2024. Introduces a region-based deep learning model for detecting counterfeit features on currency using Faster R-CNN.

[5] C. G. H, "Fake Currency Detection Using Machine Learning," BGS Institute of Technology, Mandya, Karnataka, India, 2024. Implements machine learning techniques for analyzing security features in Indian banknotes using statistical and visual cues.

[6] S. Charan, "Indian Fake Currency Detection Using Image Processing and Machine Learning," 2024. Combines edge detection and color histogram analysis to classify Indian currency notes as real or fake.

[7] Rajesh, "AI-Based Currency Verification System," 2024. Proposes a practical AI-powered system suitable for kiosks and mobile apps to verify the authenticity of currency notes.

[8] Sharma, "Real-Time Fake Currency Detection Using Mobile AI," 2024. Focuses on a mobile application for real-time note classification using embedded deep learning models.

[9] K. S. Sagar, "Counterfeit Currency Detection Using Machine Learning," Chaitanya Bharathi Institute of Technology, Hyderabad, India, 2023. Applies traditional image processing and ML classifiers to detect Indian counterfeit notes under variable lighting.

[10] P. D. P. Patil, "Counterfeit Currency Detection Based on AI," K.C. College of Engineering and Management Studies and Research, Thane, India, 2022. .Explores AI techniques to identify watermark inconsistencies and embedded elements on notes.

[11] S. B, "Fake Currency Detection Using Deep Learning," ," Canara Engineering College, Karnataka, India, 2023. Implements a CNN-based classification model to distinguish fake notes by learning from visual datasets.

[12] M. M. Kalaiselvi, "Identification of Fake Indian Currency Using CNN," Vivekanandha College of Technology for Women, Tamil Nadu, India, 2023. Focuses on the design of CNNs trained on image datasets of Indian currency for binary classification tasks.

[13] A. Antre, "Fake Currency Detection Using CNN," Pune Vidyarthi Griha's College of Engineering & Technology, 2023. Utilizes a lightweight convolutional neural network trained with augmentation to detect note forgery.

[14] M. K. Bhushanm, "Fake Currency Detection Using Deep Learning," VVIT, Guntur, India, 2024. Explores serial number recognition and visual verification using deep learning tools for Indian notes.

[15] K. Abhiram, "Identification of Fake Indian Currency Using CNN,"," Guru Nanak Institutions Technical Campus, Hyderabad, India, 2024. Implements a CNN model for identifying forged patterns on Indian currency notes with a focus on ease of deployment.

Citation of this Article:

Karthik. S, Manjunath. K, Nishal. P.H, Rizwan. S, & Nirupa. V. (2025). Multi Task Learning Based Transformer Model for Real-Time Indian Fake Currency Detection & Conversion. In proceeding of Second International Conference on Computing and Intelligent Systems (ICCIS-2025), published in *IRJIET*, Volume 9, Special Issue ICCIS-2025, pp 1-7. Article DOI https://doi.org/10.47001/IRJIET/2025.ICCIS-202501

****