International Journal of Enhanced Research in Science, Technology & Engineering
ISSN: 2319-7463, Vol. 14 Issue 12, December-2025

Authenticity Identification and Denomination Recognition of Indian Currency Notes Using a Deep Learning Approach

Vivek Sharan*[1], Amandeep Kaur[2], Parvinder Singh[3]

[1]Ph.D. Research Scholar, Department of Computer Science and Technology, Central University of Punjab, Bathinda, Punjab, India
[2]Professor, Department of Computer Science and Technology, Central University of Punjab, Bathinda, Punjab, India
[3]Assistant Professor, Department of Computer Science and Technology, Central University of Punjab, Bathinda, Punjab, India

ABSTRACT

Modern life is deeply intertwined with technology, which, while offering many benefits, also faces challenges such as the increasing circulation of counterfeit currency. Counterfeiters now employ advanced scanning and printing techniques to generate currency notes that closely resemble genuine ones. As a result, distinguishing authentic currency from forged notes has become extremely difficult for the general public, leading to adverse economic consequences. The rapid advancement of printing technologies and sophisticated counterfeiting strategies has rendered many traditional detection methods inadequate. Counterfeit currency continues to be produced and circulated in India, causing significant inconvenience and financial loss to society. Despite numerous studies aiming to address this problem, additional improvements in detection accuracy and reliability are still necessary. Extracting features from currency images presents significant challenges, when the physical condition of the notes deteriorates over time and currency having diverse circumstances. To address these issues, in this study, we have proposed a CNN model and applied it to our self-created dataset, termed as the Custom Indian Currency Dataset (CICD),) consists of 2,335 images of Indian currency notes, specifically denominations of ₹200, ₹500, and ₹2000. The images are taken under different circumstances, including inconsistent lighting, handwritten annotations, dirt, blurriness, tears, and wrinkles, front and back sides, different orientations, and background to show diverse nature. This dataset has been augmented to a total of 22,154 images. We split the entire dataset into an 80:20 ratio and trained our model using 80% of the complete dataset and evaluated it on the remaining 20%. The model attained a training accuracy of 99.84% and a testing accuracy of 98.51%, utilizing an image size of 224×224, a learning rate of 0.0001, a batch size of 64, and 100 epochs. In addition to this, the model shows 99.53% precision value, 98.51% recall value, and 98.51% F1-score value. We have also compared our proposed model with some other existing models and techniques and achieved improved results. We have also tested the model by taking individual random samples of currency images, and our model is able to identify its authenticity and recognize the denomination value correctly.

Keywords: Counterfeit currency, Image processing, CNN Model, Authenticity, Denomination recognition

INTRODUCTION

In the contemporary technology-oriented environment, while we benefit from the conveniences of technology, the rise of counterfeit currency, created through illicit scanning and printing techniques, poses a significant threat as it undermines the legitimacy of legal currency issued by authorized authorities. Counterfeiters are utilizing advanced scanning and printing technology to produce such currency which looks like similar to original currency notes with high accuracy. It becomes very difficult for common people to differentiate between real and counterfeit currency notes which leads to degrade economic behaviour.

In every nation, there exists a designated legal authority tasked with the production and distribution of legitimate currency. However, Counterfeit currency is produced and distributed without the permission of this concern authority, constituting an act of forgery.

This situation leads to increasingly difficult to distinguish between genuine and counterfeit notes using traditional methods. Without the aid of technology, individuals may attempt to verify currency authenticity, but their ability to do so is hindered by the limitations of human visual perception. While various studies have sought to tackle this issue, there remains a need for further advancements in detection accuracy and reliability. Extracting features from currency images poses significant challenges, especially when dealing with notes that are old, damaged, worn, poorly lit, blurred, or captured in varying orientations and backgrounds.

Several researchers have suggested various techniques to address the issue of counterfeit currency detection. A prevalent method entails employing the aspect ratio (the relationship between height and width) of currency images in conjunction with their color characteristics (Bhurke, Sirdeshmukh, & Kanitkar, 2015) (Jadhav, Kalbande, Katkar, Katta, & Bharadwaj, 2022) (Kumar & Singh, 2023) have emphasized that variations in the dimensions and color attributes of currency images can aid in differentiating genuine currency from counterfeit notes effectively. (Yuan, Zhou , Chen, Xiao, & Lu, 2024) For example, high-resolution printers can imitate watermarks, microprinting, and even UV-reactive inks, making it increasingly challenging to differentiate between authentic and counterfeit notes using traditional methods. To tackle these challenges and enhance the accuracy, we have proposed robust and effect CNN model in this study.

The aim of this study is to develop a system capable of verifying the authenticity of currency notes under diverse real-world conditions while delivering improved performance compared to existing methods, and simultaneously identifying the corresponding denomination. This work focuses exclusively on high-denomination Indian currency notes, specifically ₹200, ₹500, and ₹2000, as these denominations are most susceptible to counterfeiting and have a greater economic impact.

Our primary contribution in this study is the development of a CNN model and implemented on our self created dataset CICD having diverse currency circumstances. Intially currency images are captured and resize to a particular dimentions. Train the proposed model on train dataset and test the model on test dataset. The proposed system not only identify the authenticity of currency note but also recognize the currency denomination value. We have also compared our model with other existing model (ConvNeXt-Tiny, a lightweight but powerful convolutional neural network and ResNet50) and techniques and also test our model with some samples of currency images as test cases.

The remaining sections are as follows: The second section includes a literature review pertaining to the subject matter is provided. Section 3 outlines the proposed methodology along with the workflow diagram. Section 4 showcases the experimental results and includes a discussion, whereas Section 5 elaborates on the conclusions and outlines future work.

A literature review pertaining to the subject matter is provided. Section 3 outlines the proposed methodology along with the workflow diagram. Section 4 showcases the experimental results and includes a discussion, whereas Section 5 elaborates on the conclusions and highlights potential future work.

LITERATURE REVIEW

With the rapid advancement of technology, researchers have introduced a variety of approaches to identify genuine currency notes and detect counterfeit ones. A summary of the most relevant studies is presented in the following section.

(Laavanya & Vijayaraghavan, 2019) offered a novel method of counterfeit currency detection based on transfer learning. The method employs a pre-trained AlexNet model using the Adam optimizer and trained from 100 images per denomination (50 genuine and 50 counterfeit samples) of Indian currency notes (Rs50, Rs200, Rs500, and Rs2000). The study aims at extracting security-thread-based features from the images for classification. The experimental findings indicate an average detection performance of 81.5% for authentic notes and 75% for counterfeit samples.

(Kamble, Bhansali, Satalgaonkar, & Alagundgi, 2019), proposed a framework for counterfeit currency recognition based on convolutional neural networks. The suggested architecture consists of several convolutional layers, which are succeeded by a flattening layer and fully connected layers for the purpose of classification. They used a total of 40,000 images as a dataset, in which 32000 images are training samples, and 8000 images are testing samples. The experimental evaluation yielded a testing accuracy of 85.6%, although much better The performance was noted during both training and validation phases, achieving accuracies of 98.57% and 96.55%, respectively.

(Veeramsetty, Singal, & Badal, 2020) proposed a convolutional neural network-based framework for Indian currency note recognition. The authors built a custom dataset that went through different levels of augmentation to finally comprise 11,657 images, of which 9,326 were used for training and 2,331 for validation. The CNN was identified to possess excellent learning capability by showing 100% training accuracy with 87.5% testing accuracy indicating enhanced performance than the traditional approaches. Apart from this, the research extended its input into the deployment of a web-based application that combines the trained model.

Another study (Chowdhury, Jana, & Parekh, 2020) where the author uses image processing and a deep learning technique to identify the Indian currency note. They use 80 currency images, i.e., ten currency samples taken from each note of Rs10, Rs20, Rs50 (old and new), Rs100, Rs200, Rs500, and Rs2000 for training and 34 Indian currency images along with two images of US dollars for testing purposes. After extracting the color and texture features, the experiment first recognizes the Indian currency by template matching and classifying using the K-NN algorithm. Second, by directly feeding the pre-processed images to the CNN for classification. The system produces 91% accuracy with KNN and 100% with CNN.

In the Paper (Andrushia, Neebha, & Bella Mary, 2020), authors used statistical feature extraction together with SVM classification, and implemented it on a total of 120 images of Indian currency (100 real and 20 fake) with denominations of 100, 500, and 2000. The method claimed 95.8% accuracy. Yet, it considered limited features applied to a very small dataset.

For recognizing Indian currencies using multiple convolution neural networks, (Reddy et al., 2023) tested the efficacy of diverse architectures using their dataset of 995 currency images collected from publicly available sources and images captured in real-world conditions. Their evaluation shows that With the deeper models based on pre-trained architectures, the simple CNN architectures yield better classification results. Among them, the sequential CNN was the best classifier with accuracies of 97.98%, followed by VGG16, MobileNet, and AlexNet with accuracies of 92.71%, 89.07%, and 71.66%, respectively. A point they raised also was that possibly deploying such models on smartphone platforms may lead to practical challenges due to computational and hardware limitations.

The authors in the study (Smitha, Sathwika, Harshini, & Jyothi, 2023) proposed a CNN model to recognize and classify Indian currency of different values, including 50, 100, 500, and 2000. The model shows an accuracy of 94.4% compared to another model, Resnet50, with an accuracy of 83.44%, and VGG16 with an accuracy of 91.6%. This proposed system has some limitations, A limitation of this method is that it focuses solely on one side of the currency, neglecting informative features present on the reverse side.

The authors proposed a hybrid image processing and CNN-based method for authenticating Indian currency notes (Kanawade, Jangade, Mane, & Kurne, 2024). The system was able to achieve a testing accuracy of 82% with a dataset of 1,000 images from different Indian denominations.

In another study (Patil, Minal, Anuprita, Karan, & Divesh, 2024) for visually impaired people, the authors proposed deep learning based model to detect fake currency. The system is capable of text-to-audio features for easily recognizing denomination value by visually impaired people. The approach is based on the intensity value of extracted features of currency notes. However, the method is not measured in terms of accuracy, and it is also not certain if the currency is dirty, old, torn, wrinkled, etc.

Recently, the author (Almzainy, Abu-Naser, & Samy, 2025) introduced a deep learning methodology for distinguishing between counterfeit and authentic currency, utilizing a dataset comprising 92,000 images. Notably, their proposed model attains an accuracy of 98%.

In another recent study, the authors (Savaliya, Akbari, Pradhan, Patel, & Upadhyay, 2025) CNN based deep learning model to enhance performance for the detection of Indian currency. This model is used to classify currency note images across seven denominations: ₹10, ₹20, ₹50, ₹100, ₹200, ₹500, and ₹2000. The dataset, sourced from the Kaggle repository, comprises a total of 3,166 images, which were augmented using various techniques to enhance feature learning. The proposed model attained a training accuracy of 98.93% and a validation accuracy of 90.82%.

PROPOSED METHODOLOGY

This section presents Deep Learning based CNN model to identify the authenticity of the currency note with denomination. The work flow diagram of the proposed methodology based on deep learning is depicted in the **Figure 1**

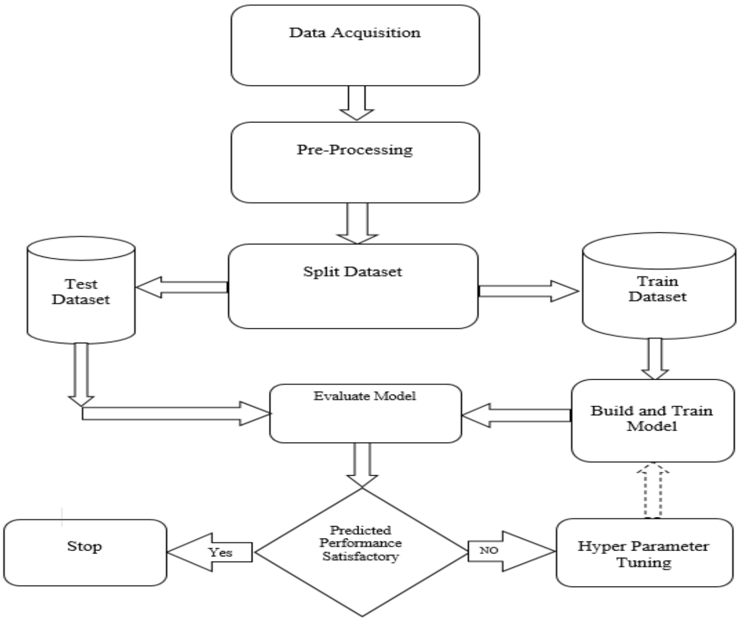

Figure 1: Work flow diagram of proposed CNN model

Phases of Proposed Methodology:
This methodology initialized from acquisition of dataset to prediction and evaluation of the proposed model and their procedures are discussed herewith.

a) Data Acquisition and Augmentation:
In this study, we have create our own dataset of Indian currency images of high denominations including 200, 500, and 2000 and named as The Custom Indian Currency Dataset (CICD) consists of 2,335 images of Indian currency notes. In this phase, we implement various augmentation techniques utilizing Python's Image Data Generator to enhance the dataset. Different augmentation techniques including- Rotation (rotate the images by 90 degree, 180 degree, 270 degree), Zoom augmentation (perform zoom_range=0.1, which means randomly zooming in and zooming out by 10% of the image) with fill_mode = nearest. The images are captured under various conditions such as non-uniform illumination, handwritten markings, dirt, blur, tears, wrinkles, front and back side, different orientations and background. After augmentation, we have total of 22,154 images in which real images are 11,252, and fake images are 10,902. As per denominations, we have total of 3696 real and 3648 images of fake currency of 200, 3762 real and 3542 fake images of denomination 500, and last 3794 real and 3712 fake images of denomination 2000.

b) **Pre-Processing:** In this step, We perform several image pre-processing techniques to make the images suitable for further analysis are-

- **Noise Reduction:** As images are taken with a camera, it is essential to eliminate noise. To achieve this, we have employed the Non-Local Means Denoising technique (NLM).
- **Image resize:** In this phase, we adjust the dimensions of all images to a specific size. This step is crucial, as the images captured vary in size. To reduce the complexity of the model and shorten the training time, we resize all images to a dimension of 224X224.

c) **Split Dataset:** In this step, we split the entire dataset into train and test set. Train set comprises of 80% of overall dataset and test set comprises 20% of the dataset.

d) **Model Build and Train:** After split the entire dataset, proposed CNN model is designed and trained on the train set and further tested on test dataset.

e) **Model Evaluation and Hyper Parameter Tuning:** After building the model, it is necessary to evaluate how efficient the model. In this sub-section, metrics like accuracy, recall, precision and F1 score are measures to evaluate models performance followed by accuracy and loss curve. Confusion matrix is also generated to better visualize the performance for each denomination. If performance is not optimal, then hyperparameter tuning is updated and again evaluate the model.

Architecture of the Proposed CNN Model
To build the CNN Model, we have used different layers. The model consists of three convolutional blocks/layers for hierarchical feature extraction, followed by a fully connected classifier. A description of the architecture of the model is presented in the **Table 1**

Table 1: Description of the CNN model architecture

Layer	Details of Each Layer	Layer Type	Output Shape
Input Layer	Input image of size 224×224×3 (RGB channels)	Input	(224, 224, 3)
Conv2D_1	32 filters, kernel size (3×3), stride (1,1), padding='same'	Convolution	(224, 224, 32)
BatchNormalization_1	Normalizes activations across each feature map	Normalization	(224, 224, 32)
Activation_1	ReLU activation function	Activation	(224, 224, 32)
Dropout_1	Dropout rate = 0.1 (10% neurons randomly ignored during training)	Regularization	(224, 224, 32)
MaxPooling2D_1	Pool size (3×3), reduces spatial dimensions	Pooling	(74, 74, 32)
Conv2D_2	64 filters, kernel size (3×3), stride (1,1), padding='same'	Convolution	(74, 74, 64)
BatchNormalization_2	Normalizes feature maps to stabilize learning	Normalization	(74, 74, 64)
Activation_2	ReLU activation function	Activation	(74, 74, 64)
Dropout_2	Dropout rate = 0.1	Regularization	(74, 74, 64)
MaxPooling2D_2	Pool size (3×3)	Pooling	(24, 24, 64)
Conv2D_3	128 filters, kernel size (3×3), stride (1,1), padding='same'	Convolution	(24, 24, 128)
BatchNormalization_3	Normalizes activations for better convergence	Normalization	(24, 24, 128)
Activation_3	ReLU activation function	Activation	(24, 24, 128)
Dropout_3	Dropout rate = 0.1	Regularization	(24, 24, 128)
MaxPooling2D_3	Pool size (3×3)	Pooling	(8, 8, 128)
Flatten	Converts 3D feature maps into 1D feature vector	Transformation	(8192)
Dense_1	16 neurons, activation='relu'	Fully Connected	(16)
Dense_Output	Output layer with softmax activation, number of neurons = number of classes	Fully Connected (Classifier)	(num_classes)

Hyperparameter Tuning
To build the CNN model, it is required to focus on the parameters to generalize model with optimze results. In this study, we have implemented different values of the parameters and consider values with optimal results. In this experment, we consider batch size = 64 for faster training, learning rate = 0.0001 to update weights, to avoid underfitting and overfitting during training the model, take epochs = 100. Different filters (32, 64, 128) are used at different layers and size of the filter used 3x3 during the experiment. We also consider adam optimizer with dropout rate = 0.1

Performance Comparison
In this study, our proposed CNN model is compared with the another deep learning model discussed in the existing study (Veeramsetty, Singal, & Badal, 2020) as well as pre-trained models ConvNeXt-Tiny, a lightweight but powerful convolutional neural network and ResNet50. All these deep learning models are implemented on our dataset CICD. Consider the image size of 224x224, learning rate 0.0001, batch size 64 with 100 epochs for all the models. To measure the effectiveness of the models, we use differentmetrices , followed by confusion matrix.

Hardware and Software Specifications
In this section, we have mentioned the software and hardware specifications upon which the model is implemented.

Hardware Specification:
Hardware specification upon which the model is build and implemented is presented in the **Table 2** below.

Table 2: Hardware specification

Component	Implemented Specifications
Processor	13^{th} Gen, i9 2.00 GHz
RAM	128 GB
GPU	8 GB NVIDIA
Storage	515 GB SSD

Software Specification:
Software specification upon which the model is build and implemented is presented in the **Table 3** below.

Table 3: Software specification

Sr. No.	Implemented Specifications
1.	Operating System- Windows 10 pro
2.	Programming Language- Python 3.9.7
3.	Deep Learning Libraries
(a)	Tensor Flow- 2.10.0
(b)	OpenCV- 4.11.0 (Image Pre-processing)
(c)	Numpy- 1.22.4 (Data Manipulation)
(d)	Matplotlib- 3.4.3 (Visualization)
4.	Environment/Tools- Jupyter Notebook

RESULTS AND DISCUSSION

In this section, results of the implemented proposed CNN model are presented and discussed. In the section 4.2, results of the proposed deep learning-based methodology is presented. We have also perform comparison of our proposed methodology as well as existing methodology and some existing models on our dataset (CICD).

Results of Proposed CNN Model
On implementation of our proposed CNN model on the CICD dataset, it is observed that our proposed CNN model achieves an accuracy of 99.84% on the training dataset and 98.51%.on the test dataset. This training value shows that the model has learned the training set extremely well — nearly all examples are correctly classified and also generalizes fairly well to unseen data (the test set). We have implemented our model with an image size of 224x224, learning rate of 0.0001, batch size of 64 with 100 epochs. The training and testing accuracy of our proposed model is depicted in **Figure 2**. In addition of accuracy, some other metrices are also used to measure the effectiveness of the proposed model on the test dataset which shows 99.53% precision value, 98.51 % recall value, and 98.51% F1-Score value.

Figure 2: Training and testing accuracy of proposed CNN model

In addition of this, accuracy and loss curves (training and test) are also presented in the **Figure 3**, and in the FIGUREYY respectively to visual diagnostics of model's behavior that how our model is learning and generalizing.

The accuracy curve shows how the proportion of correct predictions changes over epochs. The loss curve shows how the model error (according to the loss function) decreases over epochs.

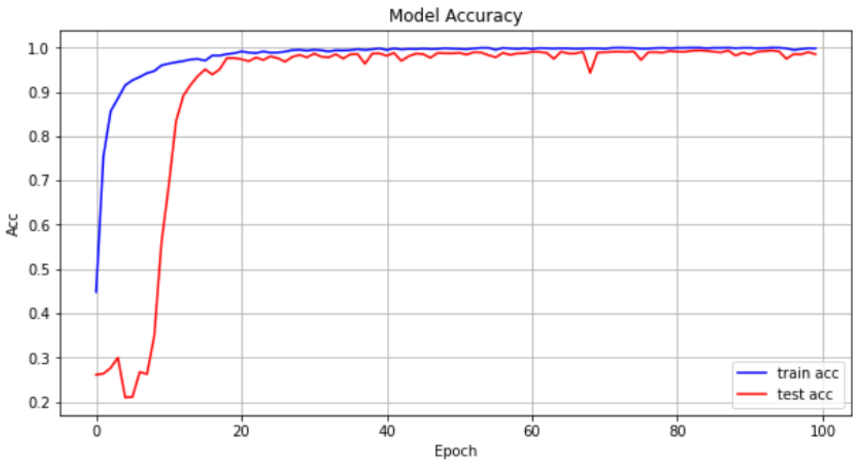

Figure 3: Accuracy curve (training vs test dataset)

In the **Figure 3**, the X-axis is epoch and the Y-axis is accuracy and the blue curve represent train accuracy and the red curve represent the test accuracy. From the curves, it is observe that early epochs, the train accuracy rises rapidly and the test accuracy starts low, remains minimum for first 10 epochs, and then jumps rapidly up. After 20 epochs both curves flatten out with small fluctuations. The gap between the two curves becomes very small (the red is just slightly below the blue) after 20 epochs. It shows that the model learns quickly. Training accuracy climbs steeply in the early epochs. That means the model is picking up patterns from the training data. The test accuracy, after a bit of lag, also climbs to nearly the training accuracy and the gap becomes small is a strong sign that the model generalises well i.e., it's not only memorising training data but doing well on unseen/test data too.

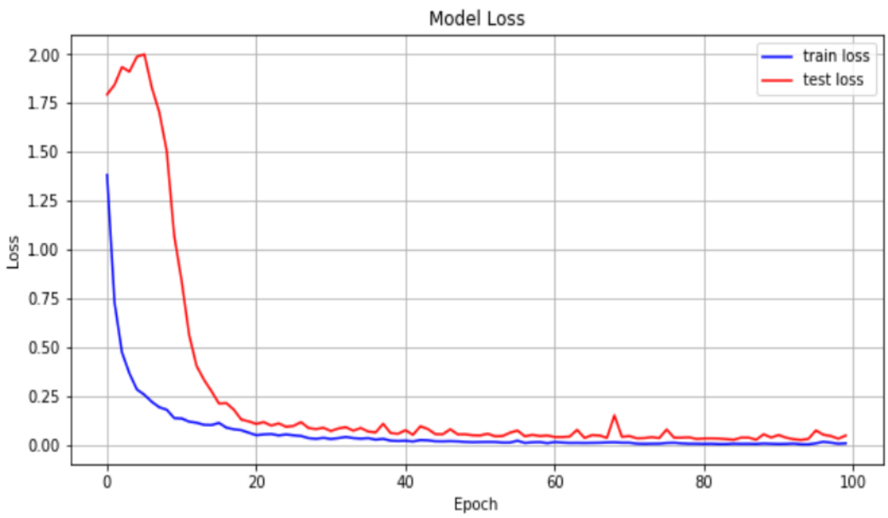

Figure 4: Loss Curve (training vs test dataset)

The graph in the **Figure 4**, shows the training and testing loss curves of our model over 100 epochs**.** X-axis (Epoch) indicate the number of complete passes through the training dataset and the Y-axis (Loss) measure of the model's error. Blue line (train loss) indicate how well the model performs on the training data and red line (test loss) indicate how well the model performs on unseen (test/validation) data. Initially (epoch 0-10) training loss (blue) drops sharply, indicating the model is learning quickly and test loss (red) initially increases a bit before dropping, this can happen due to early instability during initial learning. Between epochs 10-20, both train and test losses decrease steadily and converge to low values which indicates that the model is generalizing well and learning effectively. Onwards from epochs 20 i.e (20-100), both losses stabilize around very low values (close to zero). After analyzing this, it is concluded that the model learned efficiently and generalized well and the final loses being very low suggests high accuracy.

In addition with such metrics, confusion matrix is also mentioned in the **Figure 5** on the test dataset to better analyze the model's effectiveness on individual class of currency notes.

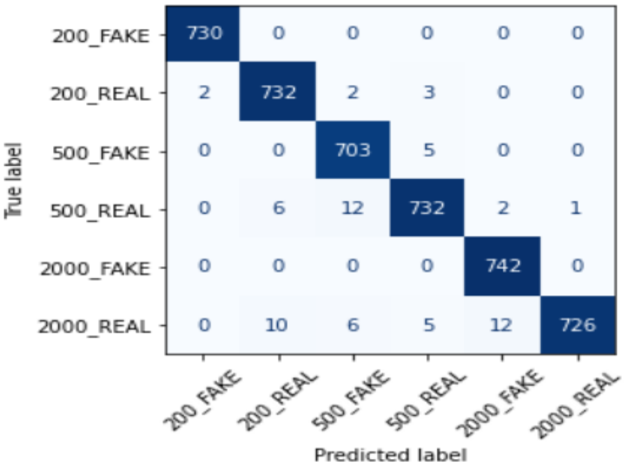

Figure 5: Confusion Matrix of proposed CNN model on test dataset

From the confusion matrix, following points can be observe which are listed below-

- 730 true instances of 200_FAKE class are correctly classified, so this class has perfect accuracy.
- In the matrix row for 200_REAL (true class): only 5 mis-classification occurs. It shows strong performance.
- 703 true instances of 500_FAKE class are correctly classified and only 5 (as 500_REAL) are wrongly predicted.
- 732 true instances of 500_REAL class are correctly classified and total 21 instances of 500_REAL class are mis-classified.
- 742 true instances of 2000_FAKE are correctly classified and there are 0 mis-classifications into other classes. It shows that it performing very well for classification task.
- 726 true instances of 2000_REAL are correctly classified and total 33 instances are mis-classified.

Performance evaluation of the proposed CNN model with existing and pre-trained models

To validate the performance of the proposed CNN model, it has been compared with the existing study.
(Veeramsetty, Singal, & Badal, 2020) as well as pre-trained models including ConvNeXt-Tiny, and ResNet50 dataset CICD in terms accuracy, which is represented in **Figure 6**. Consider the image size of 224x224, learning rate of 0.0001, a batch size of 64, a total of 100 epochs for all the models.

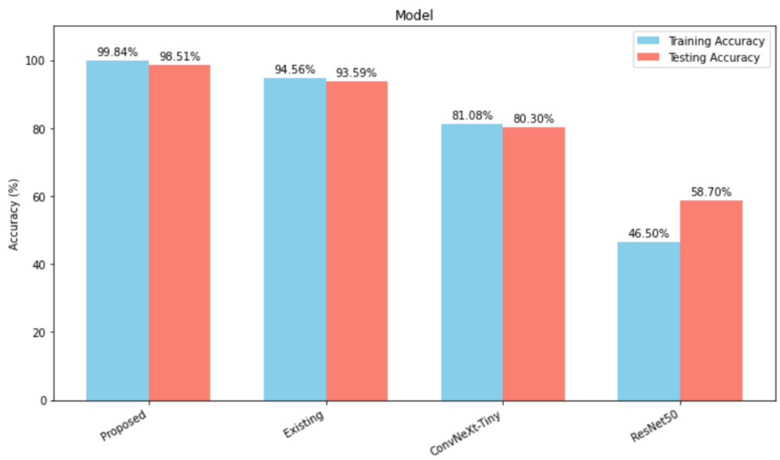

Figure 6: Accuracy comparison of proposed CNN model with existing and pre-trained models

From **Figure 6**, it is observed that our proposed technique gives the best performance among all four: highest training (99.84%) and validation (98.51%) accuracy, and a small generalisation gap. After the implementation of the existing technique on our dataset CICD, the existing model achieves training accuracy of 94.56 % on the training dataset and 93.51% on the test dataset.

While the pre-trained model ConvNeXt-Tiny achieves accuracy of 81.08% on the training dataset and 80.30% on the test dataset, the last ResNet50 model achieves accuracy of 46.50% on training dataset and 58.70%.on the test dataset It is concluded that the existing model is performing well compared to other pre-trained models mentioned here, and ResNet50 is lacking in performance compared to all the models discussed here.

In addition to accuracy, some other performance metrics on the test dataset are also observed. Precision value of the proposed technique is 98.53%, which is better compared to the precision value 93.72% of the existing technique. Recall and F1 score values of the proposed technique are 98.51% and 98.51%, respectively, which are also better than the recall 93.59% and F1 score 93.54% value of the existing technique.

Testing the Proposed CNN Model on Indian Currency Samples

In this study, after developing our model we proceeded to evaluate its performance on real-world Indian currency samples to assess how effectively it can recognize denominations and verify originality. We selected genuine notes of denominations 200, 500 and 2000, and we also included a counterfeit note of denomination 500 as a test case. The results for each sample are presented below.

- **Test 1:** The model successfully processed the real note of denomination 200, correctly recognizing the denomination and classifying it as authentic which is depicted in the **Figure 7**.

Figure 7: Test result 1: (real denomination 200)

- **Test 2:** When tested with a real note of denomination 500, the model demonstrated strong recognition capability and flagged it correctly as authentic which is depicted in the **Figure 8**

Figure 8: Test result 2: (real denomination 500)

- **Test 3:** We further evaluated a genuine ₹ 2000 note. The model again showed robust performance in recognising the denomination and confirming authenticity which is depicted in the **Figure 9**

Figure 9: Test result 3: (real denomination 2000)

- **Test 4:** We further evaluated a counterfeit denomination 2000 note. The model correctly identified this sample as counterfeit which is depicted in the **Figure 10**.

Figure 10: Test result 4: (fake denomination 500)

Across the test cases discussed above, the model demonstrated strong performance in both accurately recognising the denomination of Indian currency notes and identifying their authenticity.

CONCLUSION AND FUTURE AND SCOPE

Counterfeit currency frequently circulates worldwide without legal permission, and India is one of the nations impacted by this problem. Advanced printing technologies and intricate counterfeiting methods has made traditional detection techniques progressively inadequate. In this study, we have proposed a CNN model that can determine the authenticity of high-denomination Indian currency notes and also identify the value of the currency denomination. We have compared our model with existing pre-trained models and existing techniques on our dataset CICD, having diverse currency circumstances, which shows realistic behaviour. Our model achieves an accuracy of 99.84% on the training dataset and 98.51%.on the test dataset which is improved over ConvNeXt-Tiny having accuracy of 81.08% on the training dataset and 80.30% on the test datasetand the ResNet50 model shows accuracy of 46.50% on the training dataset and 58.70% on the test dataset. All comparisons carried out while preserving all parameters, such as an image size of 224x224, a learning rate of 0.0001, a batch size of 64, and a total of 100 epochs, remain the same. Effectiveness of the model is also measured in different metric terms, followed by a confusion matrix and an AUC-ROC curve for better understanding. Therefore, the experiment demonstrates that our model performs well, learned extremely well with good accuracy, and also fairly well on unseen data, and is able to identify the currency authenticity and recognize currency denominations.

FUTURE SCOPE

As the model is applied only to high-denomination Indian currency values, in the future, more currency values can be considered. This approach can be applied to other countries' currencies also. We can also propose some other approaches to refinement of the results, and also a web-based application for android can be created to facilitate real-time currency authentication directly on the device.

ACKNOWLEDGMENT

Thankful to my supervisor, Prof. Amandeep Kaur, Professor, Department of Computer Science and Technology, Central University of Punjab, Bathinda, for providing me the Research Lab (Computer Vision Lab-205) facility to perform the successful research work. Also thankful to my co-supervisor, Dr. Parvinder Singh, for their guidance and all the faculties of the department.

Conflicts of interest
The authors have no conflicts of interest to declare.

Data availability
The data are not publicly available. However, the data may be provided by the corresponding author upon a reasonable request.

Author’s contribution statement
Vivek Sharan: The background work, methodology, data collection, implementation, result analysis, draft preparation, revision of the paper.

Prof. Amandeep Kaur: Conceptualization, supervision, examine and correct the manuscript, work review, checked the study results

Dr. Parvinder Singh: Conceptualization, supervised the conducted study, checked the study results.

REFERENCES

[1] Bhurke, C., Sirdeshmukh, M., & Kanitkar, M. (2015). Currency recognition using image processing. *Int. J. Innov. Res. Comput. Commun. Eng, 3*, 4418--4422.

[2] Jadhav, R., Kalbande, S., Katkar, R., Katta, R., & Bharadwaj, R. (2022). Machine Learning Based Currency Classification System. *International Research Journal of Engineering and Technology (IRJET), 9*(1), 204-211.

[3] Kumar, A., & Singh, R. (2023). Currency Authentication using Color Based Processing. *2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT)* (pp. 1-7). IEEE.

[4] Yuan, J., Zhou , Y., Chen, G., Xiao, K., & Lu, J. (2024). Materials vs digits: A review of embedded anti-counterfeiting fingerprints in three-dimensional printing. *Materials Science and Engineering: R: Reports, 160*. doi:https://doi.org/10.1016/j.mser.2024.100836

[5] Laavanya , M., & Vijayaraghavan, V. (2019). Real Time Fake Currency Note Detection using Deep Learning. *International Journal of Engineering and Advanced Technology (IJEAT)*, 95-98.

[6] Kamble, K., Bhansali, A., Satalgaonkar , P., & Alagundgi, S. (2019). Counterfeit Currency Detection using Deep Convolutional Neural Network. *IEEE Pune Section International Conference (PuneCon)*, (pp. 1-4).

[7] Veeramsetty, V., Singal, G., & Badal, T. (2020). Coinnet: platform independent application to recognize Indian currency notes using deep learning techniques. *Multimedia Tools and Applications, 79*, 22569–22594. doi:https://doi.org/10.1007/s11042-020-09031-0

[8] Chowdhury, U. R., Jana, S., & Parekh, R. (2020). Automated System for Indian Banknote Recognition using Image Processing and Deep Learning. *International Conference on Computer Science, Engineering and Applications, ICCSEA*, (pp. 1-5).

[9] Andrushia, D., Neebha, M., & Mary, T. B. (2020). An Intelligent Method for Indian Counterfeit Paper Currency Detection. *Journal of Information Technology Management, 12*, 36-49.

[10] *11*.

[11] Padmaja, B., Bhargav, P., Sagar, H., Nayak, B., & Rao, M. (2021). Indian Currency Denomination Recognition and Fake Currency Identification. *Journal of Physics: Conference Series. 2089*, p. 012008. IOP Publishing.

[12] Kumar, S., Singal, G., Sirikonda, S., & R. Nethravathi. (2020, dec). A Novel Approach for Detection of Counterfeit Indian Currency Notes Using Deep Convolutional Neural Network. *IOP Conference Series: Materials Science and Engineering, 981*. doi:10.1088/1757-899X/981/2/022018

[13] Das, S., Wankhede, K., & Rituraj, A. (2022). Deep Learning Approach for Fake Currency. *International Journal of Advanced Research in Science, Communication and Technology (IJARSCT), 2*(1), 2581-9429. doi:10.48175/IJARSCT-7511

[14] Reddy, K., G, R., C, R., C, S., Kaur, M., & Soujanya, R. (2023). An Automated System for Indian Currency Classification and Detection using CNN. *15th International Conference on Materials Processing and Characterization (ICMPC 2023), 430*, p. 01077. doi:https://doi.org/10.1051/e3sconf/202343001077

[15] Smitha, K., Sathwika, S., Harshini, V., & Jyothi, P. (2023). INDIAN CURRENCY CLASSIFICATION AND FAKE NOTE IDENTIFICATION USING DEEP LEARNING. *Turkish Journal of Computer and Mathematics Education (TURCOMAT), 14*, 88--98

[16] Kanawade, M. B., Jangade, S. S., Mane, A. R., & Kurne, T. D. (2024). Counterfeit Currency Detection Using Machine Learning. *International Journal of Scientific Research in Science, Engineering and Technology, 11*(3), 399-405.

[17] Patil, N., Minal, M. I., Anuprita, V. S., Karan, R. B., & Divesh, S. P. (2024). Visual currency validator: An android app empowering the visually impaired with image processing and deep learning for fake currency detection. *Journal of Research Administration Society of Research Administrators International, 6*(1), 5627-5636

[18] Almzainy, M., Abu-Naser, & Samy, S. (2025). Detection and Classification of Faked and Genuine Money Using Deep Learning. 237--248. doi:https://doi.org/10.1007/978-981-96-5220-4_20

[19] Savaliya, J., Akbari, V., Pradhan, A., Patel, P., & Upadhyay, J. B. (2025, October). Indian Currency Note Classification Using Deep Learning. *International Research Journal on Advanced Engineering Hub (IRJAEH), 2*(10), 3862-3868. doi:https://doi.org/10.47392/IRJAEH.2025.0561