

Fake Currency Detection Using Machine Learning for Accurate and Reliable Banknote Authentication System

Nilesh Pujari¹ Bharati S. Pochal²

¹Department of Computer Science and Engineering, Visvesvaraya Technological University, Centre for PG Studies, Kalaburagi, Karnataka, India

²Department of Computer Science and Engineering, Visvesvaraya Technological University, Centre for PG Studies, Kalaburagi, Karnataka, India

Email ID: bharatipochal@gmail.com ORCID ID: 0000-0001-9562-8420

ABSTRACT

The increasing accessibility of high-resolution colour printing has intensified the problem of counterfeit banknotes. This study presents a deep-learning framework for classifying Indian currency images as real or counterfeit using the Xception architecture. The reported dataset contains 232 images of genuine and counterfeit notes and is described primarily in relation to the INR 500 and INR 2,000 series. Images were resized to 224 x 224 pixels, normalized, augmented, and divided into training, validation, and testing sets. Xception was initialized with ImageNet weights and fine-tuned, while a Python and Flask interface was used to accept images and display the predicted class. Performance was assessed with accuracy, precision, recall, F-measure, a confusion matrix, an accuracy curve, and functional test cases. The thesis reports a training accuracy of 93.34% and a validation accuracy of 97.00%. The deployed performance page reports accuracy of 0.97, precision of 0.94, recall of 0.97, and F-measure of 0.97. The confusion matrix records 56 counterfeit notes correctly classified, three counterfeit notes classified as real, no real notes classified as counterfeit, and 48 real notes correctly classified. The results indicate that Xception provides an effective basis for time-efficient counterfeit-currency detection, while further work is required to broaden denomination coverage, incorporate security features, and improve robustness to noisy images.

Keywords: Fake Currency, Machine Learning, Authentication System.

I. INTRODUCTION

Counterfeit Indian currency notes circulate as imitations of genuine banknotes and create difficulties for financial systems, users, and the Reserve Bank of India. Although digital payments have expanded, paper currency remains widely used because it is familiar, portable, and dependable. The thesis identifies advances in colour printing, scanning, and low-cost laser printing as factors that have made high-quality replication easier. It therefore treats automated identification of genuine and counterfeit notes as a practical image-classification problem.

Conventional counterfeit-detection methods commonly rely on specialized hardware or manually designed image-processing features, including the security thread, identifying mark, see-through register, microlettering, printing year, and other visible characteristics. Such methods can require careful acquisition and feature extraction. The proposed work instead uses deep learning so that discriminative features can be learned from currency images and used to predict whether an input note is real or fake.

The study has four linked objectives: to recognize counterfeit Indian currency, implement the detector with Python tools, apply the Xception architecture to banknote images, and improve detection efficiency in comparison with hardware-heavy or conventional image-processing approaches. The resulting proof chain is dataset acquisition, preprocessing, Xception-based training, binary prediction, performance evaluation, and software testing.

II. LITERATURE REVIEW

The supplied thesis situates the project within a broad body of banknote-recognition research. Reviews of banknote-recognition methods describe sensor-based and image-based techniques [1], while deep-learning systems have also been developed for euro and Mexican banknotes using real-world images [2]. Earlier approaches include multiple-kernel support vector machines for counterfeit-banknote recognition [3] and X-ray fluorescence analysis for counterfeit coins [4].

Image-driven methods have used visible-light smartphone images for counterfeit-banknote detection [5], ultraviolet-pattern segmentation for automated inspection [6], and image-analysis techniques for forgery

detection and denomination identification [7]. Convolutional neural networks have also been applied to new and old banknote recognition [8], supported by broader developments in CNN-based image classification [9].

For Indian currency, the thesis reviews CNN and image-processing approaches that use note images, serial numbers, security features, and pretrained networks [10]-[15]. Across these studies, the recurring workflow is image acquisition, preprocessing, feature learning or extraction, classification, and evaluation. The present work adopts Xception because its depth-wise separable convolutions provide a computationally efficient architecture for image classification and can be combined with transfer learning.

III. METHODOLOGY

A. Dataset and preprocessing

The primary dataset described in the thesis contains 232 images of genuine and counterfeit Indian currency. The proposed-system description focuses on INR 500 and INR 2,000 series notes, with images arranged for training and testing. The report also presents functional test cases for additional denominations and for damaged or variably illuminated images. Before training, images were resized to 224 x 224 pixels, converted to numerical arrays, normalized, and augmented. The augmentation procedures explicitly reported include resizing and rotation.

The thesis additionally documents conventional operations such as filtering, thresholding, Sobel or Canny edge detection, K-means segmentation, and Harris corner detection. These steps are retained here as supporting image-processing options; the main classification pipeline proceeds from preprocessing and feature preparation to Xception-based prediction.

Table 1. Dataset and implementation profile

Item	Details reported in the thesis
Task	Binary classification of Indian currency images as real or counterfeit
Primary dataset	232 genuine and counterfeit currency images
Primary denominations described	INR 500 and INR 2,000 series
Input size	224 x 224 pixels
Preprocessing	Resizing, normalization, array conversion, and augmentation
Model	Xception initialized with ImageNet weights and fine-tuned
Software environment	Python, Keras/TensorFlow components, and Flask
Output	Predicted result: real currency or fake currency

B. Xception model and training

Xception was selected as the central classifier. The architecture uses depth-wise separable convolutions and is described in the thesis as a 36-convolutional-stage network with entry, middle, and exit flows. The preprocessed images were divided into training, validation, and testing sets. The model was initialized with pretrained ImageNet weights and fine-tuned on the currency dataset. Learning-rate scheduling, early stopping, and regularization were used to reduce overfitting and improve generalization.

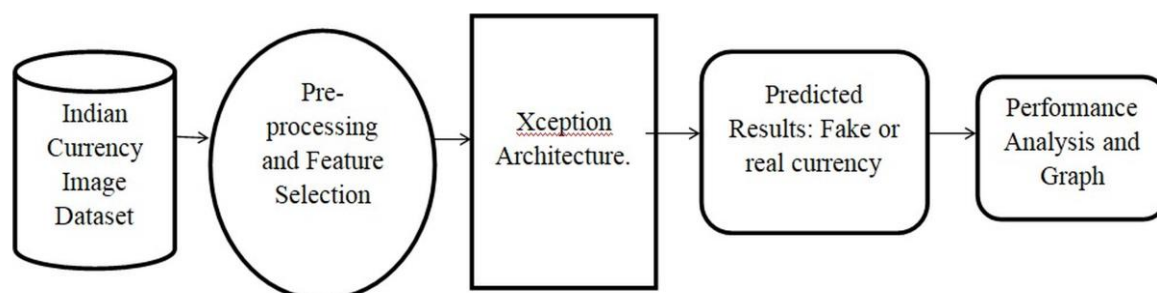


Figure 1. Proposed fake-currency detection system architecture.

C. Application and evaluation procedure

The trained classifier was integrated into a Flask-based web application. The interface provides a home page, login page, image-upload page, and prediction display. For each uploaded currency image, the system returns a real or fake label. Evaluation was based on accuracy, precision, recall, F-measure, the confusion matrix, training

and validation behaviour, and functional test cases. The thesis defines the metrics through true-positive, true-negative, false-positive, and false-negative outcomes; the source equation formatting is internally inconsistent, so the metric definitions and reported values are retained without silently rewriting the equations.

IV. DATA ANALYSIS

The dataset-distribution chart in the thesis reports 70% real notes and 30% fake notes. The confusion matrix was used to examine the direction of classification errors, while the performance page summarized accuracy, precision, recall, and F-measure. The accuracy plot compared training accuracy with validation or test accuracy across four epochs. The system-testing section further describes dataset evaluation, robustness checks under noise and distortion, cross-validation, real-time testing, unit testing, integration testing, system testing, functional testing, and output testing.

Ten functional test cases were reported. They cover genuine and counterfeit INR 10, INR 100, and INR 500 notes, a genuine INR 50 note under varying angle and background conditions, partially damaged genuine and counterfeit notes, and genuine-note images under different lighting. For every listed test case, the actual output matched the expected output. The full evidence matrix is retained in Appendix A.

V. RESULTS

A. Classification performance

The thesis reports a training accuracy of 93.34% and a validation accuracy of 97.00% for the Xception-based detector. The deployed performance-analysis page reports an accuracy of 0.97, precision of 0.94, recall of 0.97, and F-measure of 0.97. These values are presented in Table 2 exactly as reported.

Table 2. Reported Xception performance

Performance source	Metric	Reported value
Thesis text	Training accuracy	93.34%
Thesis text	Validation accuracy	97.00%
Performance page	Accuracy	0.97
Performance page	Precision	0.94
Performance page	Recall	0.97
Performance page	F-measure	0.97

The confusion matrix records 56 counterfeit notes predicted as counterfeit, three counterfeit notes predicted as real, zero real notes predicted as counterfeit, and 48 real notes predicted as real. Thus, the observed classification errors in the displayed matrix are confined to three counterfeit images that were assigned to the real class.

Confusion Matrix

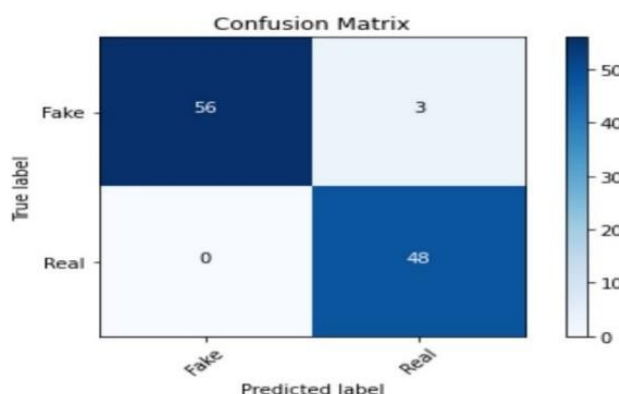


Figure 2. Confusion matrix reported for the currency classifier.

B. Training behaviour and output examples

The reported accuracy curve shows validation or test accuracy remaining close to 0.98 during the first two epochs, reaching approximately 1.00 at the third epoch, and ending near 0.98 at the fourth epoch. Training accuracy increases from about 0.86 to about 0.98 over the same sequence. The figure is reproduced from the thesis without recalculation.

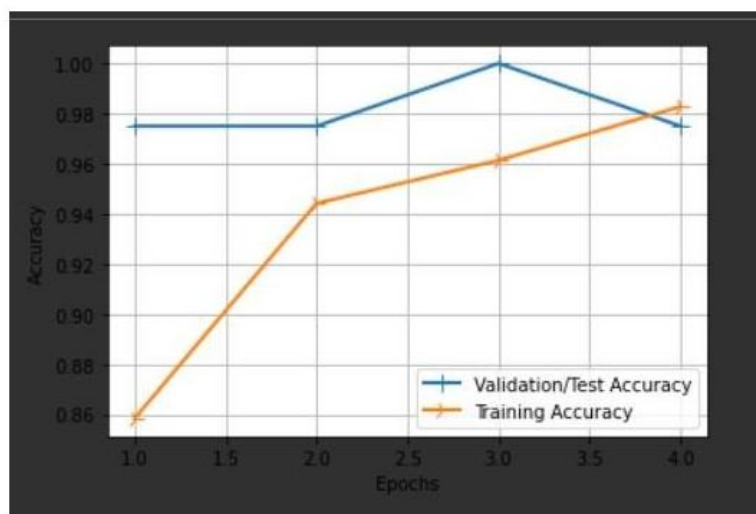


Figure 3. Training and validation/test accuracy curve reported in the thesis.

Representative real and fake classification outputs are retained in Appendix B.

C. Comparison with existing classifiers

The thesis provides a performance table for Darknet, AlexNet, ResNet, and GoogleNet. The reported values are retained in Table 3. F1-score values are present only for Darknet and AlexNet in the source table; the missing entries are therefore left unreported.

Table 3. Existing-classifier performance values reported in the thesis

Network	Accuracy	Recall	Precision	F1-score
Darknet	72.04	87.62	77.57	0.57
AlexNet	65.15	43.29	80.76	0.56
ResNet	80.94	87.62	76.57	Not reported
GoogleNet	64.64	39.17	77.55	Not reported

Discussion

The reported results support the use of Xception as the central classifier for the proposed system. Transfer learning reduces the need to train a deep architecture from random initialization, while depth-wise separable convolutions provide a compact mechanism for learning image features. The 97.00% validation accuracy and the performance-page values indicate strong classification performance on the reported dataset.

The confusion matrix provides more specific evidence about model behaviour. All 48 real-note instances in the displayed matrix were classified as real, while 56 of 59 counterfeit-note instances were classified as counterfeit. The three counterfeit images classified as real identify the principal error type in the reported evaluation and show why continued validation with diverse counterfeit samples is important.

The study remains bounded by the reported dataset of 232 images and by the denominations emphasized in the proposed-system description. The thesis itself identifies several directions for improvement: incorporating currency security features, strengthening preprocessing for noisy images, increasing the diversity of training data, and extending recognition to additional note patterns and denominations. These extensions are necessary before the system can be treated as a broadly validated field solution.

VI. CONCLUSION

This study developed a Python-based counterfeit Indian currency detector using the Xception architecture. Currency images were preprocessed, augmented, divided for model development, and classified through a Flask interface. The thesis reports training accuracy of 93.34% and validation accuracy of 97.00%, while the deployed performance page reports accuracy of 0.97, precision of 0.94, recall of 0.97, and F-measure of 0.97. The

confusion matrix contains 56 correctly classified counterfeit notes, three counterfeit notes classified as real, no real notes classified as counterfeit, and 48 correctly classified real notes. Functional tests also produced the expected outputs across the listed note conditions. The findings support Xception as an effective basis for fake-currency detection, with future development focused on broader denomination coverage, explicit security-feature analysis, noise handling, and larger, more varied datasets.

Declarations

Funding: Not reported in the thesis. Conflict of interest: Not reported in the thesis. Data availability: The thesis identifies a 232-image Indian currency dataset and reports a Kaggle-hosted source; the availability of that external source was not independently verified.

REFERENCES

- [1] J. Lee, H. Hong, K. Kim, and K. Park, "A comprehensive review of banknote recognition methodologies utilizing diverse sensors," *Sensors*, vol. 17, no. 2, p. 313, 2017.
- [2] D. Galeana Pérez and E. B. Corrochano, "Deep learning-based recognition system for euro and Mexican banknotes using real-world images," *Comput. Syst.*, vol. 22, no. 4, pp. 1065-1076, 2018.
- [3] C.-Y. Yeh, W.-P. Su, and Lee, "Counterfeit banknote recognition using multiple-kernel support vector machines," *Applied Soft Computing*, vol. 11, 2011.
- [4] M. Hida, T. Mitsui, and Y. Minami, "Forensic analysis of counterfeit coins," *Forensic Science International*, vol. 89, nos. 1-2, pp. 21-26, 1997.
- [5] T. D. Pham, C. Park, D. T. Nguyen, G. Batchuluun, and K. R. Park, "Deep learning-based counterfeit banknote detection for visually impaired individuals using visible-light images captured by smartphones," *IEEE Access*, vol. 8, 2020.
- [6] K.-H. Lee and T.-H. Park, "Image segmentation of UV patterns for automated paper money inspection," in *Proc. 11th Int. Conf. Control Autom. Robot. Vis.*, Singapore, 2010, pp. 1175-1180.
- [7] A. Bruna, G. Farinella, G. Guarnera, and S. Battiato, "Detection of forgery and value identification in euro banknotes," *Sensors*, vol. 13, no. 2, pp. 2515-2529, 2013.
- [8] Y. Liu, J. He, and M. Li, "Recognition of new and old banknotes using convolutional neural networks," in *2018 International Conference Proceeding on Mathematics and Statistics*, 2018, pp. 92-97.
- [9] M. Tripathi, "Analysis of convolutional neural network-based image classification techniques," *Journal of Innovative Image Processing*, vol. 3, no. 2, pp. 100-117, 2021.
- [10] B. J. Reddy and T. V. R. Reddy, "Identification of counterfeit Indian currency Convolutional neural networks," in *Reports of the 2022 6th International Conference on Computing Methodologies and Communication*, 2022, DOI: 10.1109/ICCMC53470.2022.9754056.
- [11] N. Kumar and N. Ahmad, "Detection of counterfeit currency notes using image processing techniques," in *Proc. 2023 Annual International Conference on Emerging Research Areas: International Conference on Intelligent Systems*, doi: 10.1109/AICERA/ICIS59538.2023.10420367.
- [12] L. Latha and D. Nivetha, "Counterfeit currency detection using image processing," in *Proc. 2021 Int. Conf. Advancements in Electrical, Electronics, Communication, Computing and Automation*, doi: 10.1109/ICAECA52838.2021.9675592.
- [13] H. Prakash and A. P., "Deep learning methods for automated detection of counterfeit Indian banknotes," in *Proc. 2023 IEEE Int. Conf. Integrated Circuits and Communication Systems*.
- [14] V. Sundari T and S. R. P. R., "Detection of counterfeit Indian currency using image processing," in *Proc. International Conference on Augmented Intelligence and Sustainable Systems*, 2022, ISBN: 978-1-6654-8962-1.
- [15] A. Rayal and S. Oli, "Detection of counterfeit currency notes using image processing techniques," in *Proc. 2023 IEEE Annual International Conference on Emerging Research Areas*, doi: 10.1109/AICERA/ICIS59538.2023.10420367.

APPENDIX A. FUNCTIONAL TEST CASES AND RESULTS

The two test-case tables in the thesis are consolidated below without changing the expected or actual outcomes. Long descriptions are shortened only for table fit; the tested conditions and classification results are preserved.

Table A1. Functional test cases 1-5

Test case	Input condition	Expected output	Actual output
TC001	Genuine INR 10 note	Genuine	Genuine
TC002	Counterfeit INR 10 note	Fake	Fake
TC003	Genuine INR 100 note	Genuine	Genuine
TC004	Counterfeit INR 100 note	Fake	Fake
TC005	Genuine INR 500 note	Genuine	Genuine

Table A2. Functional test cases 6-10

Test case	Input condition	Expected output	Actual output
TC006	Counterfeit INR 500 note	Fake	Fake
TC007	Partially damaged genuine note	Genuine	Genuine
TC008	Partially damaged counterfeit note	Fake	Fake
TC009	Genuine INR 100 note under different lighting	Genuine	Genuine
TC010	Genuine INR 50 note under varying angles/background	Genuine	Genuine

APPENDIX B. CLASSIFICATION OUTPUT EXAMPLES

The application screenshots provide implementation evidence for both prediction classes. One example is labelled as a real-currency prediction and the other as a fake-currency prediction, demonstrating the end-to-end upload and classification workflow.

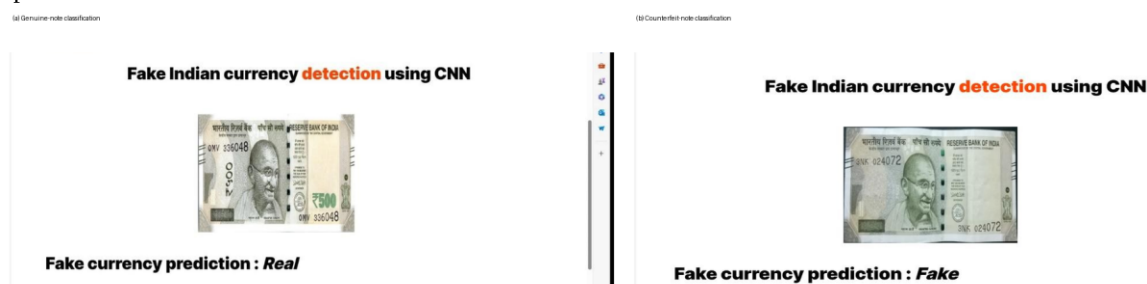


Figure B1. Application outputs for genuine and counterfeit currency images.