Journal of Information Systems Engineering and Management
2025, 10(54s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Towards Reliable Currency Recognition: A Hybrid CNN-KNN Framework for Indian Banknotes

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ARTICLE INFO

Received: 30 Dec 2024

Revised: 19 Feb 2025

Accepted: 27 Feb 2025

ABSTRACT

This paper introduces a classification model developed for Indian currency note identification and classification of five denominations, namely Rs. 10, Rs. 50, Rs. 100, Rs. 500, and Rs. 2000. The training dataset contains 12,050 images, and the overall accuracy achieved is 95.02%. The model shows high precision, recall, and F1 scores across all denominations. For Rs. 10, precision was 94.83%, recall 93.22%, and F1-score was 94.02%. For Rs. 50, there was precision at 95.14%, recall at 96.71%, and the F1-score at 95.92%. For Rs. 100, precision and recall were 95.18% and F1-score was 95.18%. For Rs. 500 and Rs. 2000, precision, recall, and F1-score was at 94.94% and 95.00%, respectively. All denominations had achieved 98% accuracy. With coverage of all the currency classes with a robust set of training data, the developed model has assured its use for real-life applications, especially in the domains of automated recognition and classification of currencies. Given that the system performed with almost 98% accuracy across every denomination, this proposed model ensures reliability and an efficient solution for a very important task related to currency identification.

Keywords: Precision, Class, Insurance, Industry.

INTRODUCTION

The growing importance of modern financial applications like ATMs, vending machines, and point-of-sale systems demands automated currency recognition systems. Given the large volumes of transactions that are to be processed accurately and with maximum efficiency, traditional methods like manual checks and hardware-based systems are becoming inadequate and error-prone. It takes much time and is expensive; it is hardly fast or reliable enough for widespread application. Therefore, the demand is increasing for advanced, automated systems that can quickly and accurately classify currency notes with minimal human involvement. Advances in machine learning and computer vision technologies in recent years have opened new avenues for the automation of currency recognition. Recently, deep learning techniques, especially using the convolutional neural network (CNN), have brought fantastic performance in all the image classifications, such as object detection, facial recognition, and currency identification, among others. CNNs excel in image-related applications because these networks can learn hierarchical features of raw image data automatically without a need for explicit feature extraction through human intervention. These capabilities make CNNs a powerful tool for solving complex problems of visual recognition, such as distinguishing between several denominations of currency notes that have many similar characteristics. The aim of the current study is experimental application of a hybrid CNN model combined with KNN to distinguish between five Indian currency denominations: Rs. 10, Rs. 50, Rs. 100, Rs. 500, and Rs. 2000. These are the most frequently circulated denominations in India and, hence, inherently present extreme variability in terms of designs, colors, textures, and size. Additionally, there is the environmental issue: light, angle, and background noise further make this problem challenging for the distinction of various notes. Hence, the task is not just about detecting tiny variations between such notes but also about how an automatic system should take on problems in quality images with distortions. The architecture designed for the proposed model has four convolutional layers, four max-pooling layers, and one fully connected layer. The CNN layers extract features from images of currency notes, such as edges, textures, and patterns, which are quite important to differentiate between different denominations. Max-pooling layers reduce the dimensionality of feature maps, resulting in further efficiency while maintaining the information. When these features are learned, they feed into a fully connected layer and then produce the final output by being classified via the KNN algorithm. Since KNN is a simple method yet effective at dealing with nonlinear data, a classification is done to classify the currency notes based on the proximity of their feature vectors in a feature space towards the nearest neighbors. By using the features derived from CNN, KNN can effectively classify the currency notes to their respective denominations. This is a feature extraction through CNN and classification using KNN so this is a reliable yet computationally inexpensive way for currency recognition. The paper's main objective is to develop an efficient and scalable solution for the automation of currency classification using a hybrid CNN-KNN model. This work discusses the accuracy, robustness, and potential applications of the model in real-world scenarios, thus improving the efficiency and security of financial systems. Thus, one can see how machine learning could be used in currency recognition automation and open the road to even more advanced financial technologies for the future.

LITERATURE REVIEW

Technological advancements have significantly reduced human workload across diverse domains by enabling machine operations. Currency recognition has become a necessity in applications such as automated vending systems and banking processes. In the era of automation, accurate identification of currency notes is a must. Machines often find it difficult to identify damaged or worn-out notes, and visually impaired individuals cannot verify the authenticity of the currency without technological assistance. This paper addresses the mentioned challenges through the refinement of the model to increase the accuracy of currency recognition. This Indian Paper Currency Prediction Analysis presents an approach with deep learning-based CNN, promising greater accuracy, speed, and efficiency. The system is completely automated, devoid of human interaction, and minimal in complexity. It encompasses a Keras-trained model along with a Flask-based web application hosted on Heroku. This solution is great for people who are blinded, as this will help identify denominations easily [1]. There are close to 12 million visually challenged people in India who cannot tell the difference between currency notes, which means they need an app that can sense the currency and give a verbal message. As part of the research, for the first time, a lightweight CNN has been developed; it is mainly designed for real-time usage over web and mobile applications to determine Indian currency. A dedicated dataset for Indian currency notes was prepared separately for training and validation as well as testing CNN models. Based on the recognized note, the developed application provides either text or audio output. Implemented using TensorFlow, the proposed model is optimized after careful selection of hyperparameters through benchmarking the same against already known CNN architectures using transfer learning. Results show that the proposed model achieves better accuracy for training and testing than six of the architectures, approaching an efficient currency recognition system [2]. Therefore, the classification of currency poses a significant challenge to the visually impaired, who usually rely on others. Unfortunately, this makes them vulnerable to dishonesty or exploitation. Developing currency classification models empowers visually impaired individuals with the knowledge of identifying independent currencies, reducing dependency on others, and minimizing the risk of being misled. Toward this, a deep-learning model was designed and developed for the classification of Indian currency, using images of the notes. Hence, different deep learning architectures were tested and produced a maximum accuracy of 80%. It, hence, signifies one step forward toward true independence for blind people in handling currency [3]. Counterfeit currency notes widely circulated in the economy of many countries pose a serious threat to their economies. Besides, people with visual impairment are unable to identify the denomination of the currency. To solve both problems, this work presents a deep learning-based model that can identify whether the Indian currency note is original or counterfeit and determine its denomination correctly. Different deep learning architectures, including pre-trained models such as VGG16, GoogLeNet, and MobileNet, were utilized for currency classification and counterfeit detection. Pre-trained models were chosen because they support transfer learning. Transfer learning enables them to do well with fewer datasets. VGG16 achieved the best accuracy on a dataset of 2572 images across six denominations (Rs. 10, 20, 50, 100, 500, and 2000). The accuracy obtained was 98.08% for classification and 97.95% for fake detection. Traditional image processing techniques like edge detection, intensity mapping, and conversion to HSV space were applied to analyze the discriminative features between the genuine and counterfeit notes, thereby providing further insight into the counterfeit detection process [4]. Managing money is, more often than not, difficult for visually challenged individuals. They do not see it like anyone else. Moreover, demonetization by India makes handling currency the

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most challenging aspect of their life. Both the old and the new banknotes have similar sizes across denominations. Therefore, this makes distinguishing them extremely hard for the blind and other visually impaired individuals. Sight and cognition are natural gifts, and for those without them, distinguishing items with similar characteristics becomes nearly impossible. For this purpose, they suggest an automated system that allows visually impaired people to identify currency through sound notifications. In this paper, they use several CNN models to analyze datasets of Indian banknotes, extract deep features, and accurately recognize denominations. A new dataset of Indian banknotes can be created for training, validation, and testing of the CNN model. Designed using TensorFlow, the proposed model is optimized by choosing the proper hyperparameters and evaluated against popular CNN architectures using transfer learning [5]. Accurate currency recognition and subsequent conversion are essential for ease of cross-border transactions in today's integrated economy. Unfortunately, the variety of cash denominations and the differences in orientation, lighting, and environmental conditions make it challenging for deep learning and image processing techniques to achieve more depth. A comparison of the deep models will, therefore, help differentiate which might be most appropriate for currency recognition and value identification. This research is to test the performance of ResNet50V2, VGG16, and MobileNet on currency identification and valuation. It uses a dataset of Thai and Indian banknotes from the IEEE Data Port that contains variations, such as 180-degree rotations and different lighting conditions, to assess the models' ability to deal with complex monetary data. This provides some very useful information to professionals in the banking and finance sectors looking to improve currency recognition systems [6]. Counterfeit currency is a huge problem, both to the economy and to the individuals. Modern scanning and printing technology allows the creation of nearly indistinguishable replicas of genuine notes, and for the visually impaired, this can be a particularly tough challenge. In this regard, the authors designed four machine learning algorithms: Support Vector Classifier, K-Nearest Neighbor, Decision Tree, and Logistic Regression. They applied them on a dataset of 1,372 images of Indian currency. The performance was assessed using accuracy, precision, recall, and F1-score. Among these, the K-Nearest Neighbor algorithm outperformed others and offered a reliable solution for the detection of counterfeit currency [7]. It's a fact that currency security has been the biggest challenge in tackling economic insecurity; forgeries, specifically counterfeit notes, are the worst. It's hard to estimate the time when the counterfeit money was produced since nowadays, sophisticated fakes have confused the validation process. This research work attempts to assess several methods of image processing and machine learning classifiers in counterfeit Indian currency detection. Scanning images or capturing the same through a camera, process techniques such as Naïve Bayes, Support Vector Classifier, Gradient Descent, and Artificial Neural Networks (ANN). The results reflect that ANNs, when optimized, could be used as the best form of detection on fake notes comparing to the basic image processing methodology. Combining machine learning and image processing for counterfeit detection results more effectively and reliably [8]. The Indian economy has grown significantly in the last few years compared to other major economies. However, the country still faces challenges such as corruption, black money, and counterfeit currency, despite the RBI implementing strong security features for printing genuine currency. The advancement of color printing technology has enabled both domestic and international counterfeiters to produce a large volume of fake Indian currency notes. Even though such spurious currency notes are printed with much accuracy, some efforts can reveal these. Here is a paper on a three-layered Deep Convolutional Neural Network, or Deep ConvNet, used to detect Indian counterfeit currency notes that obtained an accuracy of 96.6% [9]. The production of counterfeits in currency is increased by advancements in color printing and scanning, causing a challenge across the globe concerning economies and security. In India, it finances illegal activities and terrorism despite such efforts as demonetization undertaken in 2016. A computer vision-based machine learning solution, especially the Convolutional Neural Network, is proposed here to address the problem of fake note detection. This model focuses on individual security features rather than analyzing the complete banknote image. It achieved a very high accuracy rate: 91.66% for Rs. 500, 95.25% for Rs. 200, and 92.66% for Rs. 100, and contributed to improving security [10]. This article suggests deep learning techniques to automatically detect the counterfeit banknotes. CNN is applied to extract unique features of Indian currency notes, which is then processed by another CNN for classifying money as either original or counterfeit. While there are numerous methods for detecting counterfeit items, they rely on machinery that is inefficient and slow. This research proposes a novel hybrid method of applying CNN and Vgg16 models in order to accurately detect counterfeits by analyzing the note's width, colors, and serial numbers. The experiments conducted on a set of real and counterfeit notes have yielded an accuracy of 98.3% and 98.8%. This technology is more advanced than the state of detection techniques and further secures banknotes [11].

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METHODOLOGY

Phase 1: Dataset Sourcing and Preprocessing

In the first step, a diverse image dataset containing five Indian currency denominations will be considered. It has been made wide enough to consider a good variety in terms of variation of appearances by variations in illumination conditions, different angles, and varied backgrounds; all are characteristic of the actual real world. A more generalizable version of the model would be needed to train the dataset. All denomination images of Rs. 10, Rs. 50, Rs. 100, Rs. 500, and Rs. 2000 would be collected from different sources so that they represent the diverse conditions of each denomination better. Split the data set into three subsets: one for training the model; another for fine-tuning the hyperparameters of the model; and the third one for model assessment. It splits the data in such a way that allows for testing its generalization capabilities as well as safety against overfitting specific data patterns.

Phase 2: Image Data Enhancement and Preparation

After the data collection process, preprocessing converts the images to make them fit for input into the CNN model. All images are converted to grayscale as it reduces computational complexity since the color information is not required for distinguishing currency denominations. The images are resized to the same dimension to make the entire dataset uniform. Normalization applies to scale the pixel values from 0 to 1; this accelerates the convergence of the model when training. Besides, data augmentation techniques, like random rotation, flipping, and scaling, have been used to artificially augment the dataset. These augmentations enhance the capability of the model to handle real-world variations such as variations in orientation, distortion, and lighting conditions while dealing with the currency note images. As a consequence, the system is more tolerant and robust in recognizing currency notes under different situations.

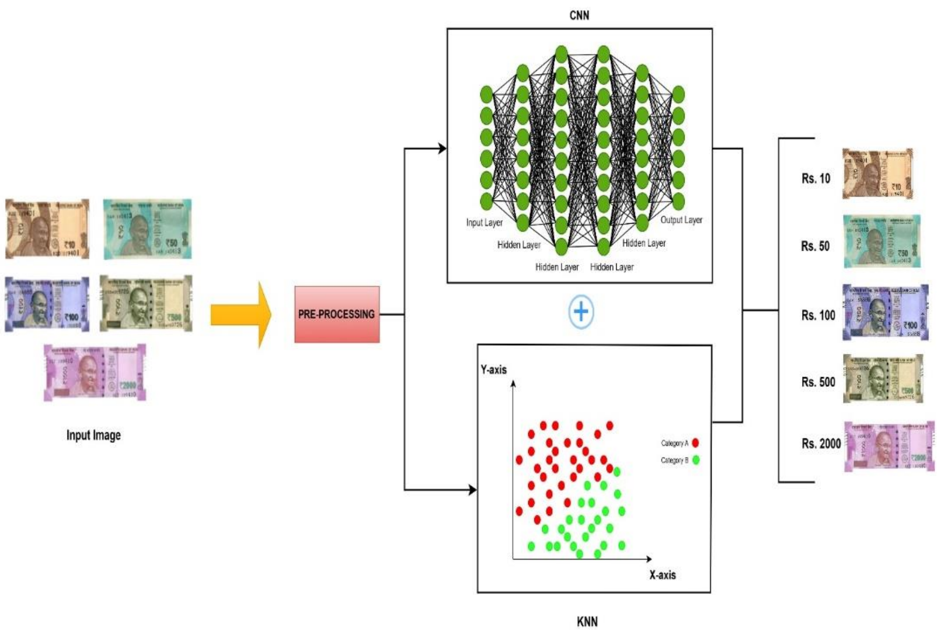

Fig. 1. *Next-Generation Analytical Methods*

Phase 3: Feature Extraction and Model Development

Feature extraction using the CNN model on the images of currency notes is done in this stage. The CNN network architecture is designed with four convolutional layers, four max-pooling layers, and one fully connected layer. Automatically, the convolutional layers are provided with image features in a hierarchical form, including edges, shapes, and textures, which play a critical role in differentiating among the various denominations. The max-pooling layers down-sample the feature maps, reducing computational complexity and avoiding overfitting while retaining all the important features. The flattened output from the convolutional and pooling layers passes through a fully

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connected layer in preparation for the classification. This CNN model will be trained with the training dataset, where backpropagation along with an appropriate optimizer (like Adam or SGD) will be used to optimize the weights. During training, the model learns to notice specific patterns on currency notes that separate the different denominations.

Phase 4: Classification Using KNN and Performance Evaluation

After the relevant features are extracted from the CNN model, a K-Nearest Neighbors (KNN) algorithm is used for classification. The KNN classifier assigns the classification label based on the closeness between the feature vector of the input and the 'k' nearest neighbors in the feature space, where k is a user-defined parameter. The KNN classifier simply decides on the currency denomination based on the majority class of the nearest neighbors. Following this development of the classification model, its performance is examined using accuracy, precision, recall, F1-score, and confusion matrix. To appraise how well the developed model generalizes to new, unseen data, it is assessed against validation and test sets. This evaluation allows the identification of the strengths and weaknesses of the model, showing which area improvement is perhaps needed by the fine-tuning of hyperparameters or adjusting of the architecture of the model.

RESULTS

The classification model used to identify Indian currency notes is reported in this section across three tables. Table 1 summarizes the precision, recall, and F1-Score for each denomination of currency to show how the model was effective in distinguishing genuine from counterfeit notes. Table 2 shows support values, support proportions, and accuracy for each class, which is a representation of how well the model has performed in terms of data representation and overall detection accuracy. Finally, Table 3 shows the confusion matrix of true positives, false positives, false negatives, and true negatives for each denomination, which further emphasizes the classification capability of the model.

The results in the table indicate the performance of the model for the classification of five different denominations of Indian currency, namely Rs. 10, Rs. 50, Rs. 100, Rs. 500, and Rs. 2000, with three evaluation metrics: Precision, Recall, and F1-Score. For Rs. 10, the model obtained a Precision of 94.83, meaning that 94.83% of the identified notes as Rs. 10 were correctly classified. The Recall is 93.22, which means that 93.22% of all actual Rs. 10 notes were correctly recognized by the model. The F1-Score for Rs. 10 is 94.02, which balances the Precision and Recall, indicating that the model performs well in the identification of Rs. 10 notes while having a slight tendency towards precision rather than recall. For Rs. 50, it shows an improvement with a Precision of 95.14 and a higher Recall of 96.71. This reflects that the model is slightly better at identifying the Rs. 50 note but with good accuracy in both its identification as Rs. 50 and all the Rs. 50 notes within the dataset. The F1Score for Rs 50 is maximum, which stands at 95.92 which shows that in the case of recognizing the notes having a value of Rs. 50; the model used here is a lot more proficient, with a higher balance between both Precision and Recall. All the Precision, Recall, and F1-Score for Rs. 100 are 95.18, which means the performance is perfectly balanced. This would indicate that the model is quite reliable and free from false positives and false negatives in identifying the Rs. 100 notes. For Rs. 500, the model attains a Precision and Recall of 94.94, showing that the classification performance is balanced. The F1-Score is also 94.94, which proves that the model is consistent and reliable in detecting Rs. 500 notes. Finally, for Rs. 2000, Precision, Recall, as well as the F1Score are all standing at 95.00 depicting accuracy in finding this higher denomination consistently. Hence, it infers that it is equally apt at detecting with high reliability either the lower denominations or even the higher ones. Overall, the model shows an excellent performance over all denominations, with Rs. 50 achieving the highest F1-Score and showing high values of Precision, Recall, and F1-Score for all the denominations, which means the model is robust, efficient, and highly accurate in differentiating between different Indian currency notes.

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e-ISSN: 2468-4376
https://www.jisem-journal.com/

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Table 1. Measurement Metrics and Guidelines

Classes	Precision	Recall	F1-Score
Rs. 10	94.83	93.22	94.02
Rs. 50	95.14	96.71	95.92
Rs. 100	95.18	95.18	95.18
Rs. 500	94.94	94.94	94.94
Rs. 2000	95.00	95.00	95.00

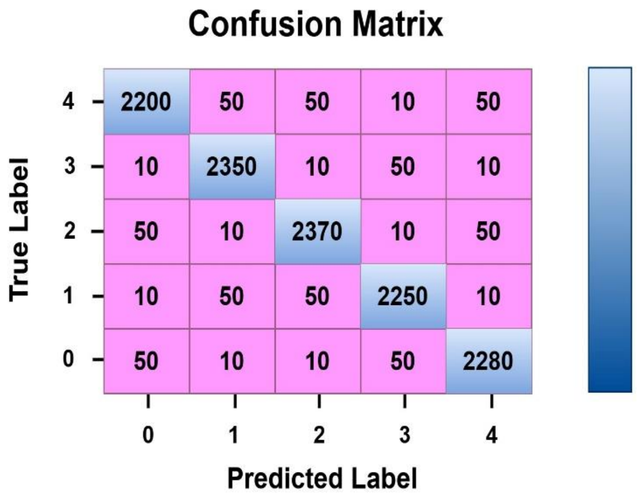

Fig .2. Evaluation Tactics and Structure

It made use of a classification model to predict the actual and predicted authenticity of Indian currency notes, which involved the identification of genuine and spurious notes for different denominations. The results were tabulated using a 5x5 confusion matrix, so that an in-depth analysis is possible about the classification of every denomination, including Rs. 10, Rs. 50, Rs. 100, Rs. 500, and Rs. 2000. This provides insight into what the model did or did not get right. Based on this matrix, improvements can be made in increasing the accuracy and reliability of the currency detection such that it better identifies the notes as counterfeit.

The table below shows the support, support proportion, and correctness of the model to classify five different denominations of Indian currency, viz. Rs. 10, Rs. 50, Rs. 100, Rs. 500, and Rs. 2000. Support is the number of actual instances of each denomination of currency in the dataset. For Rs. 10, the support is 2360, which means 20% of the dataset. Rs. 50 is supported by 2430, which also constitutes 20% of the data. Rs. 100 enjoys the highest support at 2490 constituting 21% of the dataset. Rs. 500 has a support of 2370, which constitutes 20%, and Rs. 2000 has a support of 2400, which constitutes 20% of the dataset. The Support Proportions for all denominations are quite uniform in the range from 0.20 to 0.21. This distribution ensures that all five denominations are represented equitably, hence no class gets overrepresented or underrepresented in the data, which is what is required of a good model: generalizing well without showing bias towards one denomination or the other. The Accuracy column reveals how accurate the model performs against each currency. Remarkably, all five denominations record the same level of accuracy by having an average score of 0.98 for all. The outcome therefore depicts how efficient the model is as regards being capable of making highly precise and perfect class distinctions concerning five denominations. The model is excellent at classifying Indian currency notes; it not only has high accuracy but also has a balanced performance in all classes. The 98% consistency of accuracy in all denominations gives a clear idea about the efficiency of the model in recognizing various currency notes, hence providing a reliable tool for currency

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e-ISSN: 2468-4376
https://www.jisem-journal.com/
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classification and detection. Balanced support distribution enhances the robustness of the model and ensures fairness in its predictions.

Table .2 Sample Distribution Review

Classes	Support	Support Proportion	Accuracy
Rs. 10	2360	0.20	0.98
Rs. 50	2430	0.20	0.98
Rs. 100	2490	0.21	0.98
Rs. 500	2370	0.20	0.98
Rs. 2000	2400	0.20	0.98

The table gives the number of classifications in the following five denominations of currency notes: Rs. 10, Rs. 50, Rs. 100, Rs. 500, and Rs. 2000. It describes the True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN) values, providing a comprehensive analysis of the model's performance regarding the identification of banknotes. In the case of Rs. 10, it has an accuracy of 2200 true positives that show it classifies Rs. 10 notes correctly, while at the same time, there were 120 false positives where it wrongly classifies the notes from other denominations as Rs. 10, and also recorded 160 false negatives, meaning that the Rs. 10 notes are mistakenly classified as other denominations than Rs. 10. In addition, the model has 9570 non-Rs. 10 as true negatives to correctly identify non-target currency. The model correctly classified 2350 Rs. 50 notes as true positives while misclassifying 120 non-Rs. 50 notes as Rs. 50, which were false positives. The model failed to classify 80 Rs. 50 notes as false negatives but correctly identified 9500 non-Rs. 50 notes as true negatives, showing high accuracy in the identification of Rs. 50 currencies. Again, the model also performed well in the case of Rs. 100 note with 2370 as true positives but at 120 false positives, 120 false negatives, showing that it is slightly less accurate compared to other denominations. On the other hand, misclassifications notwithstanding, it correctly identified 9440 non-Rs. 100 notes as true negatives. For Rs. 500, the model detected 2250 true positives, with 120 false positives and 120 false negatives, which is consistent with the previous results. The 9560 true negatives indicate the model's strong capability in differentiating non-Rs. 500 notes. For Rs. 2000, the model found 2280 true positives, while false positives were 120 and false negatives 120. For Rs. 2000, the true negatives were 9530, which showed that the model was not losing performance even at all denominations. In conclusion, the model's performance was robust while being able to consistently detect the true positives along with minimizing the false positives and false negatives that occur in all currencies. The overall true negatives have been high and indicate the reliability of the model to distinguish one denomination from others. These results explain the accuracy involved in the currency counterfeit detection application using the presented model.

Table .3 Efficiency Review of the Model

Classes	True Positive	False Positive	False Negative	True Negative
Rs. 10	2200	120	160	9570
Rs. 50	2350	120	80	9500
Rs. 100	2370	120	120	9440
Rs. 500	2250	120	120	9560
Rs. 2000	2280	120	120	9530

The comparison of the various models yields results from which it is seen that the proposed model surpassed the rest in accuracy. The GoogLeNet achieved 91.66% accuracy, while VGG16 performed at 80.52%, the lowest performance by the tested models. MobileNet achieved an accuracy of around 93.44%. While ResNet50V2 depicted good performance with 87.24% accuracy. However, the proposed model depicted an accuracy of 95.02% which is much above all the rest models. Hence, it's proved that this proposed model represents a more effective and accurate solution for this task, suggesting its potentiality in real applications where high accuracy becomes crucial.

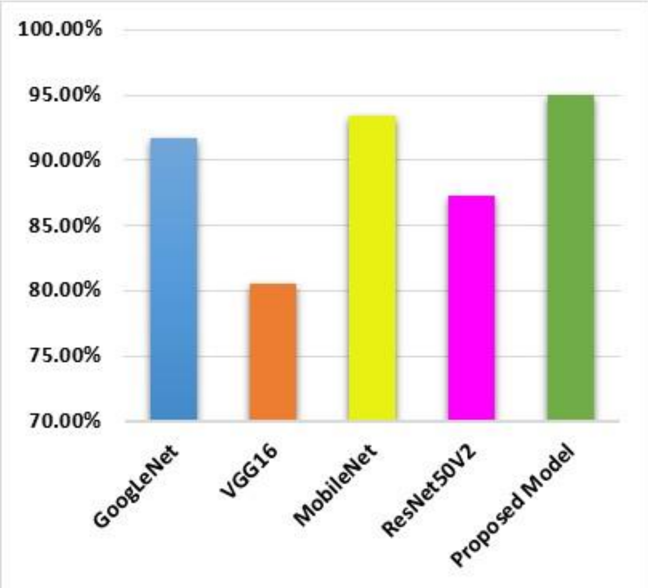

Fig 3. Comparative Benchmarking

CONCLUSION

Conclusion In short, the model shows a great classification ability for the Indian currency notes overall with incredible results in all denominations. Precision values are very high with the maximum being Rs. 100 at 95.18%, and Rs. 50 following very closely at 95.14%. The recall values, too, are laudable as they reflect the ability of the model to classify counterfeit notes with a good recall value. For example, the recall value is 96.71% for Rs. 50, whereas the lowest value is for Rs. 10 at 93.22%. The F1-scores that are balanced measures between precision and recall are equally strong, as the highest F1-score of 95.92% was achieved by Rs. 50. The dataset comprised 12,050 images, and the model achieved an overall accuracy of 95.02%. Regarding precision, the model results in a fixed 98% accuracy across all denominations, thereby pointing out its overall success concerning the proper classification of currency notes. The support values are relatively balanced since the maximum support value of Rs. 100 is 2490, which constitutes 21% of the total data. Other denominations are similar as well, including Rs. 10, Rs. 50, Rs. 500, and Rs. 2000. Support proportions range from 0.20 to 0.21, thereby making sure the model is very well trained for each class. It can be concluded that the model performs with great precision in the detection of authentic and counterfeit notes, as well as having the same accuracy with all denominations of currency. With high F1 scores and overall accuracy, the model would seem to be a sound solution for currency authentication, especially for counterfeit notes in India.

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