

An Automated System for Indian Currency Classification and Detection using CNN

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Abstract. The visibly disabled frequently experience difficulties with daily tasks that a typical person would take for granted, such as handling financial transactions. Since India's demonetization took effect, accepting money has become a difficult task. Due to the similar dimensions of new cash banknotes and the fact that some old money banknotes are still in use, India now has two banknotes for every category. Due to the current situation, it is extremely difficult to identify banknotes for those who appear to be weak. The sight and brain are gifts to humans. Detecting things with the same qualities is practically impossible for persons who are sight impaired. In keeping with this, we suggest an automated system that would enable those who are visually impaired to recognize currency through a sound notification from a variety of applications. Therefore, in this quest, we help them locate the currency notes. In this study, we apply different convolution neural network (CNN) models to datasets of Indian banknotes in order to extract deep features and recognize different currencies. To train, verify, and test the CNN model, we can produce a fresh dataset of Indian banknotes. The proposed model may be created with TensorFlow, enhanced by choosing the best hyper parameter value, and evaluated against well-established CNN architectures using transfer learning.

Index Terms—Convolutional neural networks (CNNs), Deep Learning, VGG16, AlexNet, MobileNet, Tensorflow, and Accuracy.

1. Introduction

Modern times have seen rapid advancements in mobile applications, and the field of computer vision is now crucial to our daily life. Because they encounter several obstacles in their daily life, people with visual loss find these programmes to be of great assistance.

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One of the terrible challenges that the blind and visually handicapped face every day is dealing with money. A person must maintain a location for and be able to recognize currency because it is essential to daily life for all transactions. A normal individual can easily view any banknote, but a blind person or someone who is physically incapable of performing a similar activity will find it much more challenging. The person with a visible disability requires the assistance device constantly so they can complete their daily tasks and recovery. The supportive framework assumes a significant role in friendly inclusion for visual impairments. They become dependent on others because they lack these helpful tools.

In this paper, we offer a shrewd and astute framework that the physically challenged can employ to assist themselves in identifying the currency. The suggested model makes use of deep learning. Recent developments in Deep Learning (DL), a specialised area of machine learning, have produced efficient techniques for categorization tasks. Deep Learning architectures are capable of identifying the most discriminating qualities pertinent to the issue on their own. Recent advances in technology, particularly GPUs (Graphics Processing Units), and scholarly advancements in improved algorithms like Rectified Linear Units (ReLU), may have contributed to the recent development of deep learning (DL).

This paper depicts the classification of Indian currency into seven classes using different CNN models and predicts the best accurate model for our data. CNN concept is that not all pixels are needed to identify features of an image or classify them. Our system uses two sets of data for currency classification, one is a custom-made dataset and the other is the Kaggle dataset. TensorFlow in integration with Keras is used for Image Classification.

Our system exemplifies transfer learning models, where there are various image categorization algorithms. Many transfer learning models, including VGG16, MobileNet, AlexNet, and many others, are available. We used numerous models with various hyperparameters to train and evaluate the dataset. Our suggested strategy entails gathering a dataset of various currency notes, including the Rs. 10, Rs. 20, Rs. 50, Rs. 100, Rs. 200, Rs. 500 and Rs. 2000 notes. With the help of the Image Data Generator from `Tensorflow.keras.preprocessing.image`, we can produce more data with various orientations and angles for proper model training.

2. Literature Survey

Many researchers have made various contributions to the creation of currency recognition methods. Researchers approach the recognition job differently for coins and bills due to the differences in their characteristics. N.A. J. Sufri et al. developed a well-developed vision-based automated programme [4] that uses machine learning and deep learning to recognize and categorize Malaysian Ringgit banknotes has been created. When sorting a database with three separate regions, SVM and BC perform more consistently than kNN and DTC. In testing the new database with a different orientation, Alex.Net failed to work well.

Similarly, Faiz M. Hasanuzzaman et al. [5] utilised SURF features and developed a novel component-based banknote recognition system has been suggested in order to handle various difficult situations in real-world settings and achieve high recognition accuracy. First, SURF extracts the financial aspects from each query image. Then, for each banknote category, these characteristics are put up against the previously determined SURF features of the reference regions of the ground truth image. To identify the banknote category, the numbers of matching attributes are contrasted with the predetermined thresholds of each reference source. Additionally, erroneous recognition with bad photos is avoided by using the spatial relationship of matched attributes, which also provides blind people with aiming guidance when taking pictures of bills. The system then outputs the result of the recognition.

Moreover, Vedasamhitha Abburu et al. [6] proposed image processing methods such as the Prewitt approach and Canny Edge a system for automated currency recognition. The suggested technique can be used to identify a given banknote's country of origin, denomination, and value. The system that correctly recognises a banknote's denomination and country of origin. The proposed approach, nevertheless, only takes a few different currencies into account.

Similarly, Qian Zhang et al. [7] proposed Deep Learning approach, gathering datasets is essential, therefore they were able to capture a single video in order to obtain image data for currency recognition. Prior to training the model, picture filtering has been performed. After training the model, currency classification is carried out using the extracted features, and currency identification follows. The best strategy is to use the CNN model to do currency recognition since it can extract currency features layer by layer, improving the accuracy of trial results.

Similarly, Dittimi, Tamarafinide V.et al. [9] proposed the primary components of the recovered Histogram of Gradient feature vectors are classified utilizing an effective error-correcting output code methodology based on a Multi-Class Support Vector Machine in the novel banknote recognition method that has been proposed. The banknotes' Histogram of Gradient feature was extracted, the principle components were created using the features, and the samples were then categorized using an MCSVM. The front and back of the bill were classified using a 10-fold cross validation method.

Moreover, Kitagawa et al. [10] presented a method used in this study to recognize portraits in a banknote image as input and generate rectangles that contain the portraits. Using moving windows to create candidate regions, a CNN determines the likelihood that each candidate region contains a portrait. They then generated the rectangles that had the highest likelihood of containing portraits using Non-Maximum Suppression. The technique detects portraits with good performance. However, there are numerous cases where a portrait is discovered where none should be. Given the small number of pictures on banknotes, they believed that improving the training dataset was the most crucial way to enhance this.

The most well-known use of neural networks (NNs), which are utilised widely today in numerous engineering domains, is pattern recognition. Thai banknotes, a novel type of currency, are suggested as the objects of recognition in this essay. The digitised properties of each banknote, known as slab values [11], are first retrieved from each image of a banknote. These slab values are the accumulation of each banknote's non-masked pixel values. In order for the NN to do its learning and recognising procedure, slab values are inputted second. Third, to execute the continuous learning and recognition, the NN algorithm is implemented on the DSP unit for commercial usability.

One of the most actively studied areas of technology today is banknote identification systems, which have numerous uses in Automated Teller Machines (ATMs), vending machines, and cash recognition aids for the blind. By using a modular approach, this study suggests a revolutionary method [12] for identifying Indian currency banknotes. The analysis produces a high true positive rate of 95.11 percent (desired characteristic successfully recognized). For this, a data set of 300 photographs of Indian currency notes was used to assess the proposed methods for recognizing cash denomination through identification mark detection and color matching approaches. The banking sector has to address old banknote recognition and recycling as pressing problems. The grades of variously disfigured banknotes that are to be recycled are actually very variable. The standard support vector machine (SVM) technique may perform poorly when processing such unbalanced data sets for the minority class. The prediction accuracy of ancient banknotes is improved using a new method that combines synthetic minority over-sampling technique (SMOTE) with SVM to address this issue. This

method can increase the recognition accuracy ratio by roughly 20% by analyzing the results of contrast experiments.

The Sobel algorithm's primary drawback is that as noise levels rise, the gradient magnitude of the edges similarly decreases, leading to erroneous conclusions. Consequently, it was unable to identify the proper edges. On the other hand, the Canny edge detection [3] was precise enough to deliver the desired outcomes. In Canny, the thresholding method offers effective edge detection. Figure illustrates the output image created by Canny and Sobel along with the source image to demonstrate the differences between the two. The Sobel operator produces a picture with overlapping borders that is blurred. The Canny operator, on the other hand, clearly distinguishes between edges that fall under the texture. In [14-21] authors employed machine learning techniques in their research for getting effective image feature extraction.

Using a smartphone in an uncontrolled setting (i.e., where there are many variables that could alter the image quality) makes it difficult to recognize currency. The experimental findings have demonstrated the universal applicability of the SIFT method [8] for the recognition of Jordanian banknotes, despite the fact that the system is evaluated on a more difficult dataset with photos captured under various lighting conditions. The system hinges on the object showing up at particular interest spots. The coins currency is giving less accuracy due to ill lightning conditions.

3. Methodology

The proposed justification for categorizing Indian currency notes using deep learning techniques is rather simple. Different image classification models each have their own methods. Images of currency notes divided into training and validation sets with a ratio of 70:30 make up the dataset. There are roughly 1270 photos of various Indian cash denominations.

3.1 CNN Architecture

A CNN may develop a theory to categorise new photos into their respective classes given a huge batch of images and their labels. It is accomplished by translating the picture data into the class predictions by subjecting it to a series of procedures required by the network's individual layers. The architecture of our model is shown in a simplified form in Figure 1.

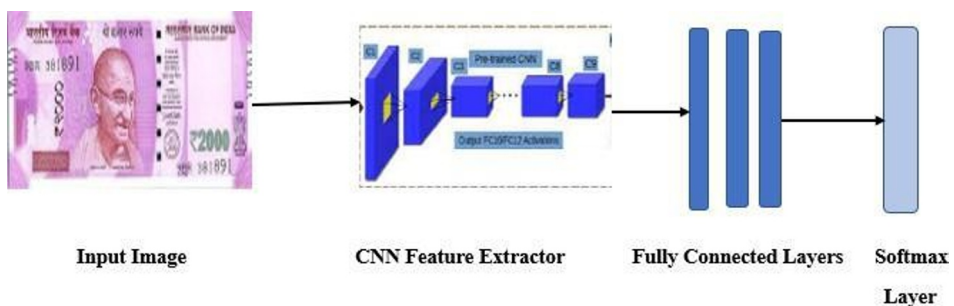


Figure 1. CNN architecture of the model

A CNN architecture is created by stacking the convolutional layers, pooling layers, and Fully Connected (FC) layers. Other crucial aspects of CNN's architecture include:

3.1.1 *Dropout Layer:*

The dropout layer is a mask and it eliminates certain neurons' contributions to the next layer, but keeps functions of all other neurons intact. Some features are eliminated when applying a dropout layer to an input vector, but if applied to the hidden layer some of its neurons are removed. The dropout layer is vital for CNN training because it prevents overt adjustment of the learning data.

3.1.2 *Activation Function:*

By calculating the weighted sum and adding bias, activation functions determine whether or not a neuron needs to be activated. The purpose of activating functions is to introduce a non-linearity in neuron's output. Since the present model is a multiclass classification problem we use Softmax activation function. The softmax activation function will convert the neural network's raw results into a graph of probabilities, which is essentially random distribution between input classes.

3.2 CNN Models

In order to interpret data having a grid pattern, like photographs, CNN uses a Deep learning model. This paper compares the accuracy of different CNN models to choose the best model.

3.2.1 *Sequential Model:*

Sequential models are linear stacks of layers where one layer leads to the next. It is simple and easy to implement, and you just have to make sure that the previous layer acts as input to the next layer. It is used for plain stack of layers where each layer has one input and one output tensor. An accuracy of 97.98% has been achieved for the Sequential model.

3.2.2 *VGG 16:*

The VGG 16 model was developed by the Visuals Graphics Group (VGG). The VGG 16 model expects color input images by default which has to be rescaled to the size of 224x224 squares. The accuracy obtained through this model is 92.81%.

3.2.3 *AlexNet:*

Convolutional neural network (CNN) architecture is what makes up AlexNet whose input image size is 227x227. It made important advancements in picture classification problems and was helpful in making deep learning more widely accepted. Eight layers make up AlexNet's architecture, with five convolutional layers and three fully linked layers coming after. An accuracy of 89% has obtained through this model.

3.2.4 *MobileNet:*

In order to meet the requirements of mobile platforms, a class of convolutional neural networks known as MobileNet [2] was created with a focus on resource efficiency and model scalability. MobileNet architecture designed for efficient image classification on mobile and embedded devices. The network takes an input image of size 224x224x3.

3.3 Transfer Learning

When building deep learning models a large amount of training data is required. The concept of using a pre-trained network that has already been trained and whose weights (parameters) have converged on a substantial dataset relevant to a problem is known as transfer learning. Once the problem has been located, the transfer learning technique can be selected. The size of the dataset and how similar it is to the dataset the network was pre-trained on can both be used to analyse the classification problem. It allows leveraging the knowledge gained from

the pre-training to accelerate training and improve performance on the target task, especially when the target dataset is small or similar to the original dataset.

4. Dataset Used

4.1 Kaggle Data

The collection includes pictures taken using cameras as well as pictures that were downloaded from the Google Images page. With a total of 995 pictures, the dataset is split into the Train and Validation directories. This dataset does not contain the 1000 Rs and 500 Rs banned notes. The background folder is provided additionally in this dataset in both the training and validation directories which contains the noisy background in the images available.

4.2 Custom Data

Images of Indian currency notes with denominations of 10, 20, 50, 100, 200, 500, and 2000 were used in the experiments. To increase the accuracy of the model, we had created the new dataset. To capture variation, we have included variables during the collection of these photographs such as folded and full view currency images and indoor/outdoor environments. The lighting conditions differ significantly between indoor and outdoor settings. For each denomination, a total of 50 images were taken under various lighting conditions. As a result, a total of 1280 pictures were captured. The dataset is exposed to augmentations with cropping and scaling of the samples created using augmentations in order to significantly expand the datasets size.

5. Results and Analysis

Indian currency classification is a crucial task for ensuring the safety transaction of money, and the use of deep learning techniques like CNN models can provide accurate and efficient solutions. Figure 2 gives the output results for the data where each currency note is identified properly and accurately with voice message.



Figure 2. Indian Currency predicted with voice message

When we apply deep learning techniques to a particular dataset, we construct a model that can accept input and output. Now, we use a metric called loss to evaluate a model's

performance. This loss explicitly calculates the model's error. A large loss number often indicates erroneous model output, whereas a low loss value indicates fewer model flaws. Training loss is a measure of how well a deep learning model matches the training data. The performance of a deep learning model on the validation set is measured instead using a statistic called validation loss. The training loss and validation loss are frequently combined on a graph in the majority of deep learning applications. Figure 3 depicts the loss and accuracy of the proposed Sequential CNN model.

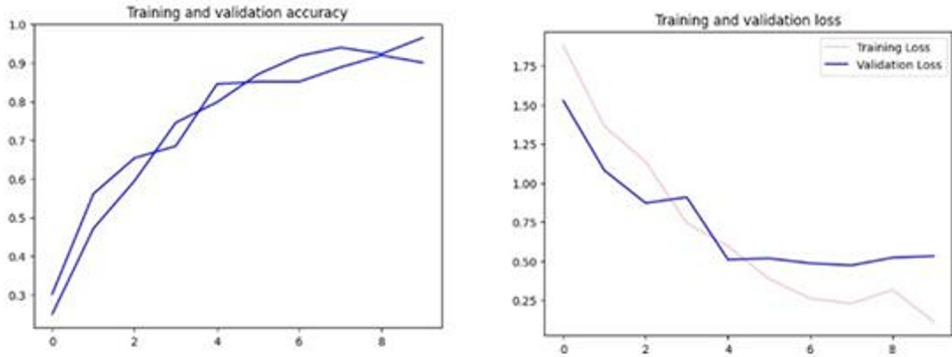


Figure 3. Graph depicting loss and Accuracy of the model

We achieved satisfactory results after completing the neural network training for currency recognition. We also need to examine the model that was employed in addition to these findings. Comparative investigation reveals that the Basic CNN model and VGG 16 models have the highest currency recognition accuracy.

6. Conclusion and Future Scope

The classification and identification of currency is the fundamental goal of this thesis. In reality, it mentions the currency's denomination. Four distinct models were put to the test, and the best one was ultimately chosen. These models have an empirical methodology foundation. Finally, the trained model could achieve 97.8% accuracy, demonstrating that the dataset used had undergone all necessary training. It can be inferred from the loss function and accuracy in Table 1 that the model did not overfit during training. Following study, it was discovered that our detection is quick and precise when the currency is in a clean state over the full screen and the angles are parallel.

Table 1. Comparing Loss And Accuracy of Various CNN Models

CNN model	Loss	Accuracy
Basic Sequential model	0.1077	97.98
VGG 16	0.3432	92.71
MobileNet	0.4432	89.07
AlexNet	0.9084	71.66

The basic CNN model and VGG16 for money recognition are the models used in this thesis' final section. The major goal of this is to research, evaluate, and contrast other models' currency recognition accuracy. The recommended method of employing the Vgg16 model is

the most accurate one for recognising currencies, according to experiments, and it is also the most practicable.

The proposed system can be extended towards coin detection and also for fake currency recognition. Denomination of other countries other than India can be added and comparison between them can be achieved. When an image is loaded from the outside into the training folder then it is not giving 100 % accuracy. This can be improved by optimizing the system. Res Net, the Inception model, and other deep learning models can all be added. Future research will focus on adapting the technique to smartphones in order to create a reliable banknote recognition application.

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