



An Automated Vision System to detect the .png format Indian Banknote taken through Smart Phone Camera by applying Convolutional Neural network

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Abstract:

Automatic Recognition of Indian banknote recognition which is an important task for handling the usage of banknotes, the main research is to use different algorithms to get the accurate identification of banknotes. Though we have sensor based machines to detect the banknotes but the cost to build to machines is more and we may not get the perfect results to detect Indian banknote. These sensors capture the images through IR recognition in various wavelengths and apply image processing tools to identify the banknote. However, some people are doing fraud stating that there is loss in withdrawal money or deposited money in the banks. So, our main aim is to capture each and every banknote and detect it and count it when withdrawing or depositing banknotes. No sensor based machines are detecting the new banknotes which are the primary issue. Meanwhile, smart phones are trending nowadays and can be used for image capture. Analyzing these issues, we proposed a model to classify the different Indian banknotes based Deep Learning approach (CNN). Though, Machine Learning can extract the feature Indian banknotes but show less accuracy. In order to increase the accuracy with the help of Machine Learning and Deep Learning we classify the Indian banknotes.

Keywords

Sensor based Machines, Banknote Detection, Smart phone, Camera, Machine Learning, Deep Learning, CNN

Introduction:

Though, in the recent days, the electronic online financial transactions taken place and the usage of paper money decreased but their importance is increased and circulating from person to person. The usage of paper money has its importance for street vendors, grocery shops, bank, pharmaceutical and respectively. But the problems involved in the automative bank note handling have some relevant problems, though its usage is more. Like to recognize the sizes of banknote, color of each banknote, denominations and type of bank note and counter fit detection. Even it also involved the serial number recognition which is recognized by electronic machines and image processing tools. Among these tasks the accuracy of recognition if Indian bank note through image processing tools is very less. But there is a situation that we are using the old Indian bank notes and new Indian bank notes which are differ in many patterns such as color , shape ,size , serial numbers and tangible marks and respectively. So for such type of situations image processing tools are not up to the mark. Even some are users are using the sensor based machines for detection but the cost to construct these machines are very high. The complexities that are involved in various

sensor detection machines include magnetic sensors, ultra violet sensors, and infrared sensors. But this is difficult to check by general users every time and they should an observer technician to check the full process.

Day to day there is an improvement in the technologies but the users have not advanced to use that particular technology especially in bank (online transaction, money withdrawal machines, money deposit machines). Meanwhile the technologies are developing but the accuracy in detecting the bank notes has not increased. Also, the transactions are taking place the camera in the machines should capture the image of the banknote and detect it. By detecting the bank notes it can be folded, having tangible marks, distinguish the old and new bank notes, horizontal and vertical directions and in diagonal directions.

To detect the banknote in all the above issues we are proposing the deep learning algorithm, this recognition is based on the images of the Indian bank notes captured through smart phone cameras under visible light condition. This study mainly aims to identify the Indian bank note that is in .png format placing a different orientation.

The main structure of the paper is as follows. Section II gives out the work related to different countries bank note detection. Section III describes the architecture of the proposed model and in section IV we explain step to step implementation and expansion of proposed method. Section V describes the result of the experiment. Finally, Section VI and section VII described the conclusion and future scope.

II Literature Review

In [1] the authors described how to detect the banknote based on genetic algorithm under visible light. Hence, they have proven that under visible light we can recognize the banknotes. In [2] they proved how to extract the different features and shape analysis for different banknotes. Whereas, in [3] the used SVM to detect whether a banknote is old or new. This is very important in our study because Indian banknotes consist of old and new banknotes. Such that, our algorithm

should detect both Indian old and new banknotes. In [4] they discussed different image processing tools and sensors to detect the banknotes. Hence, we also extracted the disadvantages of these sensor based methods to detect banknotes. In [6] the entire paper given information about how to capture the images by UV and detected using image segmentation. Hence we listed few disadvantages by using multiple sensors and UV rays detection of notes.

III Architecture and Contributions

a. Architecture

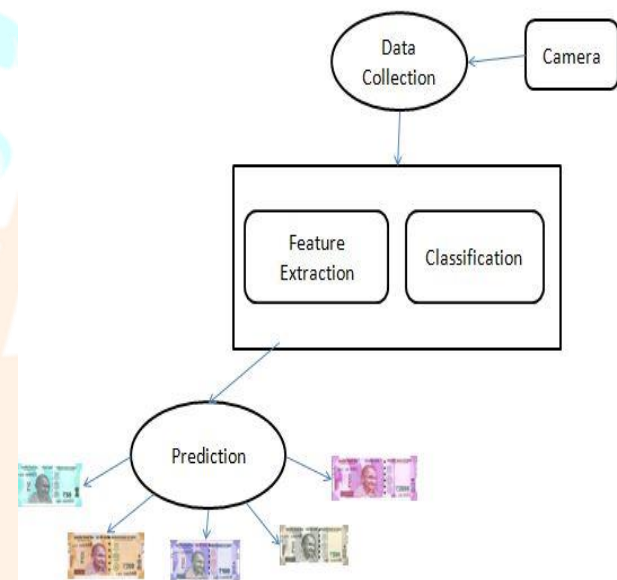


Figure 1

The above Figure 1 gives the detail architecture of our proposed model. Initially, we capture images of Indian bank note i.e., Rs. 10, Rs.20, Rs. 50, rs.100, Rs.200, Rs.500, Rs.1000, Rs. 2000 through smart phone camera. The Indian bank note images are captured at different orientations like horizontal direction, vertical direction, diagonal and folded ways. Then by collecting the differed bank notes we construct the dataset. Initially the data set is unstructured but by applying the preprocessing tools like data cleaning, data standardization, data normalization and removing outliers we convert into structured data. This dataset will be the inputs for CNN. In CNN approach both the classifications and future selection are done parallel to give the output. In CNN the classification mainly consists of

Convolutional layer, ReLU and Pooling layer whereas the feature extraction mainly consists of flattened layer and fully

connected layer. And finally, we classify the different Indian banknote and gives the output.

b. Contributions

Category	Method	Advantages	Disadvantages
Sensor based method	<ul style="list-style-type: none"> Using IR rays and visible light and IR images are used for banknote detection 	<ul style="list-style-type: none"> We can extract all the features related to security. 	<ul style="list-style-type: none"> Cost is high to buy the sensor based detectors. The is also complexity in the usage of these machines.
Software method	<ul style="list-style-type: none"> Images are still captured through IR. Used ML algorithms which does not give accurate results. 	<ul style="list-style-type: none"> Only important F=features are extracted very easily compared to sensor based 	<ul style="list-style-type: none"> Does not give accurate results.
	<p>PROPOSED METHOD</p> <ul style="list-style-type: none"> The Indian banknote images are captured through smartphone camera. Used Deep learning approach to give more accuracy 	<ul style="list-style-type: none"> All the features are extracted to give accurate output. Time taken to detect is very less. 	

IV Proposed Method

a. Overview of Proposed method

The figure 2 shows the entire procedure of our proposed method. The input we give is image of the bank note which is captured through a smart phone and cropped on the given bounding box. As we observe the input image the cropped mainly done at center areas of the banknote in 2 different sizes i.e., half of the input image and 2/3rd of the input image. These cropped images are sent to CNN for classification. The resolution 100*100 which is to be inputted for the classification in CNN. The output

from the CNN classifier the input bank note into its labels (Rs. 10, Rs.20, Rs. 50, rs.100, Rs.200, Rs.500, Rs.1000, Rs. 2000).

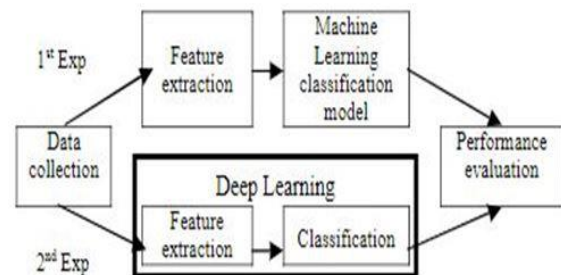


Figure 2

b. Machine Learning Analysis

Machine learning mainly concentrate that the computer is capable to learn without any programming. We have different classification models to classify the labels based on the training. Machine learning mainly extract the pattern from the raw data by using different classification and clustering algorithm. The main aim of ML is that the system is to be learned from experience before going to the deep learning approach first we have to analyze our study through different classification techniques. Some of the techniques are Decision tree classifier, SVM, ANN, One-R, Zero-R, Logistic Regression, Naïve Based, K-Nearest neighbor and respectively. But in machine Learning the classification and feature selection are not done at the same time and the accuracy is very low so that the classification doesn't give the perfect results as shown in Figure 3 consists of different confusion matrix of classification algorithms. Hence in order to increase the accuracy we prefer Deep Learning approach.

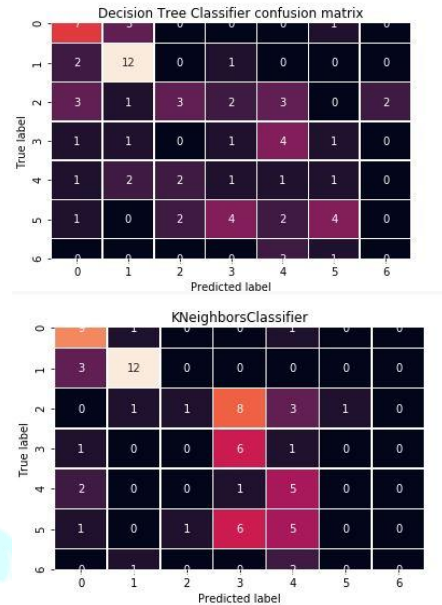
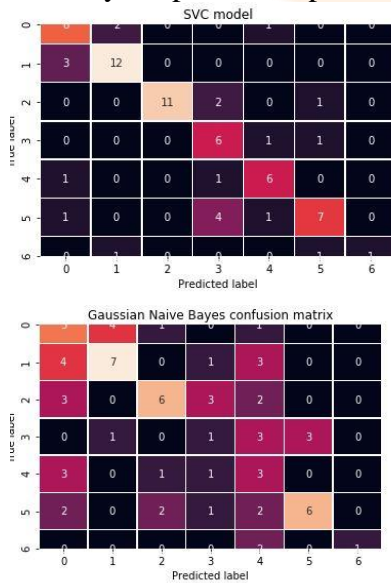


Figure 3 Confusion matrix of SVC, Gaussian Naïve Bayes, Decision Tree and kNeighbor classifiers

c. Input Bank Note Image

In our study we captured the images of Indian Banknote through smartphone camera which are held by hand, on table. We also place that bank note in different orientation like horizontal direction, vertical direction and diagonal direction. Even the half fold banknote images were captured through phone. We mainly extract the feature by capturing the banknote completely front side and complete backside as shown in the figure 4. When we capture the image of the banknote and set the bounding boxes mainly where we extract the feature and then crop the image based on the bounding box. This resultant image is then forwarded as the input to CNN. As shown in the figure, we can see the different alignment of Indian banknote (horizontal, vertical, diagonal). Then we crop the images we can include the background in the box on four corners. We can also remove the unwanted backgrounds mainly at the center of the image. We should make on note that, the current Indian banknote has different sizes, so we should set the bounding box sizes difference with respect to different bank note sizes. Thus, we provide these input images to the CNN model.



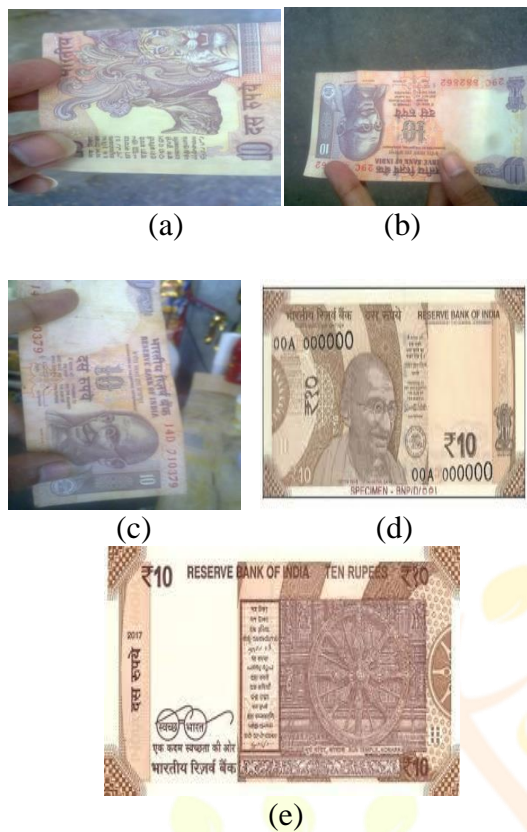


Figure 4 Examples of images captured (a) folded (b)front side (c)vertical direction (d)front side new note (e) backside newnote

d. CNN Model

In our study we classify our banknote images into by using CNN. In our work AlexNet showed good performance in classifying the different Indian banknotes. In this study, we conduct the different experiments with our proposed model using the architecture as shown in the figure 5. IN order to classify the different Indian bank notes we should follow the following steps.

1. Convolution
2. ReLU
3. Pooling
4. Flattened layer
5. Fully connected layer and Soft max

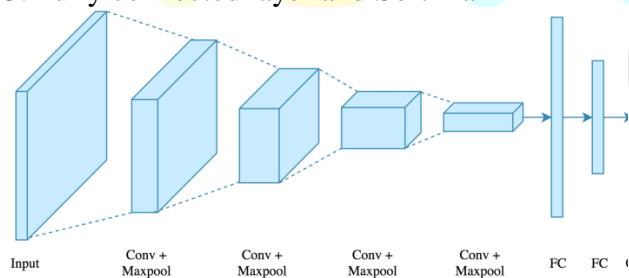


Figure 5 CNN

1. Convolution

It is the first layer where we can extract the future from the input Indian banknote image. It preserves the input image in the form of pixel by using Small Square or matrices of input data. In this layer mainly we perform the operation which takes the input

- a. Image matrix
- b. Kernel

Then after multiplying the image matrix and filter matrix, the resultant output matrix is called feature map. By applying the filter matrix, we can perform some certain operations on the input image such as blurring the image, sharpening the image, edge detection of image. The various filters are shown in the below figure 7. The output image is called Convolved Image. The entire process that performs these operations is called Convolution. The filter matrix is taken by the CNN itself we need not provide the filter matrix. Finally, the input i.e., provided by the data set to the CNN convert into the pixel value, and multiply with the filter matrix, which has set of ways, we apply the filter systematically to the input image to generated feature map as shown in figure 6.

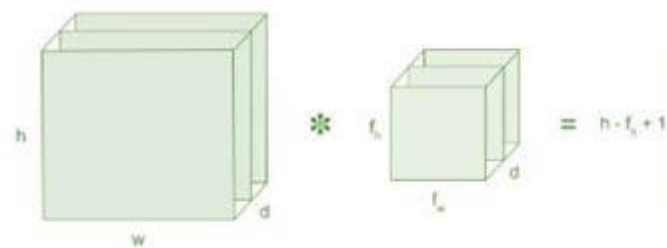


Figure 6 Feature Map

Operation	Filter	Convolved Image
Identity	$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	
	$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix}$	
Edge detection	$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$	
	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	
Sharpen	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	
Box blur (normalized)	$\frac{1}{9} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$	
Gaussian blur (approximation)	$\frac{1}{16} \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$	

Figure 7 Various Filter matrixes

2. ReLU

ReLU is a non linear operation and its output is $\max(0, x)$. Once the feature map is obtained the non linear pixel values are converted to linear pixel values (nonnegative values) as shown in figure 8. Here, each pixel value is performed $\max(0, x)$ function to get non negative values. It is a transfer function where we can replace the negative values with positive values or zero.

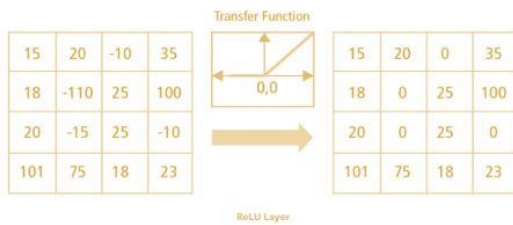
$$f(x) = \max(0, x)$$


Figure 8 ReLU Activation Function

3. Pooling

The main aim of pooling layer is to reduce the pixel value or pixel matrix when the taking input images is too large. Indirectly it reduces the dimensions of each feature map, but retains its original information. The pooling can be

1. Max Pooling
2. Avg Pooling
3. Sum Pooling

In max pooling the main function is takes the largest elements from the feature map, average pooling performs the average of all the element in the feature map and Sum Pooling performs the sum of all the values of the elements in feature map. In our proposed model since we are using AlexNet model it performs Max Pooling for all the large feature maps to 2*2 feature map matrix.

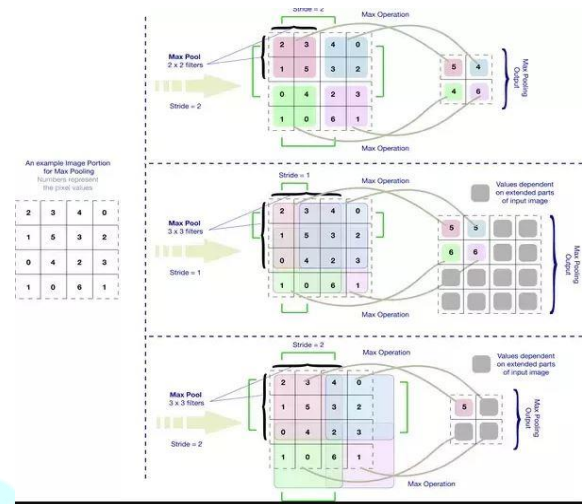


Figure 9 Max Pooling

4. Flattened layer

Also called as FC layer. Here the matrix is converted into vector and forward it as input to the fully connected layer.

5. Fully Connected Layer and Softmax

All the Convolutional layers are finally connected to fully connected layer at the end. In AlexNet model there are 3 fully connected layers hence our study consists of 3 fully connected layers. With the help of this layer, we combine all the features of the bank note together to create a model. Finally, we use soft max activation function to classify the Indian banknote as Rs. 10, Rs.20, Rs. 50, rs.100, Rs.200, Rs.500, Rs.1000, and Rs. 2000.

V. Experimental Results

a. Experimental Dataset

The Indian banknote dataset is used for study consists of Eight Indian Bank Note. The total numbers of denominations are eight (Rs. 10, Rs.20, Rs. 50, rs.100, Rs.200, Rs.500, Rs.1000, Rs. 2000). They used scanner and camera on One Plus 6T and Vivo V15Pro smartphone to capture the images on both the sides of old and new Indian Bank Note. For captured images we used HP Color Laser Jet CP4525 printer to obtain color bank note images and then cropped to make banknote image, we hold the Indian banknote with our hands in different directions placing in front of Camera. Examples of captured images are shown in the figure 4.

b. Training and Testing for Indian banknote Classification

Initially we perform cross-fold validation for training in CNN model. We divided the dataset into three parts randomly, two of which are used for training and remaining one for testing. The training and testing were conducted on a desktop computer having configuration: Intel(R) Core(TM) i3-6100U CPU @ 2.30GHz, 2301 Mhz, 2 Core(s), 4 Logical Processor(s). We use AlexNet as

CNN architecture for training. We used image data generator for fitting the CNN to the images. The step by step training of the dataset is shown in figure .

- Condition: Target_size = (100,100)
- Batch_size = 32
- Steps_for_epoch = 80
- Epoch = 50
- Validation_steps = 3

```

Found 234 images belonging to 7 classes.
Found 179 images belonging to 7 classes.
Epoch 1/50
00/80 [-----] - 123s 2s/step - loss: 2.0135 - accuracy: 0.1902 - val_loss: 1.9146 - val_accuracy: 0.1667
Epoch 2/50
00/80 [-----] - 131s 2s/step - loss: 1.8405 - accuracy: 0.1915 - val_loss: 2.1518 - val_accuracy: 0.1566
Epoch 3/50
00/80 [-----] - 134s 2s/step - loss: 1.8209 - accuracy: 0.2197 - val_loss: 1.9803 - val_accuracy: 0.1250
Epoch 4/50
00/80 [-----] - 128s 2s/step - loss: 1.8527 - accuracy: 0.1919 - val_loss: 2.0945 - val_accuracy: 0.1084
Epoch 5/50
00/80 [-----] - 124s 2s/step - loss: 1.8400 - accuracy: 0.1855 - val_loss: 1.9055 - val_accuracy: 0.1667
Epoch 6/50
00/80 [-----] - 122s 2s/step - loss: 1.8535 - accuracy: 0.1910 - val_loss: 1.7856 - val_accuracy: 0.2169
Epoch 7/50
00/80 [-----] - 123s 2s/step - loss: 1.8449 - accuracy: 0.1915 - val_loss: 2.4520 - val_accuracy: 0.1146
Epoch 8/50
00/80 [-----] - 122s 2s/step - loss: 1.8499 - accuracy: 0.1944 - val_loss: 1.9086 - val_accuracy: 0.1687
Epoch 9/50
00/80 [-----] - 123s 2s/step - loss: 1.8545 - accuracy: 0.1846 - val_loss: 1.9702 - val_accuracy: 0.1250
Epoch 10/50
00/80 [-----] - 122s 2s/step - loss: 1.8604 - accuracy: 0.1880 - val_loss: 2.0405 - val_accuracy: 0.2048
Epoch 11/50
00/80 [-----] - 122s 2s/step - loss: 1.8517 - accuracy: 0.1829 - val_loss: 1.8485 - val_accuracy: 0.1875
Epoch 12/50
00/80 [-----] - 123s 2s/step - loss: 1.8598 - accuracy: 0.1906 - val_loss: 1.8703 - val_accuracy: 0.1807
Epoch 13/50
00/80 [-----] - 121s 2s/step - loss: 1.8534 - accuracy: 0.1889 - val_loss: 1.8696 - val_accuracy: 0.1250
Epoch 14/50
00/80 [-----] - 120s 1s/step - loss: 1.8472 - accuracy: 0.1906 - val_loss: 1.7933 - val_accuracy: 0.2048
Epoch 15/50
00/80 [-----] - 121s 2s/step - loss: 1.8467 - accuracy: 0.1880 - val_loss: 1.9200 - val_accuracy: 0.1250
Epoch 16/50

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(a)

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Epoch 16/50
00/80 [-----] - 122s 2s/step - loss: 1.8307 - accuracy: 0.1970 - val_loss: 1.9698 - val_accuracy: 0.1687
Epoch 17/50
00/80 [-----] - 121s 2s/step - loss: 1.7424 - accuracy: 0.2671 - val_loss: 2.1971 - val_accuracy: 0.1146
Epoch 18/50
00/80 [-----] - 122s 2s/step - loss: 1.7650 - accuracy: 0.2662 - val_loss: 2.1402 - val_accuracy: 0.2530
Epoch 19/50
00/80 [-----] - 126s 2s/step - loss: 1.7889 - accuracy: 0.2850 - val_loss: 2.2939 - val_accuracy: 0.2292
Epoch 20/50
00/80 [-----] - 121s 2s/step - loss: 1.6852 - accuracy: 0.3415 - val_loss: 2.1800 - val_accuracy: 0.1887
Epoch 21/50
00/80 [-----] - 123s 2s/step - loss: 1.5443 - accuracy: 0.3709 - val_loss: 4.5374 - val_accuracy: 0.2188
Epoch 22/50
00/80 [-----] - 121s 2s/step - loss: 1.4535 - accuracy: 0.4132 - val_loss: 2.7619 - val_accuracy: 0.2530
Epoch 23/50
00/80 [-----] - 122s 2s/step - loss: 1.3934 - accuracy: 0.4449 - val_loss: 3.8116 - val_accuracy: 0.2604
Epoch 24/50
00/80 [-----] - 121s 2s/step - loss: 1.2913 - accuracy: 0.4825 - val_loss: 7.6177 - val_accuracy: 0.3253
Epoch 25/50
00/80 [-----] - 123s 2s/step - loss: 1.3724 - accuracy: 0.4513 - val_loss: 2.2575 - val_accuracy: 0.3229
Epoch 26/50
00/80 [-----] - 120s 2s/step - loss: 1.1742 - accuracy: 0.5274 - val_loss: 4.6363 - val_accuracy: 0.3373
Epoch 27/50
00/80 [-----] - 123s 2s/step - loss: 1.1428 - accuracy: 0.5479 - val_loss: 2.5889 - val_accuracy: 0.3854
Epoch 28/50
00/80 [-----] - 121s 2s/step - loss: 1.1125 - accuracy: 0.5564 - val_loss: 4.4311 - val_accuracy: 0.4096
Epoch 29/50
00/80 [-----] - 123s 2s/step - loss: 1.0388 - accuracy: 0.5957 - val_loss: 2.1923 - val_accuracy: 0.4479
Epoch 30/50
00/80 [-----] - 122s 2s/step - loss: 0.8991 - accuracy: 0.6487 - val_loss: 2.7715 - val_accuracy: 0.3614
Epoch 31/50
00/80 [-----] - 121s 2s/step - loss: 0.8341 - accuracy: 0.6726 - val_loss: 4.5987 - val_accuracy: 0.4479

```

(b)

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Epoch 35/50 ----- 121s 2s/step - loss: 0.7282 - accuracy: 0.7281 - val_loss: 4.9384 - val_accuracy: 0.4699
Epoch 36/50 ----- 122s 2s/step - loss: 0.6593 - accuracy: 0.7504 - val_loss: 4.5281 - val_accuracy: 0.5000
Epoch 37/50 ----- 128s 1s/step - loss: 0.6412 - accuracy: 0.7607 - val_loss: 3.2435 - val_accuracy: 0.5422
Epoch 38/50 ----- 121s 2s/step - loss: 0.6313 - accuracy: 0.7667 - val_loss: 4.8913 - val_accuracy: 0.4688
Epoch 39/50 ----- 128s 2s/step - loss: 0.5451 - accuracy: 0.8017 - val_loss: 2.7330 - val_accuracy: 0.6386
Epoch 40/50 ----- 122s 2s/step - loss: 0.4588 - accuracy: 0.8265 - val_loss: 6.9519 - val_accuracy: 0.5833
Epoch 41/50 ----- 128s 2s/step - loss: 0.4319 - accuracy: 0.8474 - val_loss: 4.5234 - val_accuracy: 0.5381
Epoch 42/50 ----- 122s 2s/step - loss: 0.3773 - accuracy: 0.8641 - val_loss: 7.5061 - val_accuracy: 0.5729
Epoch 43/50 ----- 123s 2s/step - loss: 0.3553 - accuracy: 0.8778 - val_loss: 3.9488 - val_accuracy: 0.5800
Epoch 44/50 ----- 122s 2s/step - loss: 0.3155 - accuracy: 0.8765 - val_loss: 5.3624 - val_accuracy: 0.5938
Epoch 45/50 ----- 122s 2s/step - loss: 0.3418 - accuracy: 0.8774 - val_loss: 6.3992 - val_accuracy: 0.5542
Epoch 46/50 ----- 122s 2s/step - loss: 0.3348 - accuracy: 0.8855 - val_loss: 2.9402 - val_accuracy: 0.6354
Epoch 47/50 ----- 121s 2s/step - loss: 0.2626 - accuracy: 0.9081 - val_loss: 3.7177 - val_accuracy: 0.5542
Epoch 48/50 ----- 122s 2s/step - loss: 0.2591 - accuracy: 0.9183 - val_loss: 6.2218 - val_accuracy: 0.5729
Epoch 49/50 ----- 128s 2s/step - loss: 0.2521 - accuracy: 0.9158 - val_loss: 8.1098 - val_accuracy: 0.6627
Epoch 50/50 ----- 121s 2s/step - loss: 0.2682 - accuracy: 0.9064 - val_loss: 6.0288 - val_accuracy: 0.6146
Epoch 51/50 ----- 121s 2s/step - loss: 0.2605 - accuracy: 0.9197 - val_loss: 4.5084 - val_accuracy: 0.5793
    
```

(c)

Figure 9 All (a),(b),(c) shows the process of training the dataset

c. Discussion

Figure shows the correctly recognized Indian banknote images in the test dataset as in figure 10. The class label consists of Rs. 10, Rs.20, Rs. 50, rs.100, Rs.200, Rs.500, Rs.1000, Rs. 2000.

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 76, 76, 32)	68032
max_pooling2d_1 (MaxPooling2D)	(None, 38, 38, 32)	0
conv2d_2 (Conv2D)	(None, 14, 14, 32)	640032
max_pooling2d_2 (MaxPooling2D)	(None, 7, 7, 32)	0
Flatten_1 (Flatten)	(None, 1568)	0
dense_1 (Dense)	(None, 128)	200832
dense_2 (Dense)	(None, 7)	903
Total params: 901,799		
Trainable params: 901,799		
Non-trainable params: 8		

Figure 10 Results

VI Conclusion

We proposed a Indian banknote detection that uses a Convolutional Neural network and images of Indian banknote captured through camera under visible light. Our method classify Indian banknote into 8 labels. The results showed a good performance with good accuracy.

VII Future Scope

Through our model we can create software with low cost for the banking sector. It capture the images when the people are depositing or withdrawing the currency notes from the machine. So that any frauds can be detected when a person conveys that he got incorrect number of banknotes.

It can be also used for visually impaired people or color blinded people by inserting the sound function.

We can easily classify the denominations of each note without any observer presence.

This software can be easily inserted in the smartphone and easily we can detect the banknote for foreigners.

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