INDIAN CURRENCY CLASSIFICATION

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1 ABSTRACT

Currency is an indispensable part of our daily life. Despite the quickly expanding utilisation of master cards and other electronic types of payment money is broadly utilised for ordinary exchanges because of its convenience. In this paper we have introduced a web application and a mobile application for currency recognition that recognises Indian currency in different views on scale. It is easy for a normal human being to perceive and recognise any back note effortlessly but it is really difficult for any visually impaired or blind person to perform the same task. Banknotes generally have different designs according to the denomination and can be sorted with more human errors in the bank. This leads to problems in classifying and recognition. If computers or mobile app currency recognise it will greatly improve the accuracy of recognition and reduce people's workload efficiently As money has an important role in daily life for any business transactions, real-time detection and recognition of banknotes become a necessity for person especially who is blind or visually impaired or for a system that sorts the data. The model which we worked on basically classifies the currency note into 1000/100/20/10/50/500 denominations. The currency will be recognized and classified by using image processing techniques, deep learning techniques. We have used the concept of transfer learning which is a technique of deep learning where we will basically reuse the weights in one or more layers from an already trained model into a new model by either keeping the weights fixed, fine tuning them or adapting the weights entirely when training the model. On the web application/mobile app the user would upload a picture of currency note and it will provide an audio output.

Keywords: **Image processing, transfer learning, deep learning**

2 INTRODUCTION

The ability to identify currency (both coins and bills) without human input is unfavorable for a number of applications. Currency (which includes paper notes and normal coins) is basically a medium for switching of goods and services. It is quite a simple task for a human to identify denomination currency or classify the currency accordingly because our brain is skillful enough to do that. However, in case of computer vision, classifying the currency might not be that easy especially when there are cases of currencies becoming damaged, old and even faded due to wear and tear. In this thesis we mainly use deep learning as the framework, employing convolutional neural networks(CNN) to extract the features of paper currency so that we can much accurately recognize the denomination of the currency, both front and

back. In this thesis the following points are proposed: (1) data collection and processing, (2) data augmentation, (3) currency feature extraction, (4) currency identification, (5) result analysis of currency recognition.
This system is used to detect the currency through the automated system which is through convolution neural networks, in deep learning. Deep learning excels in the task of recognition and classification of images over large data sets, which is also primarily used in object category recognition.
The proposed model is compared with widely used neural network based models like VGG16, VGG19, Xception, InceptionV3, AlexNet and ResNet50 in terms of training and testing accuracy.

3 RELATED WORK

The classification of Indian currency notes has been addressed in various approaches. Over the years, a substantial number of researches have been done in this field of currency note recognition. The authors have done recognition based on color, texture, security features, etc. The commonly used methods include artificial neural networks, currency characteristic comparison, principal component analysis, local feature descriptors comparison, hidden markov models and naive bayes classifier, etc. There are a number of methods known to detect faces using neural networks. For instance, in 1994 Vaillant et al. searched for regions that may contain a face in the input image using a neural network, and used another neural network to determine if it truly contained a face. Also, in 1998 Roley et al. proposed to detect faces using a neural network learned using the Bootstrap method, achieving a high performance in detecting frontal faces. This method was later expanded so that it is robust to the rotation of the face. In 2002 Garcia et al. presented a neural network that can detect faces in input images of different sizes, with various lighting conditions, and varying orientation of the faces. Further, in 2005 Osadchy et al. succeeded in real time face detection and pose estimation using a Convolution Neural Network (CNN). Not only have neural networks shown their high performance in face detection, but they have demonstrated usefulness in detecting objects other than faces. And in recent years, training deep neural networks has become possible, leading to detection of multiple simultaneous objects. Thus we have used transfer learning techniques which use a pretrained model and recognize images for better accuracy.

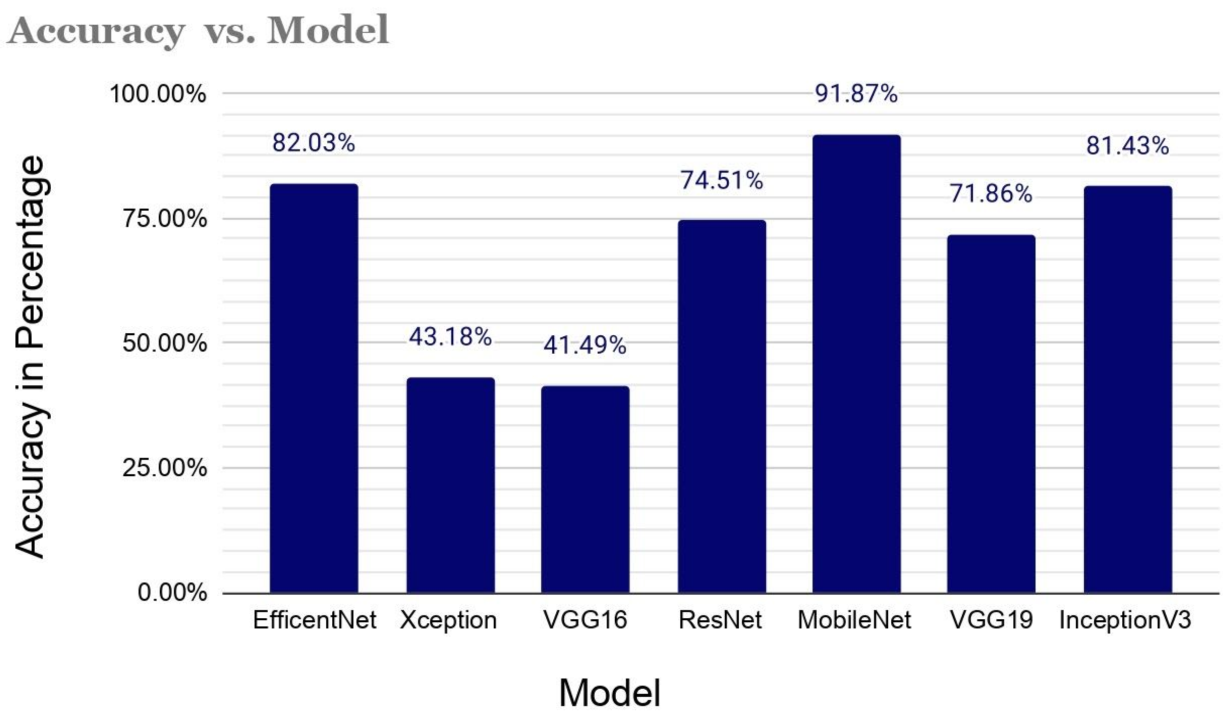
4 METHODOLOGY

The problem statement is quite straightforward- classifying Indian currency notes using deep learning approaches. There are many image classifier models each following its own methodology.
The dataset used is basically images of currency notes separated into training and testing set by ratio of 85:15 as shown below. There are approximately 2570 images of different denominations of Indian currency notes as shown below.

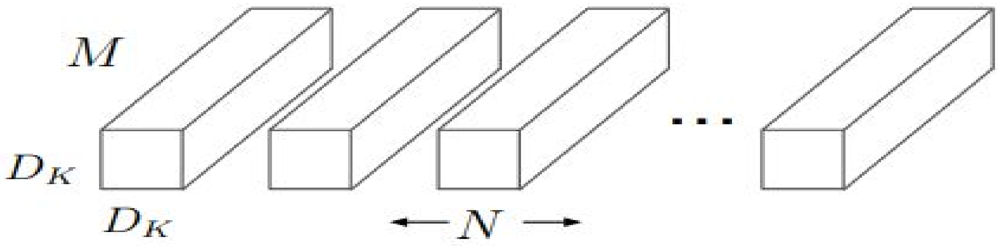
Notes	Training	Testing	Total
Ten	369	66	435
Twenty	371	66	437
Fifty	379	68	447
Hundred	351	62	413
Five hundred	341	61	402
One thousand	371	66	437

The method we proposed is transfer learning in which there are different models for image classification. A framework has been defined for better understanding of transfer learning which is defined as follows:-

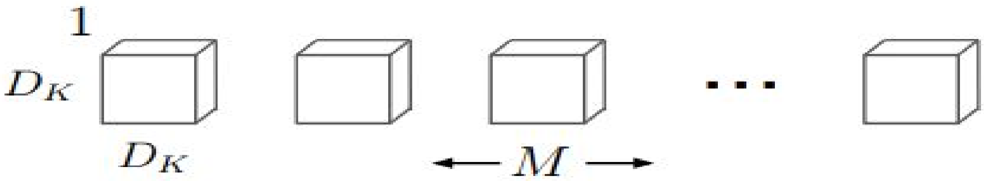
There are many models which we can use for transfer learning like EfficientNet, Xception, VGG16, MobileNet and many others. We have trained and tested our dataset through a number of models with different hyper parameters as shown in fig below.



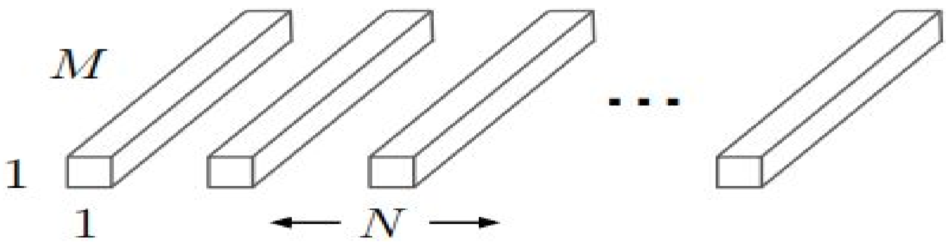
After training 6-7 models we got the best results for MobileNet,EfficentNet,InceptionV3. We can conclude from the bar graph it shows that the Mobilenet has the highest accuracy of classifying as an image correctly and confidently so for further training and testing of models we used MobleNet as our model for classifying the images. MobileNets are based on a streamlined architecture that uses depth-wise separable convolutions to build light weight deep neural networks. We introduce two simple global hyper-parameters that efficiently trade off between latency and accuracy. These hyper-parameters allow the model builder to choose the right sized model for their application based on the constraints of the problem. We shall be using Mobilenet as it is lightweight in its architecture. It uses depthwise separable convolutions which basically means it performs a single convolution on each colour channel rather than combining all three and flattening it. For MobileNets the depthwise convolution applies a single filter to each input channel. The pointwise convolution then applies a 1×1 convolution to combine the outputs the depthwise convolution. A standard convolution both filters and combines inputs into a new set of outputs in one step. The depthwise separable convolution splits this into two layers, a separate layer for filtering and a separate layer for combining. This factorization has the effect of drastically reducing computation and model size.



(a) Standard Convolution Filters



(b) Depthwise Convolutional Filters

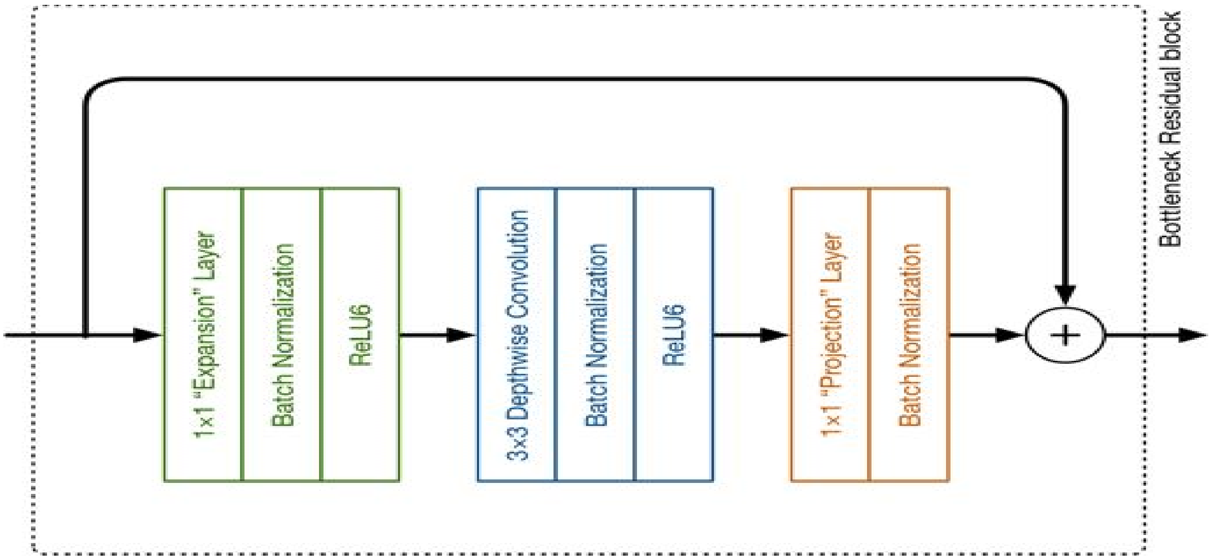


(c) 1×1 Convolutional Filters called Pointwise Convolution in the context of Depthwise Separable Convolution

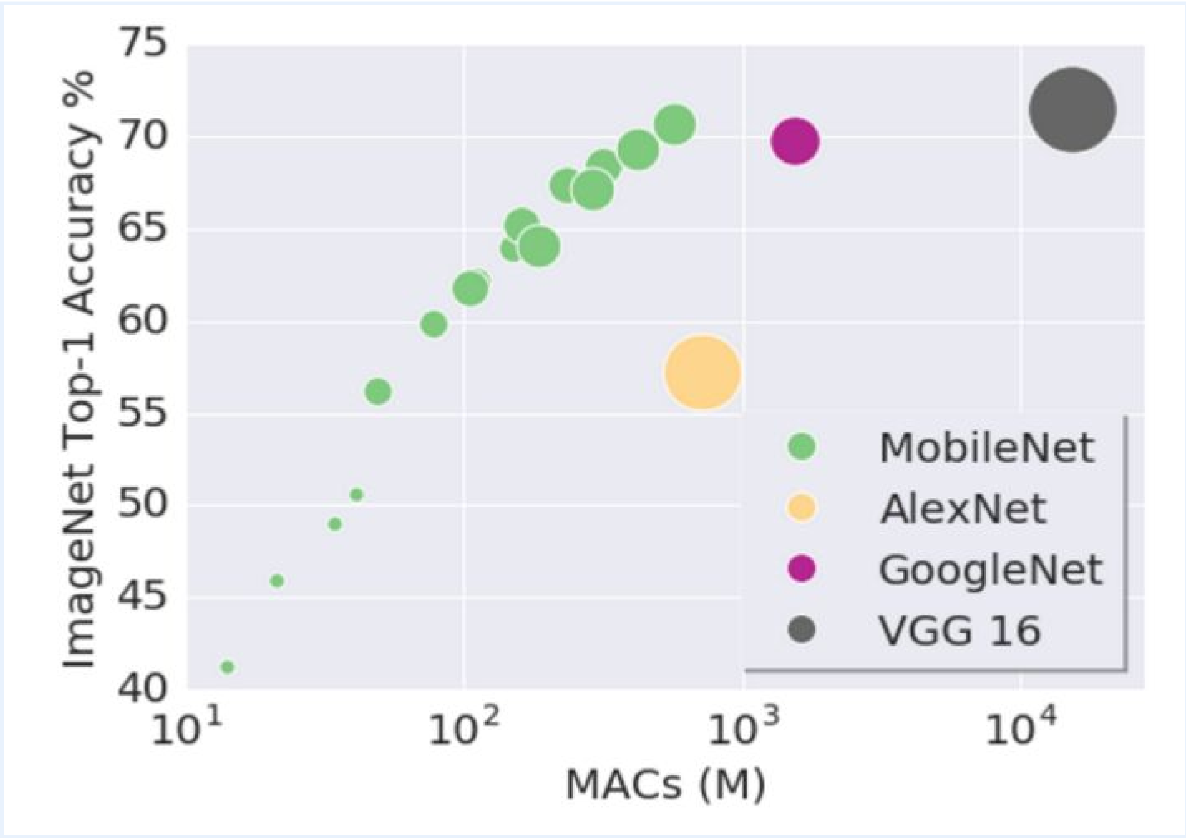
So the overall architecture of the Mobilenet is as follows, having 30 layers with

1. **convolutional layer with stride 2**
2. **depthwise layer**
3. **pointwise layer that doubles the number of channels**
4. **depthwise layer with stride 2**
5. **pointwise layer that doubles the number of channels**

MobileNet is a neural network architecture that runs very efficiently on mobile devices. Its architecture looks like as shown in figure below:

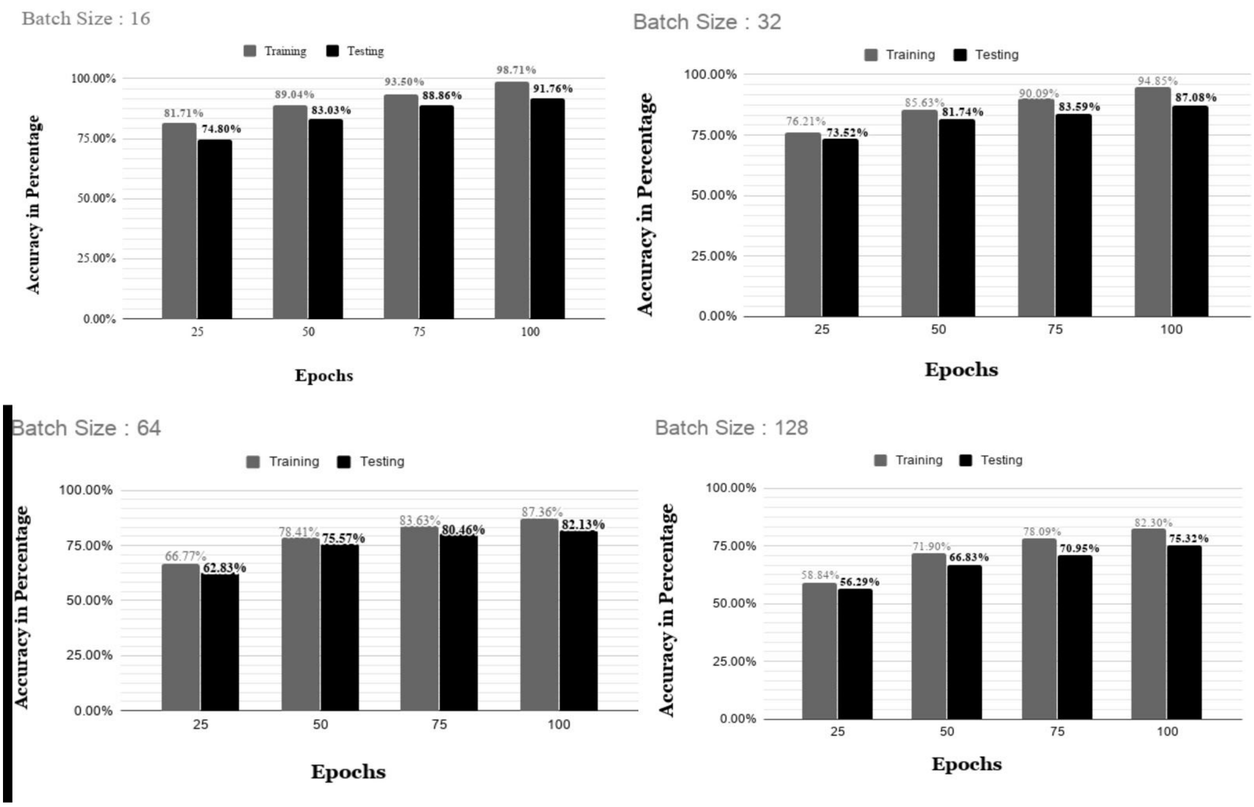


It is also very low maintenance thus performing quite well with high speed. There are also many flavours of pre-trained models with the size of the network in memory and on disk being proportional to the number of parameters being used. The speed and power consumption of the network is proportional to the number of MACs (Multiply-Accumulates) which is a measure of the number of fused Multiplication and Addition operations.

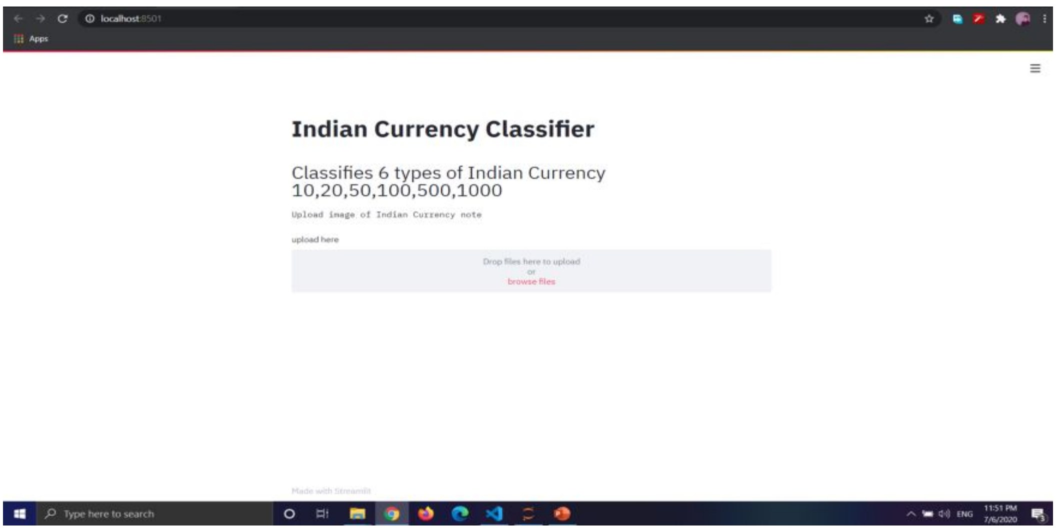


5 EXPERIMENTAL RESULTS

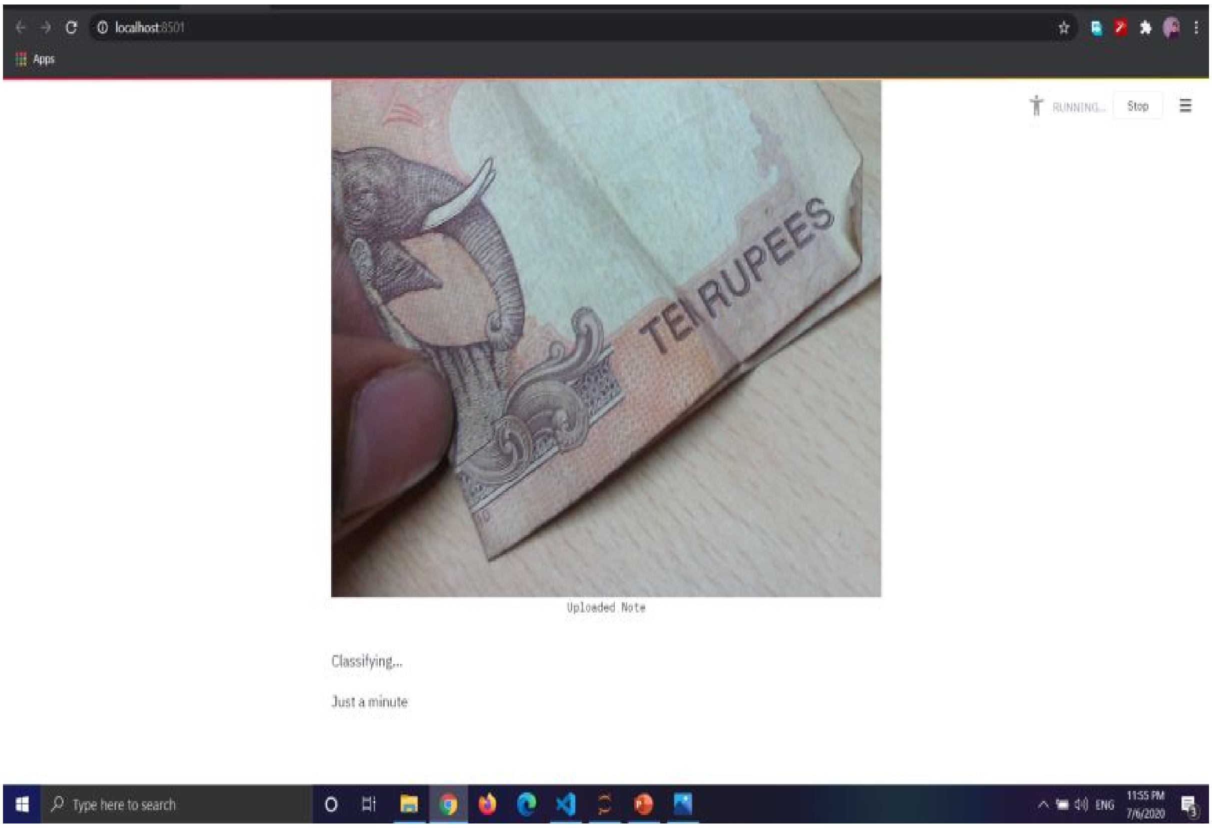
The figure below is the representation of the accuracy in percentage for different numbers of epochs. We can conclude that from different batch sizes we got the highest percentage of accuracy in batch size 16.



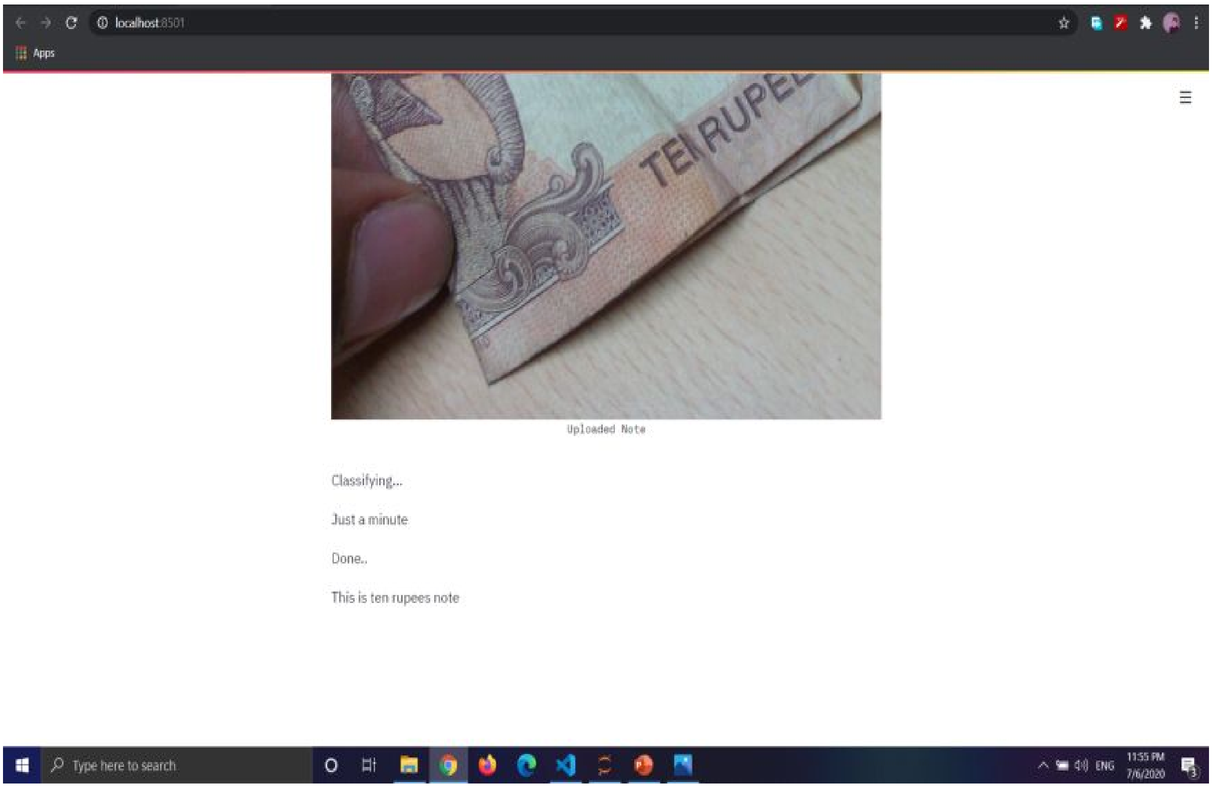
The web application UI is shown below with working of model and output.
The following steps for recognition of currency notes:
Step 1: Browse the picture you want to recognize which type of currency your picture is and upload the picture.



Step 2: When you have uploaded the picture it shows some output as processing/classifying the image.



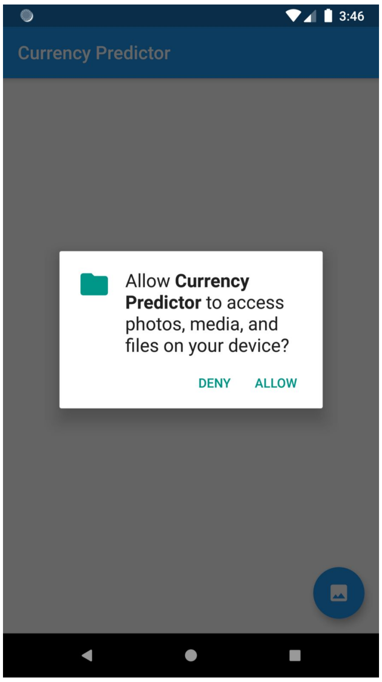
Step 3: After the model has classified the image correctly it shows the output as shown in the picture below.



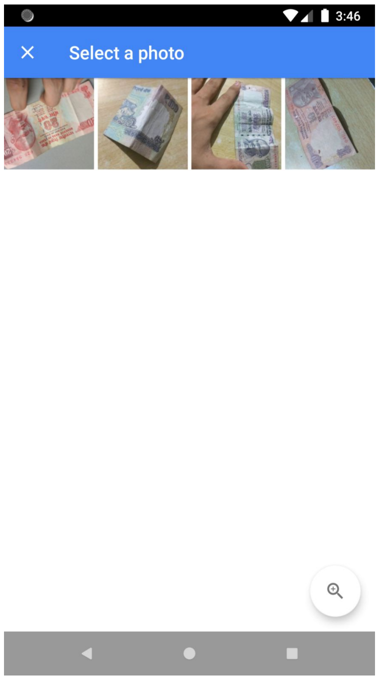
The deployment of android application is shown below in 3 steps same as web application:

Step 1

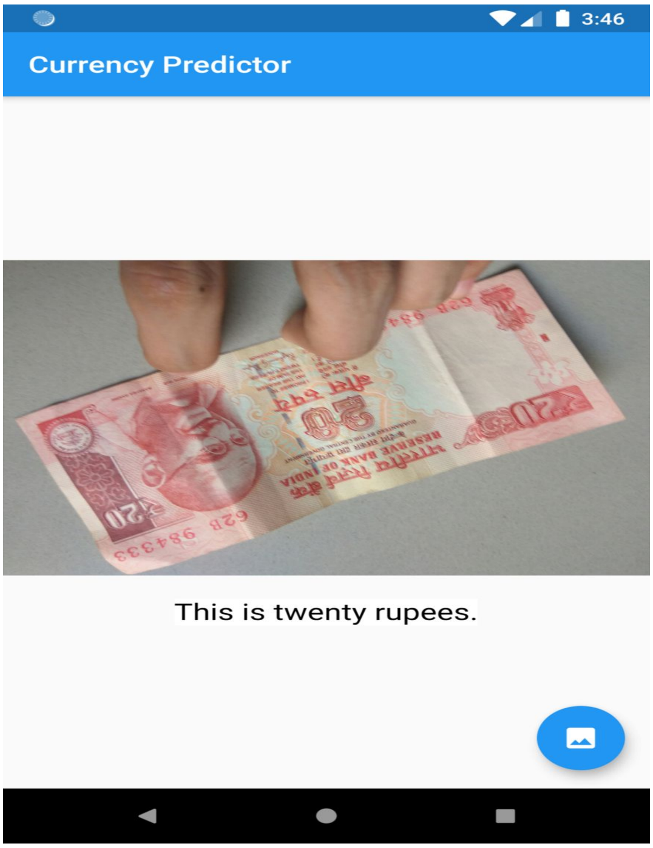
Step 2



Step 3



Step 4: The final output of the model



6 CONCLUSION

In this paper we have explained about our model we built for the purpose of classifying Indian currency notes. We have also explained about the concept behind this, i.e., convolution neural network (CNN) algorithm and transfer learning; which helped in extracting features of the currency note. We also tested for each model to aim for better accuracy. We tried on models like VGG16, ResNet, MobileNet and other models as well using some hyper-parameters like epoch, batch size, learning rate. Out of all the models we tested, MobileNet gave us the highest accuracy for our dataset.

We then deployed the model with a web-app using a library called Streamlit in python and an android app using framework Flutter developed by google to make it usable for the user.

Our current limitations include a lack of risk analysis . Due to given time constraints , we aim to work for optimization and better accuracy in the next phase . In the future we will improve on a better dataset. Thereafter, giving much better accuracy and results.

We also aim at the web-app uploaded on cloud in order to make it public since currently ours works on local machines. We can also aim to work on UI part of web-app as well as android app to make it more understandable for the end user in future.

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