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Fake Indian Currency detection using Deep learning

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ABSTRACT - In this methodology, the Automatic Fake Currency Recognition System is intended to recognize fake paper money to check whether it is real or unique. The current fake issue because of demonetization influences the financial framework and different fields. Another methodology of Convolution Neural Network towards the distinguishing proof of phony money notes through their pictures is analyzed in this approach which is nearly better compared to past picture handling strategies. This technique depends on Deep Learning, which has seen enormous outcomes in picture characterization assignments lately. This strategy can help the two individuals and machines in distinguishing a phony cash note progressively through a picture of something very similar. The Accuracy of the proposed framework is assessed utilizing precision.

Keywords - Convolutional Neural Network, Counterfeit, Demonetization, Image processing, Deep learning, Vgg16, Automatic detection.

I. INTRODUCTION

Consistently Reserve bank of India faces fake cash notes or annihilated notes. Treatment of an enormous volume of fake notes forces unexpected issues. In this manner, including machines with the help of human specialists makes the notes recognizable proof cycle less complex and more productive. For the discovery of produced notes (take a bank for instance) it requires recognizing the division each time they utilize the gadget which comprises of bright light. The bank representative keeps the paper cash note on the gadget and attempts to track down whether the watermark ID, chronic number, and different qualities of the notes are appropriate to get the group and take a look at its validation. This expands crafted by the representative. All things considered, assuming the financier utilizes this framework, the outcome could be more precise. The Same is the situation with regions like shopping centers, and trading companies where such frameworks can be utilized.

The prompt need is to make a more straightforward method for distinguishing the money notes. Programmed Fake money acknowledgment is vital in numerous applications, for example, programmed dealers' products machines and programmed teller merchandise machines. By utilizing this framework, we can identify legitimate Indian cash notes. The framework we will utilize incorporates six stages picture procurement, grayscale transformation, edge discovery, highlight extraction, picture division, and examination of info and result. The programmed machine is more useful in banks as well as in any little shop since they deal with issues of fake money notes. Along these lines, utilizing this machine's acknowledgment of notes is less complex and more deliberate.

Right now, the utilization of paper cash stays one of the principal choices for the trading of items and administrations. Nonetheless, one of the leftover issues is the discovery of fake banknotes, which progressively look unique making it hard for somebody who is certainly not a specialist in that frame of mind to identify them. Then again, there are machines for recognizing fake banknotes [1]; be that as it may, these are many times costly, so the ID and maintenance of fakes wind up falling on monetary and government substances with negligible local area inclusion [2].

Falsifying alludes to an unlawful duplicate of the money of the beginning. Subsequently, fake money isn't endorsed by the public authority. RBI is the main body liable for printing banknotes in India. Consistently, the RBI needs to manage the issue of fake banknotes once separated and put available. As of now, with the advancement of better picture handling strategies, new techniques for distinguishing proof of cash are planned by breaking down unambiguous security data present in the money.

As a general rule, to shape a profound brain organization, we want an enormous arrangement of picture information for the action to be finished. However, because of the exchange learning procedure, where we just need a few informational collections. What we do is take a model previously prepared in an enormous informational index and utilize our loads to remake the little informational collection. Along these lines, a huge informational index isn't required and the model is likewise planned accurately. Consequently in this approach moved learned Vgg16 is utilized by calibrating the last layer of this model to get the ideal exactness.

II. LITERATURE SURVEY

In this article, Gouri Sanjay Tele et al. proposed the discovery of Fake Indian cash. Security features of cash are fundamental for settling on certifiable and counterfeit cash. Essential security features integrate watermarks, torpid pictures, security string, and optically factor ink. This technique for fake cash areas removes the overall attributes of inactive pictures and recognizes ID marks from the picture of cash. Extricating properties from pictures of money notes can get exceptionally complicated as it incorporates the extraction of a few observable and imperceptible features of Indian cash. They use programming to distinguish the phony notes using the image-taking care methodology.

Navya Krishna G, et al. [6], proposed the Recognition of phony money notes utilizing CNN. The Automatic Fake Currency Recognition System (AFCRS) is planned to recognize the phony paper cash to check whether it is phony or unique. The ongoing phony issue in light of demonetization influences the monetary system and various fields. One more philosophy of Convolution Neural Networks towards conspicuous verification of phony notes through their pictures is reviewed in this paper, which is moderately better compared to past picture handling systems. It relies upon Deep Learning, which has seen enormous achievements in picture grouping of late. This strategy can uphold the two individuals and machines in perceiving counterfeit notes continuously through a picture of the same. The proposed structure, AFCRS can moreover be conveyed as an application in the cell phone that can help the overall population in recognizing the first and phony notes. The precision of the endeavor can be extended through the first phony notes.

N.A.J Sufri, et.al.[7], proposed a system based on Banknote Recognition Using Different Deep Learning and Machine Learning algorithms. They involved the RGB values as highlights and utilized calculations DT, NB, KNN, SVM, and profound learning alexnet. Both KNN and DTC accomplished 99.7% exactness, however, both SVM and BC performed better by accomplishing 100 percent precision.

Veeramsetty et al. [8], in this exploration, the novel-lightweight-Convolutional Neural Network (CNN) framework for perceiving Indian cash notes were laid out for web and cellphone applications proficiently. Besides, to make the informational collection a sum of 4657 pictures were taken. All adequate money notes incorporate Old- new 10-rupees notes, old-new 20-rupees notes, old-new 50-rupees notes, old and new 100-rupees notes, and new 200, 500, and 2000-rupees notes were utilized. Before giving the photographs to the models as data sources, they are undeniably resized to 1024x1024 pixels. The cash note pictures are expanded with information to build the informational collection size. Zoom, Rotation-90, Rotation-270, Tilting, Distortion, and Flipping are the different sorts of increases utilized. There were 11657 pictures in the dataset after information expansion. The CNN is utilized as follows: 1. Input pictures, 2. Convolution, 3. ReLU was used for Non-linearity tasks, 4. Pooling layer, 5.Smoothing, 6. Fully-Connected. As per discoveries, the proposed model outflanks six generally perceived existing structures in preparing and testing exactnesses.

Chowdhury et al. [9] proposed a framework using picture handling and profound learning strategies to foster a programmed model for perceiving banknotes in India free of situating the face sides of the banknotes. Additionally, pictures were accumulated from sweeps of the first duplicates that were open on the web and by shooting certified banknotes. The framework involved eighty unique pictures from eight classifications for the preparation set with ten examples for every class (this incorporates both front and inverse sides). Moreover, the eight denominational classes are - ten rupees, twenty rupees, fifty rupees (old), fifty rupees (new), hundred rupees, 200 rupees, 500 rupees, and 2,000 rupees. Also, 34 pictures for the test set. The examples of the notes were being changed to their unique even heading in the wake of being pre-handled assuming that they were turned to the position. The divisions were recognized in 2 ways: first, separating variety and surface information as a component for each banknote and ordering them utilizing KNN. The subsequent way is taking care of pre-handled examples banknotes in India to the CNN; Simultaneously, every one of the examples was turned with a specific portion, sub- examined to the framework highlight map, then ordered by a thick layer with SoftMax-classifier relating to referenced highlight maps. The all-out precision of KNN was 91%, while CNN has a 100 percent exactness rate.

III. BLOCK DIAGRAM

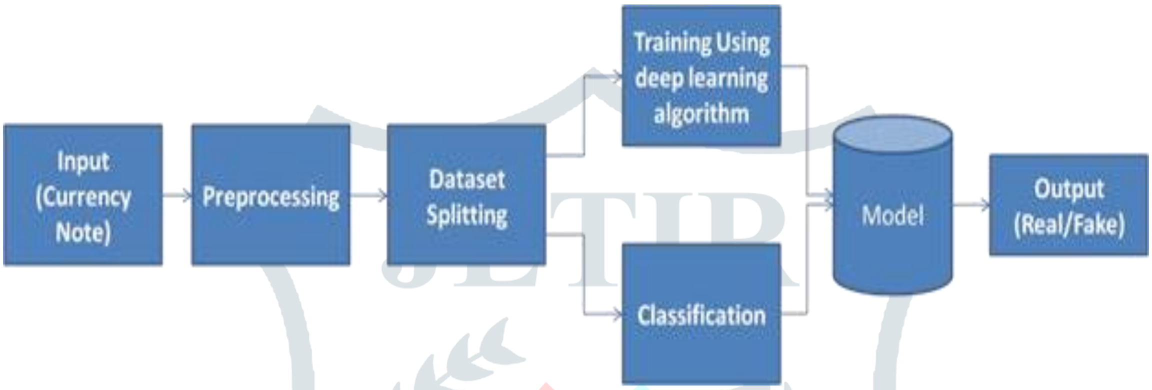

Fig. 1. Block diagram of the proposed system

a. Data Collection

The data set of phony and genuine cash is made progressively. The cash notes of 10, 20, 50,100, 200, 500, and 2000 are considered for the assessment. The pictures are caught involving a telephone camera of goal 12 MP in various light circumstances and every which way. The new money notes are taken for assessment and counterfeit the kids' banknotes are taken. Examples of genuine and counterfeit notes are displayed underneath.

Fig.2 (a) Real note

Fig.2 (b) Fake note

b. Pre-processing

The caught picture with the camera is loud; Hence pre-handling is expected to eliminate the undesirable commotion from the picture. The proposed framework uses a middle channel to kill the salt and pepper clamor. Middle sifting is an important nonlinear cycle in diminishing hasty or salt-and-pepper clamor. It is additionally useful in saving edges in a picture while decreasing irregular commotion. Hasty or salt-and-pepper commotion can happen because of an irregular piece blunder in a correspondence channel. In a middle channel, a window slides along the picture and the middle force worth of the pixels inside the window turns into the result power of the pixel being handled.

c. Training Using CNN

CNN's are a class of Neural Networks that have demonstrated extreme viability in regions like picture acknowledgment and grouping. CNN's are a sort of feed-forward brain network comprising many layers. CNN comprises channels or pieces or neurons with learnable loads or boundaries and predispositions. Each channel takes a few information sources, performs convolution, and alternatively follows it with a non-linearity. An ordinary CNN engineering should be visible as displayed in Fig.3. The construction of CNN contains Convolutional, Pooling, Rectified Linear Unit (ReLU), and Fully Connected layers.

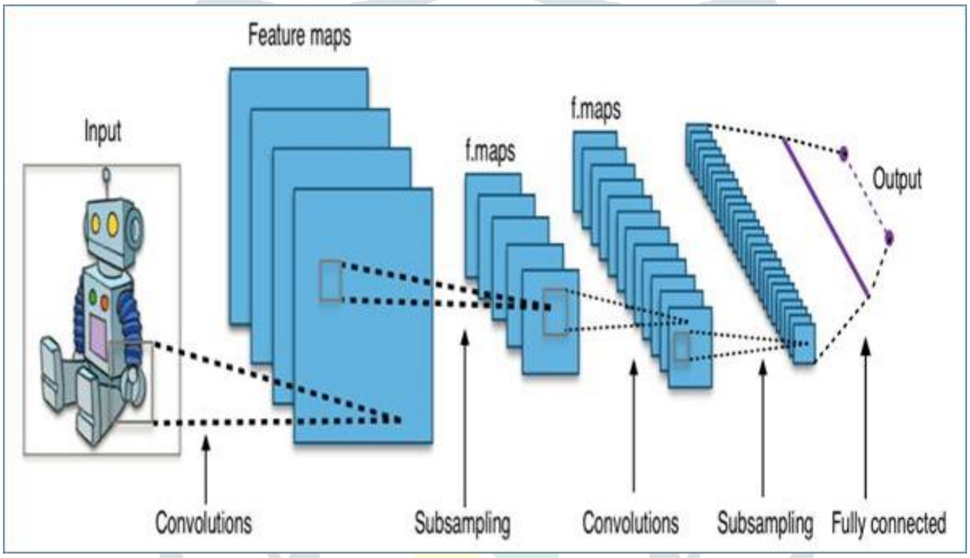

Fig 3. Architecture of CNN

Each block of CNN architecture is explained below

1. Convolutional Layer

The Convolutional layer plays out the center structure block of a Convolutional Network that does a large portion of the computational hard work. The basic role of the Convolution layer is to separate highlights from the info information which is a picture. Convolution saves the spatial connection between pixels by learning picture highlights utilizing little squares of the information picture. The information picture is tangled by utilizing a bunch of learnable neurons. This creates an element guide or enactment map in the resulting picture from that point forward, the component maps are taken care of as information to the following Convolutional layer. It is numerically addressed as

$$G[m,n]=(f* h)[m,n]=\sum j\sum kh[j,k]f[m-j,n-k]Gm,n=f* hm,n=\sum j\sum khj,kf[m-j,n-k]\text{………}(1)$$

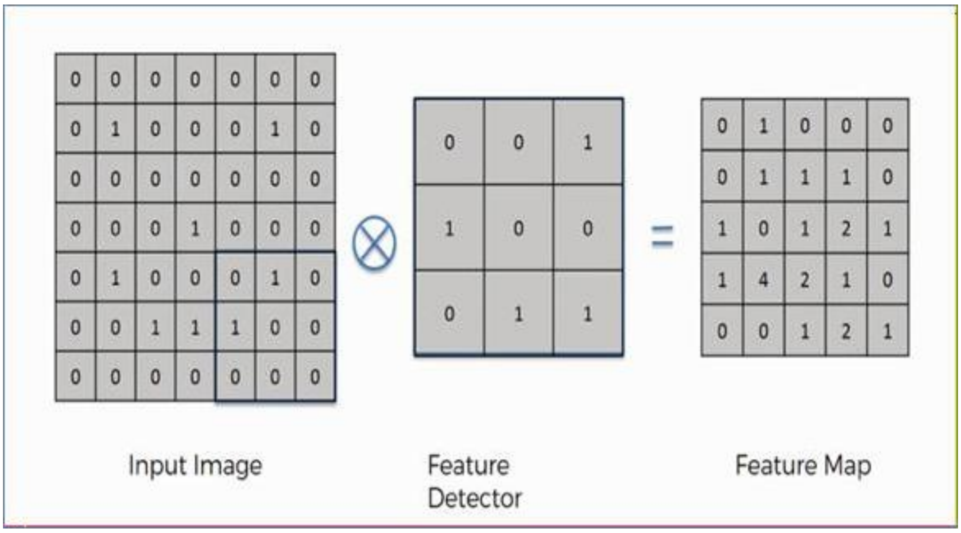

Fig 4. Convolutional Layer

2. ReLU Layer

ReLU is a non-straight activity and incorporates units utilizing the rectifier. A component-wise activity implies it is applied per pixel and reconstitutes all bad qualities in the element map by nothing. To comprehend how the ReLU works, we expect that there is a neuron input given as x and from that, the rectifier is characterized as,

$$f(x)= \max (0,x)f(x)=\max(0,x)\ldots\ldots(2)$$

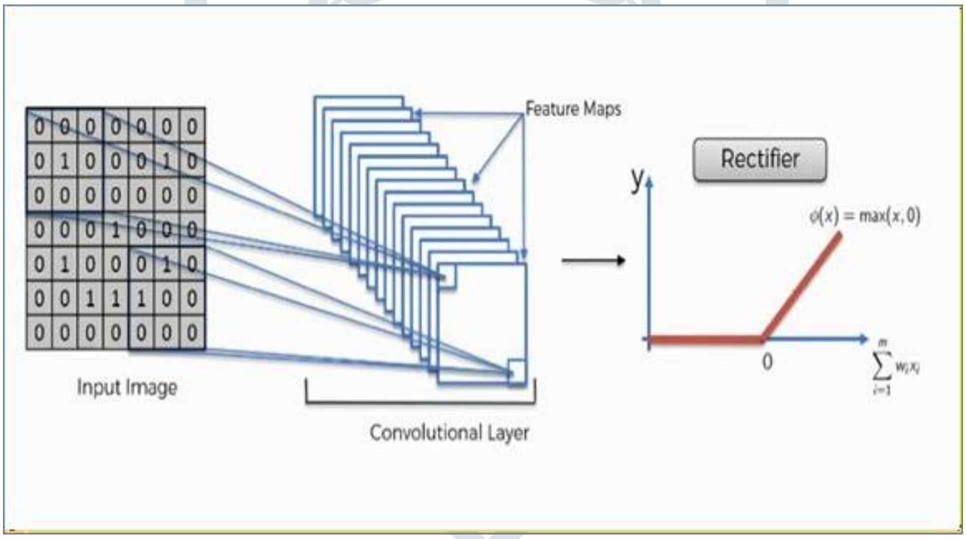

Fig 5. ReLU

3. Pooling Layer

The pooling layer lessens the dimensionality of every initiation map however keeps on having the most fundamental data. The info pictures are separated into a bunch of non-covering square shapes. Every district is down-inspected by a non-direct activity like normal or most extreme. This layer accomplishes better speculation, quicker assembly, vigor to interpretation, and contortion are generally positioned between Convolutional layers.

The maximum pooling layers are very basic and do no learning themselves. They take some k×kk×k locale and result from a solitary worth, which is that the greatest around there. as an example, if their feedback layer is an N×NN×N layer, they'll yield an Nk×NkNk×Nk layer, as each k×kk×k block is decreased to only a solitary worth through the most capacity.

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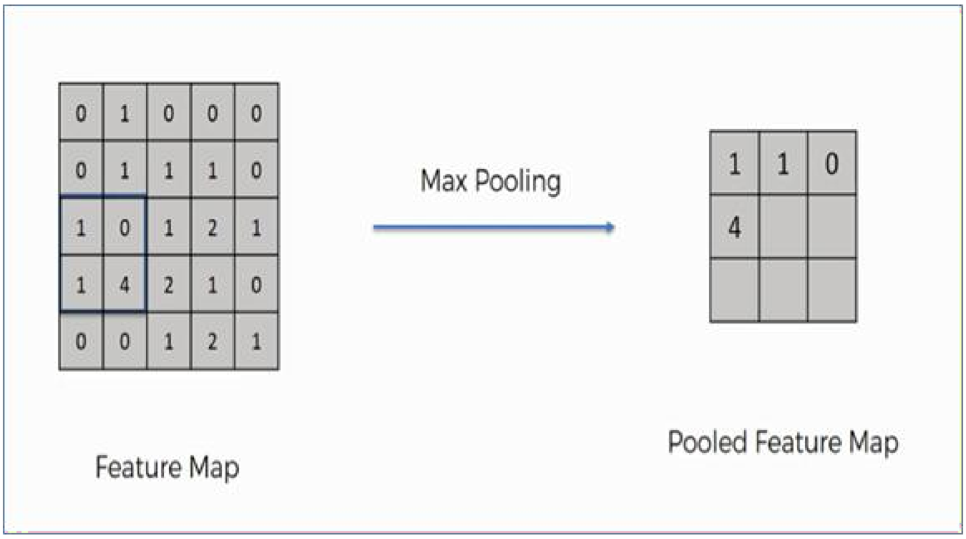


Fig 6. Max Pooling

4. Flatten Layer

After completing the past two stages, we must always have a pooled highlight map at this time. because the name of this progression suggests, we are going to straighten our pooled highlight map into a bit like within the picture beneath.

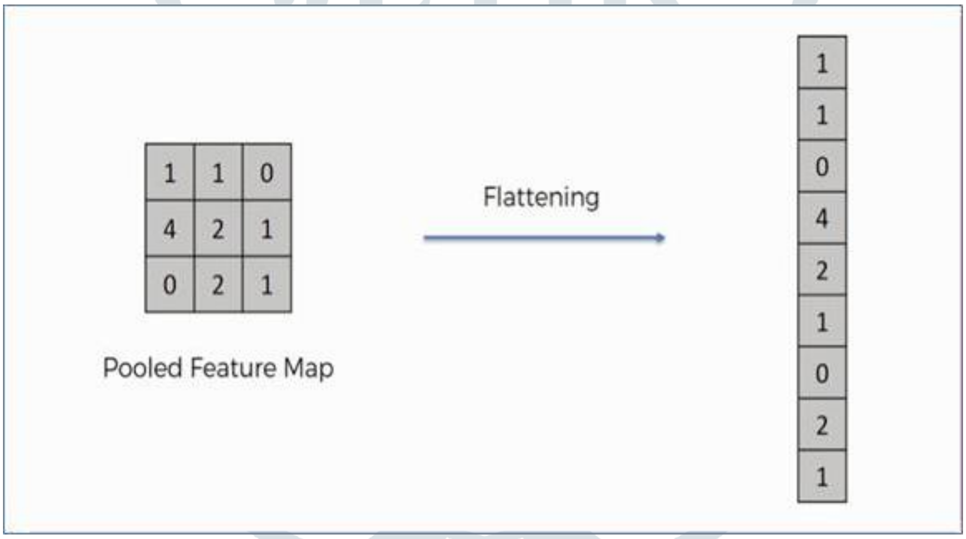


Fig 7. Flattening Layer

5. Fully Connected Layer

the target of utilizing the FCL is to utilize these highlights for characterizing the information picture into different classes due to the preparation dataset. FCL is viewed because the last pooling layer taking care of the highlights to a classifier that utilizes the SoftMax enactment work. the quantity of result probabilities from the Fully associated layer is 1. this is often guaranteed by involving SoftMax because the actuation work. The SoftMax work takes a vector of inconsistent genuine esteemed scores and squashes it to a vector of values somewhere within the range of nothing and one that aggregates to 1.

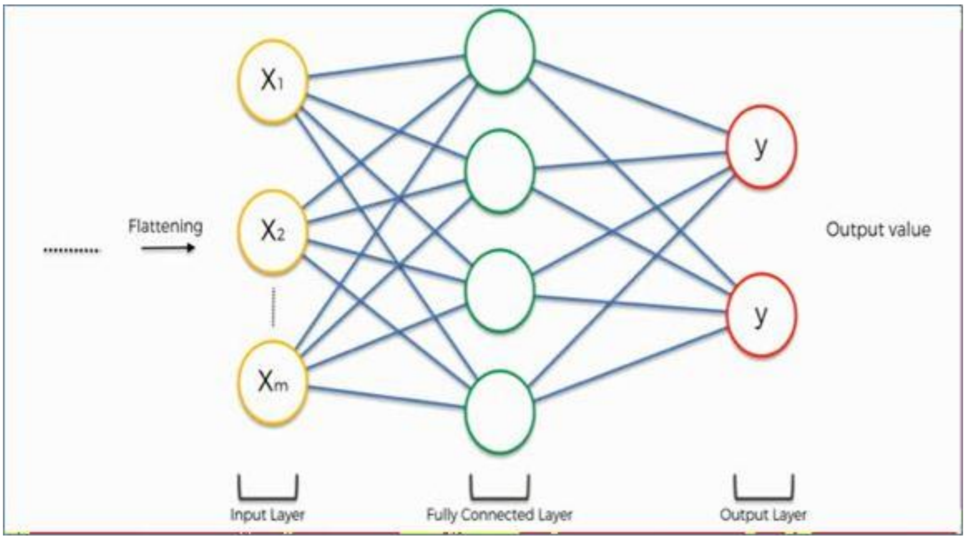


Fig 8. Fully Connected Layer

VI. RESULTS

The consequences of the proposed framework are talked about during this part. In Phase I, the information set is gathered online furthermore as continuous catch. the info set dissemination for the proposed framework is as displayed beneath in Table.

	Training	**Testing**
Real	1130	347
Fake	1019	384

Table 6.1. Database Distribution

The results of the system are presented in qualitative and quantitative analysis.

- **Qualitative Analysis**

The purpose of chemical analysis may be a finished itemized portrayal. No endeavor is created to carried out frequencies to the etymological elements which are identified within the information and uncommon peculiarities get (or must get) similar measure of consideration as additional successive peculiarities. The subjective investigation considers fine differentiations to be drawn because it is not important to shoehorn the data into a finite number of classifications. Ambiguities, which are inborn in human language, are often perceived within the examination. The input image samples of 10,20,50,100, 500, and 2000 real notes are shown in Fig. 6.1.

- **Quantitative Analysis**

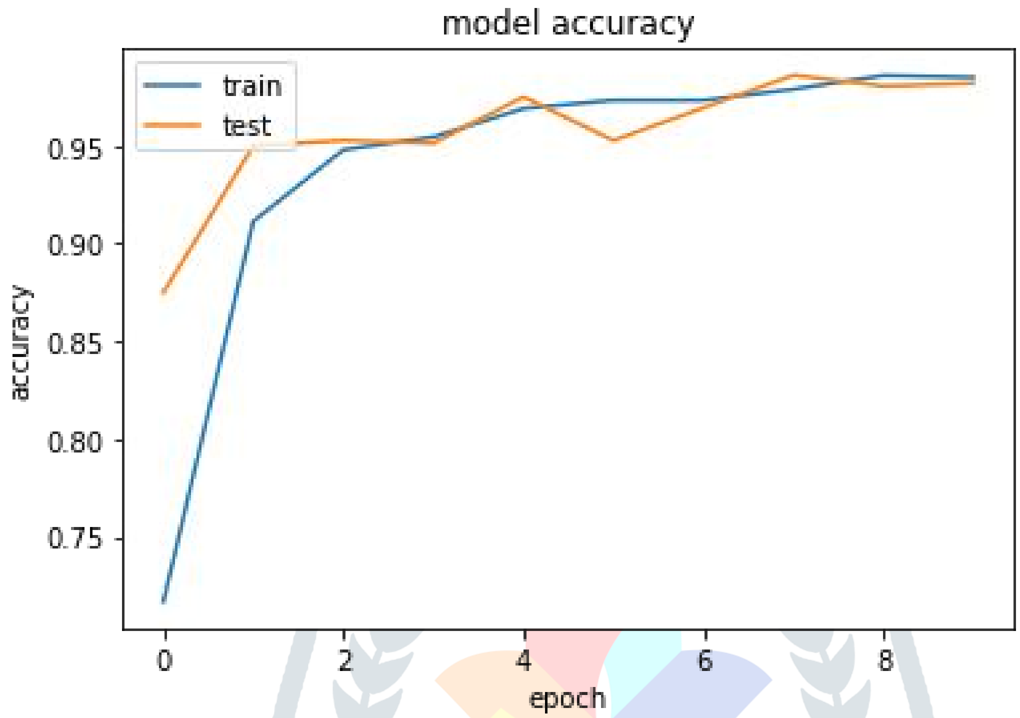
The methodology is to order includes, count them, and even develop more mind-boggling factual models trying to form sense of what's noticed. Discoveries are often summed up to an even bigger populace, and direct correlations will be made between two corpora, insofar as legitimate testing and significance methods are utilized. during this way, quantitative examination permits us to seek out which peculiarities are likely to be veritable reflections of the way of behaving of a language or assortment, and which are only possible events. The more fundamental errand of simply taking a gander at a solitary language assortment permits one to urge a precise image of the recurrence and uncommonness of specific peculiarities, and during this manner their overall ordinariness or irregularity

The quantitative examination of the proposed framework is set utilizing a precision boundary. The precision of the phony money acknowledgment framework is given as (Eq.5.1.)

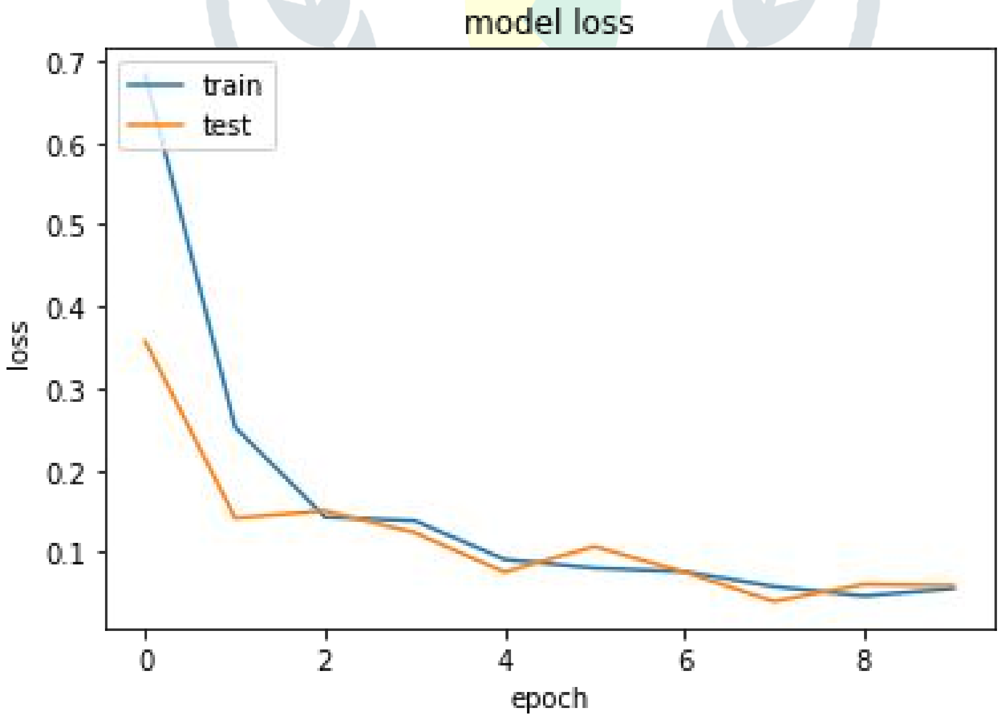
$$Accuracy = \frac{No\ of\ sample\ correctly\ detected}{Total\ no\ of\ samples} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5.1)$$

The progress of the CNN algorithm for fake currency detection is given below

CNN output



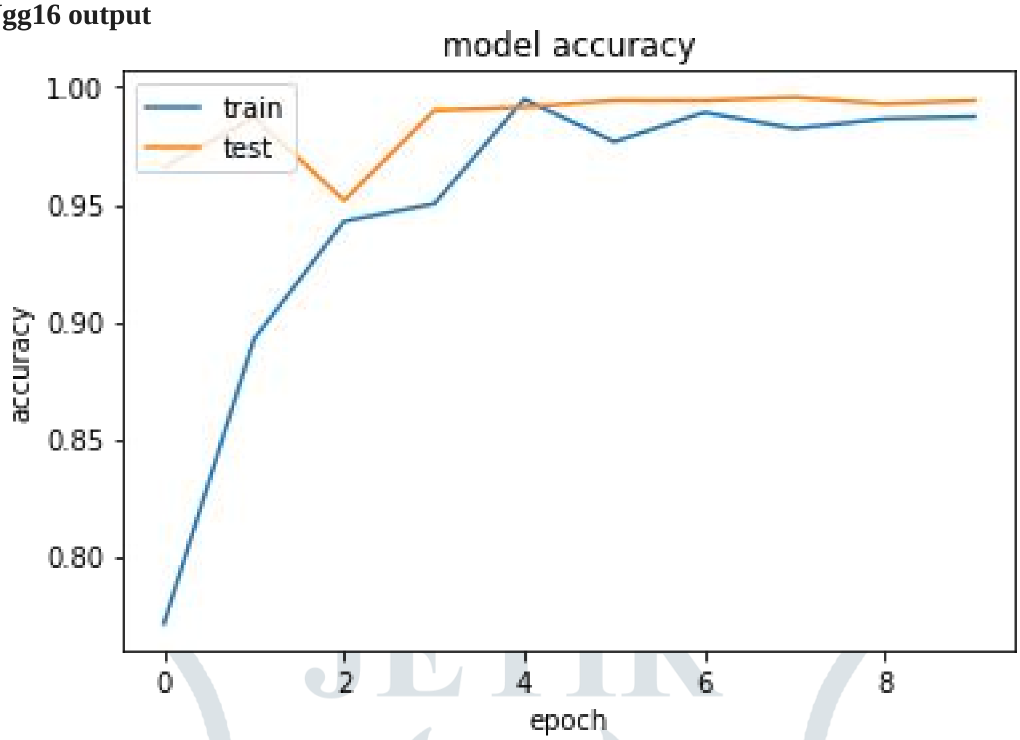
(a) Accuracy



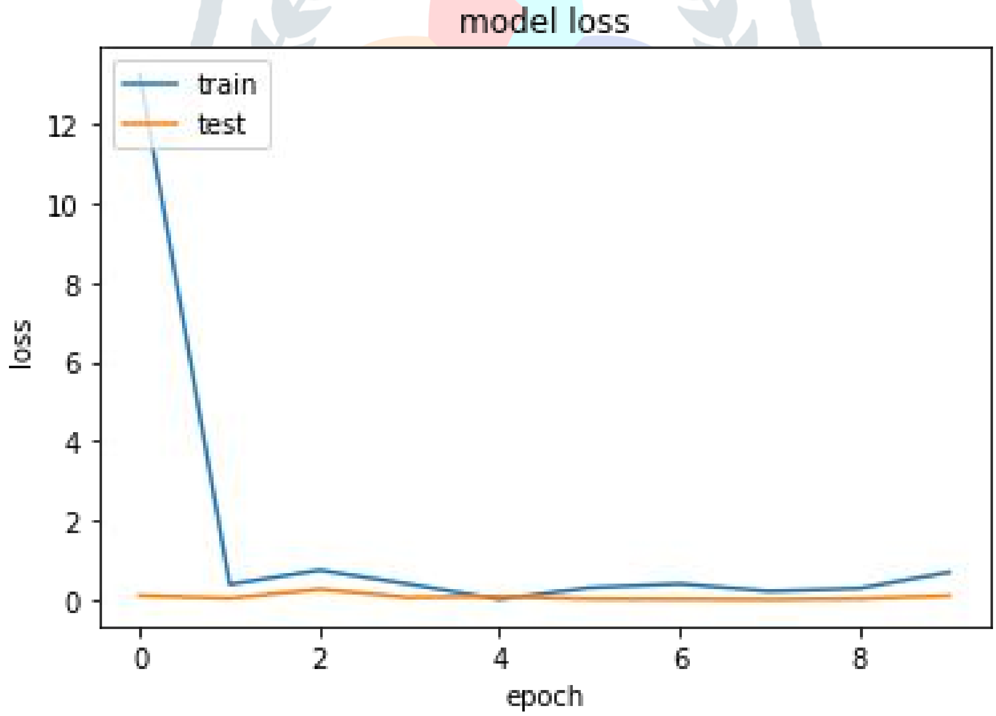
(b) Loss

Fig 5.5 Training progress graph of CNN algorithm

Vgg16 output



(a) Accuracy



(b) Loss

Fig 5.6 Training progress graph of Vgg16 algorithm

The comparative analysis of the CNN and vgg16 algorithm for fake currency recognition system is as tabulated in Table 5.1.

Algorithm	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
CNN	0.9850	0.9819	0.0557	0.0593
Vgg16	0.9874	0.9943	0.6964	0.1056

Table 5.1. Accuracy of the proposed system

V. CONCLUSIONS

In this project, the detection of pretend Indian currency notes are going to be done by using the image processing principle. this may be a low-cost system. The system will work for denominations of 10, 20, 50, 100, 500, and 2000 for the Indian currency. By using this method we are going to be getting precise and accurate results. the method of identification of counterfeit notes are going to be speedy and easy. during this system input are taken by camera and output are going to be displayed on the PC. during this system, CNN and Vgg16 algorithms are wont to train and test the fake currency. The qualitative and measurement of the proposed system shows that the vgg16 algorithm outperforms the CNN algorithm.

VI. ACKNOWLEDGEMENT

On this incredible event of accomplishment of our undertaking on "Fake Indian Currency notes using Deep Learning".

An abundance of thanks goes to all teachers and guides who have given their full exertion in directing the group in accomplishing the target furthermore as their consolation to stay up with our advancement on course.

At last, collectively of the colleagues, i would want to determine the worth within the entirety of my gathering individuals for his or her help and coordination, i really want to believe that we'll accomplish more in our future undertakings.

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