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Fake Currency Detection using Deep Learning

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ABSTRACT - In this method, the banknote detection system detects counterfeit banknotes is intended to detect and verify whether it is genuine or unique. The current problem of fakes caused by demonization is affecting the financial framework and various fields. Another method used by convolutional neural networks to identify counterfeit banknotes by image is analyzed in this approach. This is almost superior compared to previous image processing strategies. This technique is based on deep learning and has recently achieved great results in image characterization. This strategy helps both humans and a machine to gradually distinguish between counterfeit and very similar bills by means of images.

Keywords- Convolutional Neural Networks, Counterfeit, Demonetization, Image Processing, Deep Learning, Vgg16, Automatic detection.

I. INTRODUCTION

The Reserve Bank of India faces counterfeit and damaged banknotes all the time. Dealing with large amounts of counterfeit banknotes creates unforeseen problems. In this way, using a machine with the help of a human expert makes the proofreading cycle easier and more productive as notes can be recognized. To search for generated banknotes (such as bank notes), the department must be recognized each time a device configured with bright light is used. Bank employees hold banknotes in their gadgets and check whether watermark IDs, chronic numbers, and various grades of banknotes are suitable to each the group, and examine their verification. This is manually augmented by delegation. Overall, results are likely to be more accurate if investors use this framework. The same is true for areas that can take advantage of these framework conditions, such as shopping centers and trading companies.

There is an urgent need to develop an easier method for distinguishing between banknotes. Confirmation of programmed counterfeit bills is important in many applications such as programmed merchant product machines and programmed vending machines. By using this framework, you can identify legitimate Indian banknotes. The framework we use includes six stages: image acquisition, grayscale conversion, edge detection, highlight extraction, image slicing, and information and result exploration. Programmed machines are more useful in banks and small shops as they deal with the problem of counterfeit banknotes. In this sense, using this machine memo confirmation is less complicated and more intentional. Using banknotes is now one of the primary options for trading and managing items.

Nonetheless, one remaining problem is detecting counterfeit banknotes. This gradually becomes more unique and difficult to identify for those who are not experts in the field. On the other hand, there are counterfeit bill detectors [1]. However, these are many times more expensive, leaving the identification and control of counterfeit goods up to money and government agencies, with little local involvement [2].

Counterfeiting alludes to the illegal duplication of the original money. Therefore, fake money is not supported by public authorities. RBI is the main responsible for banknote printing in India. Therefore, RBI should handle the issuance of counterfeit notes after they have been separated and made available. In the future, as better image processing strategies evolve, new techniques are planned for identifying evidence of cash by decomposing the unique security data present in the money.

Forming profound brain tissue usually requires a vast array of visual information to complete an action. However, due to the exchange learning method, the required information gathering is small. Take a previously created model with a huge information index and use load to recreate the small information collection. In this sense, a large index of information is not required and the models are carefully planned. Therefore, in this approach, we use the learned moving Vgg16 to adjust the last layer of this model to get the ideal accuracy.

II. LITERATURE SURVEY

This article suggested the discovery of counterfeit Indian banknotes by Gouri Sanjay Tele et al. The cash security feature is fundamental to accounting for provable counterfeit cash. Key security features include watermarks, inert images, security codes, and optical element inks. This counterfeit cash domain technique removes the global attributes of inactive images and detects ID marks on cash images. Extracting properties from images of banknotes can be quite complex as it requires extracting observable and unrecognizable features of Indian currency. They use programming to identify fake notes using image grooming methods.

Navya Krishna G, et al. [6], proposed, "The Recognition of phony money notes utilizing CNN". The Automatic Fake Currency Recognition System (AFCRS is designed to detect counterfeit banknotes to verify whether they are counterfeit or original. The ongoing counterfeit problem in the face of demonization is affecting the monetary system and various fields. This article describes another philosophy of convolutional neural networks that conspicuously checks false notes through images. This is slightly better than previous image processing systems. It relies on deep learning, which has recently had great success in grouping images. This strategy helps both humans and machines to continuously recognize counterfeit banknotes through the same image. The proposed AFCRS structure can also be conveyed as a mobile phone application. This helps the public to identify primary and false tones. The accuracy of the attempt can be strengthened by the first erroneous note.

N.A.J Sufri, et.al.[7], proposed "A system based on Banknote Recognition Using Different Deep Learning and Machine Learning algorithms". They used his RGB values as highlights and used DT, NB, KNN, SVM and Deep Learning Alexnet calculations. Both KNN and DTC achieved 99.7% accuracy, while SVM and BC both performed better with 100% accuracy.

Veeramsetty et al. [8], in this exploration, the novel-lightweight-Convolutional Neural Network (CNN) framework for detecting Indian banknotes was well designed for web and mobile phone applications. A total of 4657 images were also taken for information gathering. All banknotes used are old and new 10-rupee notes, old and new 20-rupee notes, new and old 50 rupee notes, old and new 100 rupee notes, new 200 rupee, 500 rupee and 2000 rupee certificates. The photo is definitely resized to 1024x1024 pixels before it is served to the model as a data source. The invoice image is augmented with information to build the information gathering size. Zoom, Rotation-90, Rotation-270, Tilt, Distort, and Mirror are different types of magnification used. After information augmentation, the dataset had 11657 images. CNN is used as follows: 1. input image, 2. convolution, 3. ReLU was used for nonlinear tasks. 4. pooling layer, 5. smoothing, 6. fully connected. According to our findings, the proposed model outperforms six commonly recognized existing structures in preparing and testing accuracy.

Chowdhury et al. [9] proposed a framework framework that uses image manipulation and speech learning strategies to facilitate a programmed model of banknote recognition in India that does not require banknote faces to be placed. In addition, images were collected from sweeps of the first duplicates opened on the Internet and from photographing authenticated banknotes. The framework contained 80 unique images from his 8 classifications in the preparatory set and 10 examples of each class (which includes both fronts and backs).

The eight denomination classes are Rs 10, Rs 20, Rs 50 (old), Rs 50 (new), Rs 100, Rs 200, Rs 500 and Rs 2,000. 34 photos for the test set. After pre-editing, I changed the sample notes to their own even headings, provided they were rotated to the correct position. Subdivision he perceived in two ways. The first is to separate the grade and face information as constituents of each bill and use ANNs to organize them. The following routes are sent to CNN via banknote specimens manufactured in India. At the same time, each sample was shot at a specific part, examined the highlight map of the frame, and then he sorted by thick layer using a SoftMax classifier on the referenced highlight map. The overall accuracy of the ANN was 91%, while the CNN accuracy is 100%.

III. BLOCK DIAGRAM

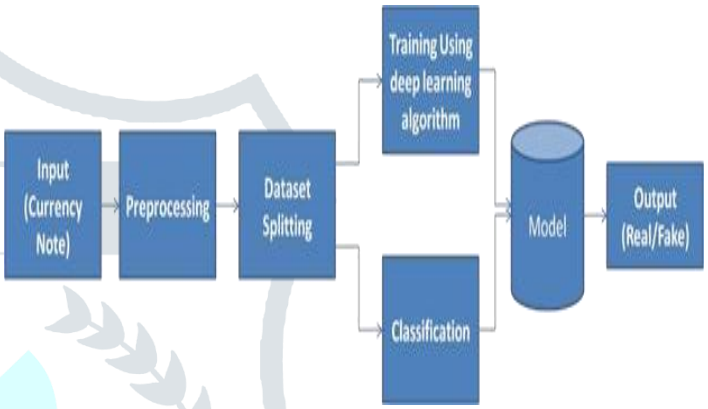

Fig. 1. Block diagram of the proposed system

a. Data Collection

Step by step create a counterfeit and specie data set. Notes of 10, 20, 50, 100, 200, 500 and 2000 are considered for evaluation. The photos are taken in different lighting conditions and with a phone camera with a resolution of 12 MP in all aspects. A new bill will be obtained for evaluation and a forged child bill will be obtained. Below are examples of genuine and counterfeit banknotes.

Fig.2 (a) Real note

Fig.2 (b) Fake note

b. Pre-processing

There is noise in the image captured by the preprocessing camera. Therefore, preprocessing is expected to remove unwanted noise from the image. The proposed frame uses the center channel to kill salt and pepper noise. Intermediate screening is an important non-linear cycle that reduces impatience and cries of deception. It also helps preserve image edges while reducing random noise. Random piece errors in corresponding channels can cause hasty or sesame excitement. In the middle channel, a window slides along the image and the average intensity of pixels within the window becomes the intensity of the processed pixel.

c. Training with CNN

CNNs are a class of neural networks that have proven very useful in areas such as image verification and grouping. A CNN is a kind of feedforward brain network that spans many layers. A CNN consists of channels or pieces or neurons with learnable loads or limits and predispositions. Each channel receives some source of information, performs a convolution, and in turn follows it with non-linearity. Normal CNN engineering should appear as shown in Figure 3. Building a CNN involves convolution, pooling, rectified linear units (ReLU), and fully connected layers.

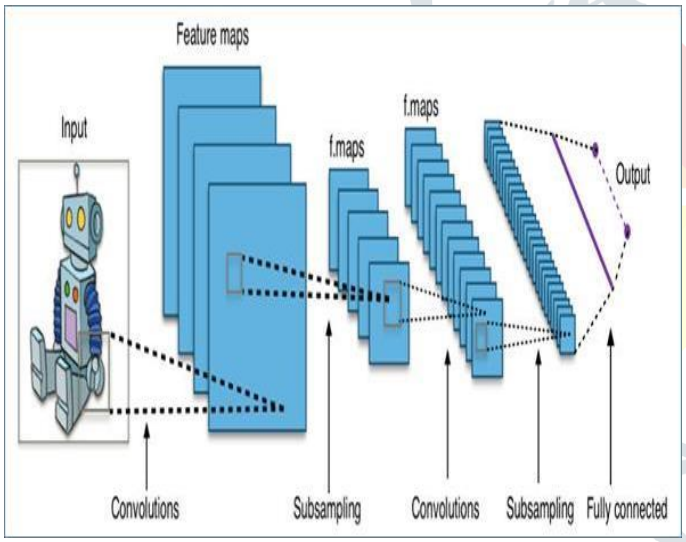

Fig 3. Architecture of CNN Each block of CNN architecture is explained above

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]=∑j∑kh[j,k]f[m−j,n−k]Gm,n=f∗hm,n=∑j∑khj,kf[m−j,n−k]……(1)

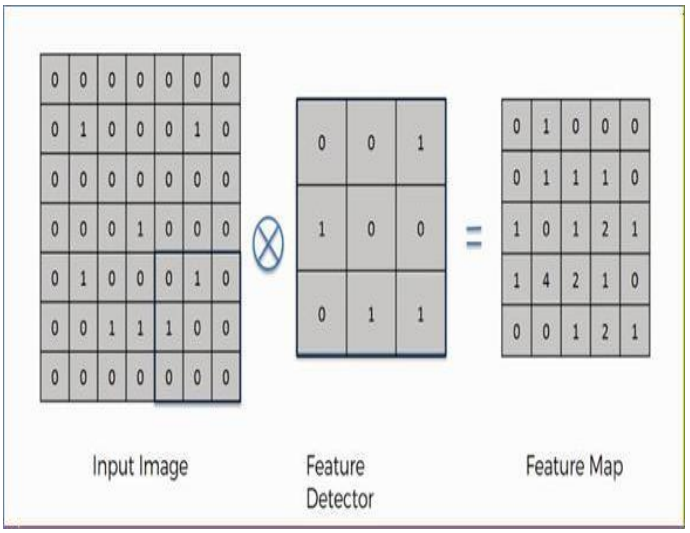

Fig 4. Convolutional Layer

2. ReLU Layer

ReLU is a non-linear activity and contains units that use rectifiers. A per-component activity means that it is applied per-pixel and does nothing to restore all bad properties in the element map. To understand how ReLU works, we have a neuron input designated as x, and the resulting rectifier is expected to be shown as
f(x)=max(0,x)f(x)=max(0,x)).)……(2)

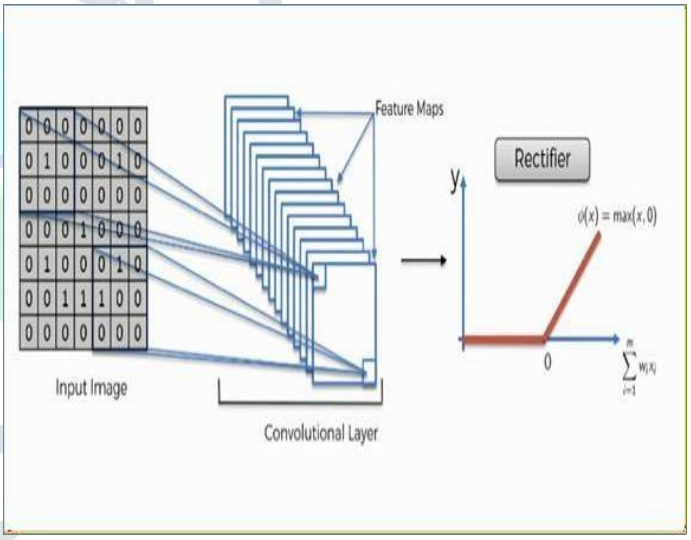

Fig 5. ReLU

3. Pooling Layer

The Pooling Layer reduces the dimensionality of each Initiation Card, but retains the most basic data. The info image is divided into a series of discreet squares. Each district is inspected by indirect activities such as normal or most extreme. This layer allows for better inference, faster assembly, and better interpretability, and distortions are typically placed between convolutional layers.

The max pooling layer is very simple and does not learn itself. Getting the k×kk×k locales will give you the largest single value there. For example, if those feedback layers are N×NN×N layers, then each k×kk×k block is reduced to a single value by the maximum capacity, thus producing Nk×NkNk×Nk layers.

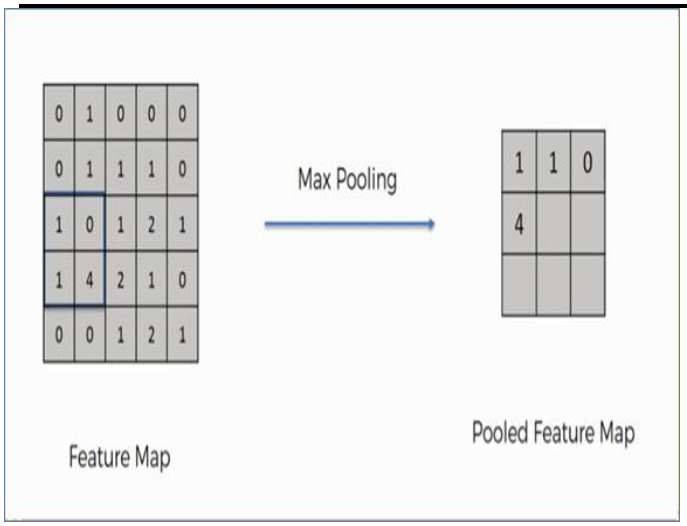

Fig 6. Max Pooling

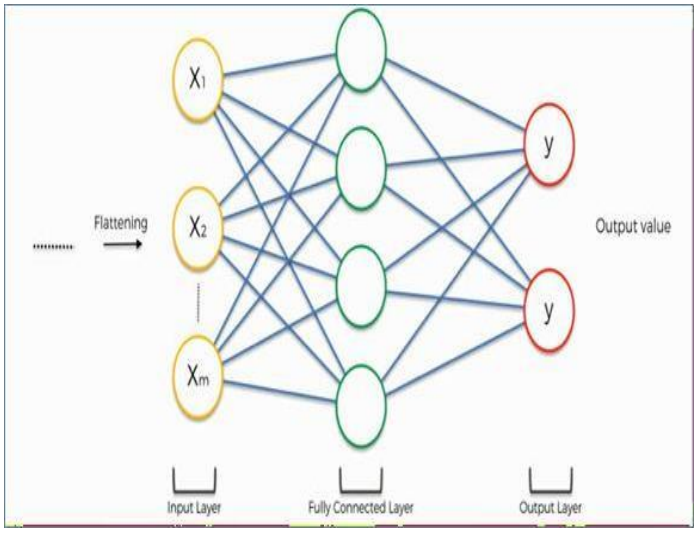

Fig 8. Fully Connected Layer

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.

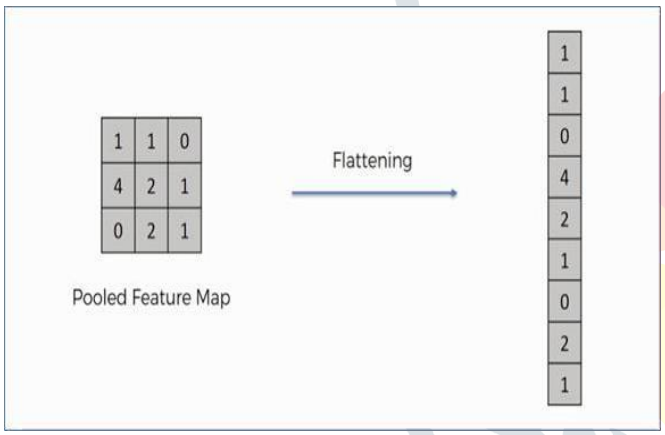

Fig 7. Flattening Layer

5. Fully Connected Layer

The purpose of using the FCL is to use these highlights to characterize information images into different classes based on a prepared data set. FCL is seen as the final pooling layer that handles the highlighting of classifiers that utilize SoftMax transformation work. The resulting probability number from a fully mapped layer is 1. This is often ensured by including SoftMax in the activation work. What SoftMax does is take a vector of inconsistent real ratings and squash them into a vector of values somewhere between zero and sum to one.

Qualitative Analysis

The purpose of chemical analysis is to complete an individual presentation. No attempt is made to use frequencies for etymological elements identified in the information, and unusual features receive (or should be considered) the same level of consideration as additional contiguous features. For subjective investigation, sniffing the data with a finite number of classifications is not important, so fine differentiation is deemed appropriate. The ambiguity inherent in human language is often recognized in exams. Figure 6.1 shows input image examples of 10, 20, 50, 100, 500, and 2000 bills.

Quantitative Analysis

This methodology consists of ordering inclusions, enumerating them, and developing models of more interesting facts that attempt to make sense of what is remembered. Findings are often aggregated into larger populations, creating direct correlations between the two corpora if legitimate testing and importance methods are used. In this way, quantitative investigation can discover which features are likely to be actual reflections of language or set behavior, and which are merely possible events. A more basic interest in merely glancing at an isolated assortment of languages allows us to pinpoint the recurrence and anomalousness of particular peculiarities and thus their general commonality or irregularity. Quantitative studies in the proposed framework are specified using precision limits.

V. CONCLUSIONS

In this project, detection of counterfeit Indian banknotes is performed using image processing principles. This could be a cheap system. The system works in 10, 20, 50, 100, 500 and 2000 denominations of Indian currency. This method gives accurate and accurate results. The method of identifying counterfeit banknotes becomes quick and easy. In this system the input is captured by a camera and the output is displayed on the PC. In this system, CNN and Vgg16 algorithms train and test counterfeit currency. The quality and measurements of the proposed system show that the vgg16 algorithm outperforms the CNN algorithm.

VI. ACKNOWLEDGEMENT

For this wonderful event of completing the project of fake Indian currency notes using deep learning. As a consolation to keep our progress on track, I would like to express my sincere gratitude to all the teachers and guides who have done everything in their power to guide the group to continue to reach their goals.

Secondly, I would like to judge the value of the help and cooperation of the assembled people. I really want to believe that I can achieve much more in my future endeavors.

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