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Identification of Fake Indian Currency using Convolutional Neural Network

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ABSTRACT:

The development of shaded printing technology has increased the rate at which large-scale counterfeit notes are produced. Banknotes are still in circulation due to their dependability and simplicity of use, even if computerised financial exchanges are becoming more common and the use of paper money has been declining recently. Counterfeiting is the practise of making copies of legitimate currency. As a result, the Indian government does not support fake money. Only the RBI is in charge of printing money in India. The RBI must deal with the problem of counterfeit banknotes every year once they have been vetted and issued onto the market. The considerable technological developments in the printing and scanning fields contributed to the escalation of the counterfeiting issue. Therefore, counterfeit money affects the economy and devalues legitimate currency. Therefore, there is a greater need to detect counterfeit money. Older systems rely on hardware and image processing techniques. Finding phoney currency using these methods is more difficult and less successful. We have suggested employing a convolutional neural network to identify fake Indian currency in order to solve the aforementioned issue (CNN). Our method recognises fake currency by analysing the photos of the currency. The CNN is trained to learn the feature map of the corresponding Indian money using data sets for the 2000 and 500 rupee notes. After learning the feature map, the network is equipped to detect fake currency in real time. The suggested technique is quicker and successfully finds counterfeits of the 2000 and 500 currencies. Our proposed model had a validation accuracy of 97.52% and a training accuracy of 94.25%.

Keywords: Convolutional Neural Network **(**CNN), Fake currency, Counterfeit money

1. Introduction

The detection of fake currency is a severe problem that has an impact on the economies of practically every nation, including India. Both the chemical characteristics and the physical characteristics of the currency can be used as potential solutions. To extract elements like security thread, intaglio printing (RBI logo), and identification mark, which have been implemented as security features of Indian currency, image processing methods have been used [1]. For the automated system to be accurate and reliable, the currency picture must be sufficiently extracted for monetary properties. It is difficult for system designers to solve this problem. The Reserve Bank of India (RBI) deals with damaged or fake currency notes every year. The handling of a huge quantity of fake currency presents new challenges. Therefore, using machines (either independently or in support of human experts) streamlines and improves the efficiency of note recognition [2]. The security thread feature of a currency note can be extracted to detect counterfeit money. The most often used deep neural network technique for spotting counterfeit money is transfer learning with Alex net [3]. The ideal tool for computational work and analysis is MATLAB. The difficult task of feature extraction in digital image processing. It entails the extraction of both hidden and exposed properties of Indian banknotes [4]. Utilizing a variety of image processing methods, the security aspects are extracted, and phoney currency is then identified via template matching. The approach is unusual since it uses image processing to derive security aspects from a given image of cash. Using many security features instead of just one is another innovative innovation [5]. Because banks have to deal with the issue of damaged or counterfeit money notes, automatic machines are more useful. Consequently, using a machine makes the note recognition process more simple and organised [6]. A significant number of fake Indian currency notes were printed and sold in the market thanks to the development of colour printing technology. Even though counterfeit money is printed accurately, it may probably be identified with some effort [7]. Although the printing firm has the ability to produce fake paper money, anyone can now print fake bank notes at home with just a computer and a laser printer. To resolve these issues the system for recognising Indian banknotes is quite helpful. Automated Recognition of money notes is introduced with the use of feature extraction, classification based on SVM, and neural networks to address this type of issue [8]. To recognise and verify the value of currency, extracted features from the image of the note will be used. If a currency image is fake or real, an application-based system must be created to provide accurate results [9]. However, as technology advances, there is also an increase in the methods used to produce fake versions of these currencies. These fake or counterfeit notes harm society in a number of ways [10].

CNN is used in the suggested method. A dataset of 232 photos is used to test the created model. It uses a dataset image of authentic 500 and 2000 rupee notes and counterfeit notes for Indian cash. Training Accuracy was 94.25%, while Validation Accuracy was 97.52% for the identification of counterfeit

Indian cash. The remaining of paper as follows: Section-II presents proposed system with methodology. Section-III propounds results and discussion and finally, section-IV concludes the paper.

II. Proposed Work Explanation

Our significance in this system proposal focuses on the identification of fake currency that is prevalent in the Indian market. In our approach, counterfeit currency is found by removing the security thread component from the currency note. CNN was used to create our suggested system for identifying fake cash. The photos of currency note dataset is created in order to train the suggested system. Images of notes worth 2000 and 500 rupees are created using augmentation. To boost the dataset count, augmentation techniques like resizing and rotating are used. All currency photos are annotated after augmentation, and the images are then saved in a separate folder with labels. The network and images are now prepared for training. The network learns the characteristics of genuine cash notes for 2000 and 500 rupees once the training procedure is complete.

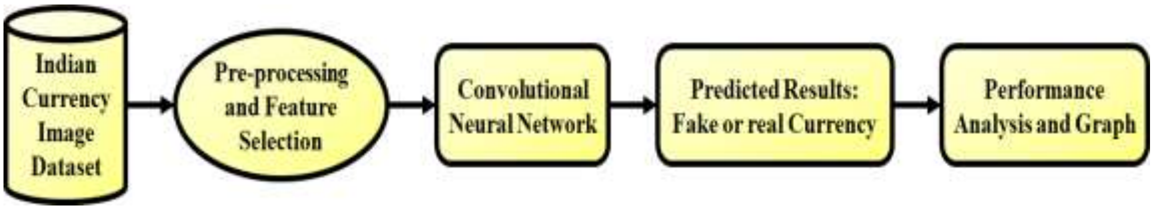

Fig 1. Proposed system

2.1 Indian Currency Image Dataset

Many categories of Indian currency vary in value estimation, colour utilisation, printing quality, printing medium, and other factors that allow for easy visual differentiation. In any case, due to the similar measures of the various currencies, content and colour will not at all help the visually impaired individual, and measurement can cause confusion.

2.2 Pre-processing and Feature Selection

The currency photos are collected with appropriate spatial and brightness resolutions, where the former refers to the number of pixels or dots in each inch of a digital image, in order to efficiently extract the features of paper money from them. The brightness resolution idea focuses on how closely the brightness of a digital pixel can approximate the intensity of the original image. To prepare the images of the documents for feature extraction, a series of data pre-processing techniques are typically conducted to the images.

2.3 Convolutional neural networks

ConvNets are made to handle data that is presented as numerous arrays, such as a colour image made up of three 2D arrays that each include the pixel intensities for the three different colour channels. There are many different types of data modalities that take the shape of numerous arrays, including 1D signals and sequences for language, 2D visuals or audio spectrograms, and 3D video or volumetric images. Local connections, shared weights, pooling, and the utilisation of many layers are the four fundamental concepts that underpin ConvNets, which exploit the characteristics of natural signals. A typical ConvNet's architecture is divided into various stages. Convolutional layers and pooling layers make up the initial few phases of the process. Convolutional layers organise its units into feature maps, and within each feature map, each unit is related to specific local patches in the feature maps of the preceding layer using a collection of weights called a filter bank. A non-linearity like a ReLU is used to further process the output of this local weighted sum.

The filter bank used by all units in a feature map is the same. A layer's feature maps may use various filter banks. This architecture has two motivations. First, in array data, such as photographs, local clusters of values are frequently highly correlated, generating easily recognisable local themes. A feature map's filtering process is mathematically a discrete convolution, hence the name. Although the convolutional layer's job is to find local conjunctions of the preceding layer's features, the pooling layer's job is to combine semantically related features into a single feature.

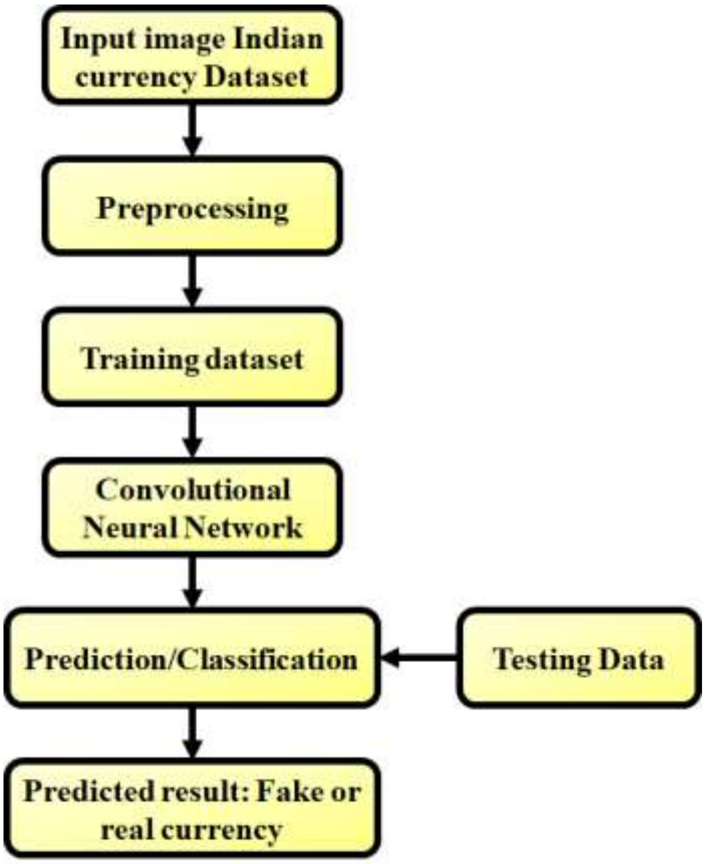

Fig 2. Prediction flow chart

The relative positions of the components that make up a motif can differ slightly, hence it is possible to accurately identify the motif by coarse-graining the position of each feature. In a common pooling unit, the maximum of a local patch of units in a feature map is calculated (or in a few feature maps). Convolution, non-linearity, and pooling are stacked in two or three levels, followed by additional convolutional and fully-connected layers. ConvNet's Backpropagating gradients function is as straightforward as that of a standard deep network, making it possible to train all of the filter banks' weights. The fact that many natural signals are compositional hierarchies, in which higher-level properties are produced by assembling lower-level ones, is a trait that deep neural networks take advantage of. Localized edge combinations create motifs in images, which then combine to create pieces and objects.

III. Results and Discussion

Fig 3. Identification of fake Indian currency

The suggested approach is thought to operate precisely for Indian currency of Rs. 500 and Rs. 2000 and requires little to no effort to use in order to identify various properties of a cash note.

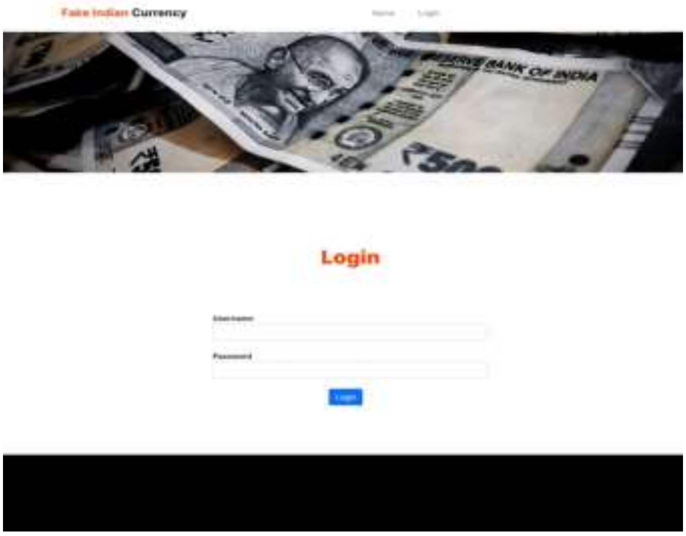

Fig.4 Login ID

Fig.5 Uploaded File

A web application that reads uploaded images displays the results as shown in Fig. 5—either the real note, a false note, or a request to upload the image again after reading the image and returning the probability value.

Fig .6 Prediction output

Following a successful image an upload verification results are shown in Figure 6.

Fig.7 Prediction output

An image processing principles are used to detect fake Indian rupee notes. A prediction output is shown in the figure 7. This system is inexpensive. For Indian currency, the mechanism is functional for denominations of 500 and 2000. Additionally, the technology offers reliable and accurate findings.

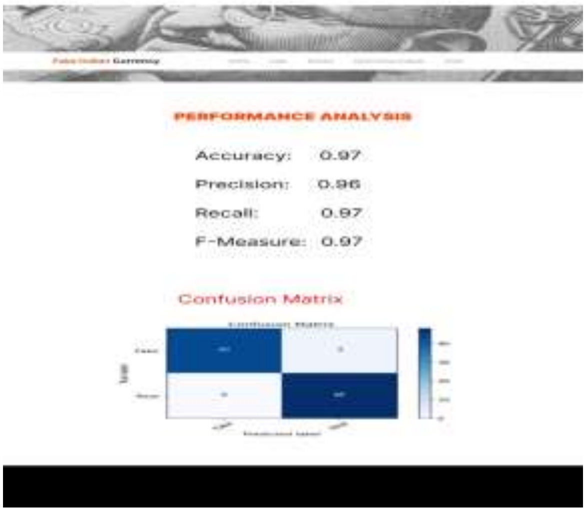

Fig .8 Performance analysis

Fig.9 Chart analysis

IV. Conclusion

The number of counterfeit notes on the market is rising quickly day by day. Different technologies are currently being utilised to assess whether a note is genuine or fraudulent money. The use of CNN in this study to identify counterfeit Indian cash has been suggested. We have chosen CNN as our paradigm for this proposed system's fake currency detecting process. Since the monetary distinctive attributes are gradually learned, the detection accuracy is at its highest. Here, the entire money picture has been taken into account, but in the future, we'll work to incorporate all of the security characteristics of cash by using appropriate structural design and training data. The acquired image may also contain noise, which must be taken into account as part of the pre-processing step in the currency detection process. By taking into account the surface patterns of the cash as characteristics, the recognition and fake currency detection can also be improved. The outcomes demonstrated the CNN's effectiveness, with Training Accuracy of 94.25% and Validation Accuracy of 97.52%.

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