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Counterfeit Currency Detection using Deep Convolutional Neural Network

Kiran Kamble
Department of Computer Science and Engineering
Walchand College of Engineering
Sangli, India
kirankamble5065@gmail.com

Anuthi Bhansali
Department of Computer Science and Engineering
Walchand College of Engineering
Sangli, India
anuthibhansali@gmail.com

Pranali Satalgaonkar
Department of Computer Science and Engineering
Walchand College of Engineering
Sangli, India
pranalisatalgaonkar@gmail.com

Shruti Alagundgi
Department of Computer Science and Engineering
Walchand College of Engineering
Sangli, India
shrutialagundgi@gmail.com

***Abstract*—Counterfeit money refers to fake or imitation currency that is produced with an idea to deceive. According to recent reports, demonetization led to all-time high inflow of fake notes into banks, resulting in a spike in suspicious transactions. The existing works to detect a counterfeit note are mostly based on image processing techniques. This paper deals with Deep Learning in which a convolution neural network(CNN) model is built with a motive to identify a counterfeit note on handy devices like smart phones, tablets. The model built was trained and tested on a self–generated dataset. Images are acquired using the smart phone camera and fed to the CNN network. The results obtained are encouraging and can be improvised by further research and improvements in the architecture of Deep CNN model. The testing accuracy obtained is about 85.6%, training and the validation accuracy were 98.57% and 96.55% respectively.**

Index Terms—Fake or imitation currency, deep convolution neural network, demonetization

I. INTRODUCTION

In the last eight years more than 3.53 lakh cases of counterfeit currency detection in India's banking channels is heighten according to latest government reports. The practice of counterfeiting became more refined with the arrival of paper currency. The Indian Government has taken a astonishing stride of demonetizing 500 and 1000 Rs. notes. Prime Minister Shree. Narendra Modi stated that one of the cognition for this policy was to counter the climbing menace of counterfeit Indian Currency notes. However, the Indian banks acknowledged an all-time peak amount of fake currency and also noticed an over 480% increment in doubtful transactions after demonetization, a first ever report on questioning credits ended in the wake of 2016 notes ban has discovered [9]. The Reserve Bank of India(RBI) is the only one which has the singular authority to issue bank notes in India. The RBI being the highest monetary authority in the country, prints the currency notes of all denominations from Rs.2 to 2000. Several security features [8] have been published by the RBI so that the counterfeit notes can be detected by the general public. However, distinguishing a counterfeit note just by visual per lustration is not an easy task. Moreover, an average person is unaware of all the security features. Developing applications which can detect a currency note to be counterfeit by a camera image can help solve this problem. Deep learning models have witnessed a tremendous success in image classification tasks [4]. Our model proposes a binary image classification task with two classes-fake or real. The Deep CNN model we have built helps us detect the counterfeit note without actually manually extracting the features of images. By training the model on the generated dataset, the model learns on it and helps us detect a counterfeit note.

II. LITERATURE STUDY

Tremendous research has contributed to this idea [1, 2, 3, 5, 6, 7] and proposed many different works. Few of promising are listed below.

A. Counterfeit Detector Pen

It is simply a equipment which has been designed to infer whether the note is real or forged. The ink (containing tincture of iodine) present in the pen will turn black or dark blue [3] if it is fake else it turns yellow. Limitations of a pen is they unworkable for starch free papers and success is much lower.

A. Image Processing Techniques

Most of the approaches proposed [1, 2, 6, 7] are based on image processing techniques. Firstly image capturing process is done through digital camera. The crucial component in dig- ital image processing is feature extraction of images. Invisible and observable features of Indian currency notes are take out. The following steps need to be followed[1,2,3]:

- Image acquisition
- Image pre-processing
- Edge detection
- Feature extraction
- Image segmentation

The image is captured by an image acquisition device such that all the higher and lower level features are highlight. The image is then stored for further processing.

B. VGG16 model

The VGG16 model built had successfully overcome the drawbacks of image processing. The model has been trained and tested on an artificial dataset. Deep CNN works as a feature extractor. Such a model when built into mobile app can help any person detect a suspicious note by uploading an image. VGG-16 model has been reported to take up to 550 MB of device memory [10]. The model works as per the following steps.

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- **Fine Grained Image Classification**: The main task is to classify image as fake or real. Here there is classification among categories which are both visually and semantically very similar. This is a very difficult regime which is even challenging for humans without careful training. Examples include fine distinction into species of animals and plants [10], of car and motorcycle models, of architectural styles.
- **Transfer Learning:** The weights of the Deep CNN pre-trained on a huge dataset are used and then fine tuning of weights and bais parameter of pre-trained network is done by passing through forward and backward pass of the back-propagation on new data-set. This methodology [10] is known as transfer learning. The accuracy of VGG16 is 100% for 2000 rupee note while that of 500 rupee was 66%. The image was categorized to be a counterfeit one depending on the 'see through register' [10] security feature visible when held across light in real currency. Firstly, there was a huge drawback of over fitting for 2000 rupee note; secondly it is best fit only in a phone with a high-end processor.

III. OUR APPROACH

Approach we followed is as follows:

Step 1: In the beginning, due to the lack of data-set, self-generating it was obligatory.10,000 images of each category were generated. So, there were a total of 40,000 images.

Step 2: Then, the data-set was divided into a ratio of 80:20 for training and testing respectively, resulting into 32,000 images for training and 8,000 images for testing.

Step 3: The images for training were pre-processed by apply- ing median-blur filter.

Step 4: Thereafter, the architecture of the model was imple- mented with 5 convolution layers, a flatten layer and 4 fully- connected layers.

Step 5: The training data-set was again sub-divided into 30,000 images for training and 2,000 images for cross-validation.

Step 6: Based on the designed architecture, the model was trained and the training and cross-validation accuracy were obtained.

Step 7: Then, the testing data-set was loaded by pre-processing (applying median-blur filter) each and every image.

Step 8: Later, the results were predicted and confusion matrix was obtained.

IV. DATASET GENERATION

Post demonetization, the new Rs. 500 and Rs. 2000 notes have 17 security features, out of which 4 are on the back of the note and 2 are especially for the visually impaired ones. As the images in the data set are generated holding the currency against light (to expose most of the security features), even the 4 features which are on the back play vital role. Also, the 2 features designed for the visually impaired people are considered. For this purpose, four data-sets are generated [14] as shown in Figure 1: Rs. 500 real and fake, Rs. 2000 real and fake.

(a) 500 Real Currency, holding currency against the light

(b) 500 Fake Currency, holding currency against the light

(c) 2000 Real Currency holding currency against the light

(d) 2000 Fake Currency, holding currency against the light

Fig. 1. (a) Depicts watermark of Mahatma Gandhi in right white part;(b) Depicts blank white part in right, absence of security thread, angular breed lines and raised print in right corner; (c) Depicts watermark of Mahatma Gandhi in right white part; (d) Depicts blank white part in right

- **Data-set for Rs. 2000 and Rs. 500 real currency:** At the initial stage, there were 100 images of Rs. 2000 and Rs. 500 real currency each. As the 'watermark of Mahatma Gandhi's portrait/'and the 'see-through register' were to be exposed, all the images were clicked by holding the notes against light. All the notes occupy almost 85-90% of the image.
- **Data-set for Rs. 2000 and Rs. 500 fake currency:** In this case, the images in the dataset consisted of those mentioned in the above case. To train the model with fake currency as well, the real images of the currency were manually photo shopped with the help of the tools. Several security features were digitally disturbed in order to generate fake currency images. So, this generated 100 images of Rs. 2000 and Rs. 500 fake currency each. Here, too, the notes occupied nearly 85-90% of the frame. As the original data-set consisted of only 100 images of each category, there was a need to augment the existing data and feed to the classifiers. Figure 2 depict data augmentation result. Following data augmentation techniques from Open CV [11] library were used for the above mentioned purpose.
  1) **Image Rotation**: A single image was rotated from -15 degrees to +15 degrees with an increment of 1 degree in each step. The image was rotated along the central axis. The axis for rotation passes through the center of the image and black pixels fill the void created by rotation.
  2) **Image Cropping**: Every image was cropped to re- duce the background. A total of 40,000 images were generated in the data augmentation process. Every image generated 90 copies of itself on applying the above mentioned techniques. 10,000 images of each category were generated in this process.

Original Image Rotated Image Cropped Image

Fig. 2. Data augmentation result

- **Security Features:** Four prime security features were focused upon in training this model.
  1) The watermark of Mahatma Gandhi's portrait.
  2) The see-through register.
  3) Angular bleed.
  4) Raised print of rectangle/circle.

The model has given encouraging results in identifying a counterfeit note which differ based on the above mentioned 4 security features.

V. METHOD

The primary objective of the system is to detect a counterfeit note through a smart phone which can be used by any common person using deep learning algorithm on an Android platform. A flowchart in Figure 3: shows the actual methodology. The user has to capture an image or upload a picture from gallery. This image is uploaded to the real - time database firebase in order to obtain real-time results. The image is then fed to the CNN model and the produced results will be displayed on the screen within fraction of seconds. Fire-base is used as a real time database so that real time result can be computed. The image is uploaded to the real time database so that the real time result can be computed. Image which is in the database is fed to the CNN model and the predicted results are pushed back into the database. Conversion of the image to 80 x 80 pixels and image pre-processing is performed. Convolution neural networks are most widely used these days for image classification tasks. CNN contains three components [13]:

- **Convolution layers:** Convolution is the first layer to extract features from an input image. Convolution layers performs a mathematical operation which requires the image matrix and the filter as an input. The outcome of this operation helps it learn the features of the image thereby preserving the relationship between the pixels. It is the first layer and the feature extraction is done using small squares of input data. In order to introduce non-linearity to the model, a ReLu activation function is applied to the output.

- **Pooling layers:** The pooling layer reduces the spatial size of the image so that the number of parameters and computation in the network gets minimized. Every feature map is processed. There are different kinds of pooling layers - max pooling, average pooling, etc. Max pooling is the most common approach used.

- **Flatten layer:** After the feature extraction, the feature map matrix obtained is then fed to the flatten layer. In the flatten layer, the matrix is transformed into a single column whose output is then fed to the fully connected layer for processing.

- **Dense (fully connected) layers:** Fully Connected layers are used to detect specific global configurations of the features detected by the lower layers in the network. In a dense layer, each node in the layer is connected to every node in the earlier layer.

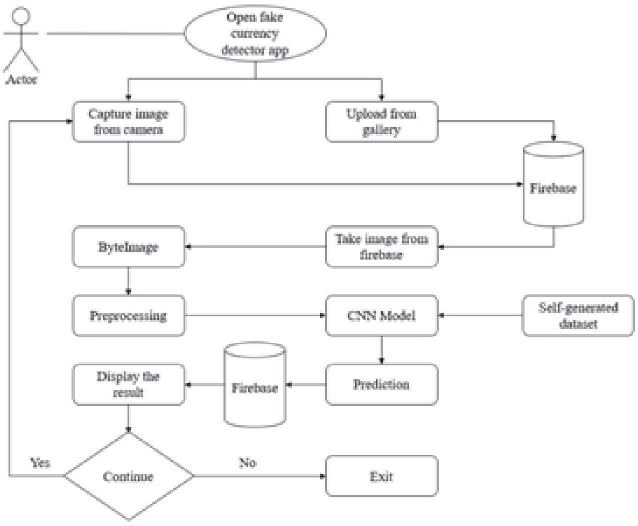

Fig. 3. Flowchart of the Proposed System

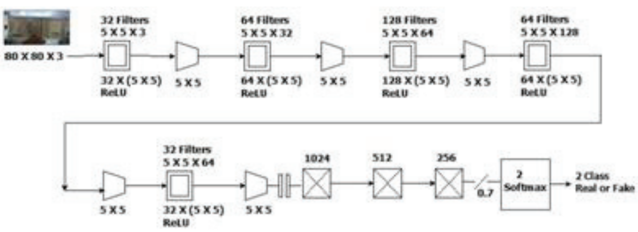

Fig. 4. CNN Architecture: Our Custom Model

Figure 4 depict custom CNN Architecture. The model has been trained and tested by using the Tensorflow, OpenCV and Tflearn python libraries. Due to sufficient availability of data-set, instead of using the concept of transfer learning i.e. using existing pre-trained models like VGG16, ImageNet, an architecture comprising of five convolution layers followed by flatten and four fully connected layers with learn-able parameters i.e. weights and biases is built. The activation function is applied at each layer and regression is used to obtain the 2 class classification-real or fake. Input image of size 80 by 80 with 3 channel (RGB) first convolution with 32 filters each of has 3 channels (As input has 3 channels) of size 5 by 5. Image is padded by two rings of zero all around before convolution. Stride of 2 in vertical and horizontal directions during convolutions with each filter. Output is 32 channels as we used 32 filters followed by max pooling of block size 5 by 5. Similarly of the reaming layers convolution with utility layers is proceed. After the results have been predicted by the model and uploaded to the database, the android application fetches the results instantly and the results will be displayed on the app.

		Actual	
		Real	Fake
Predicted	Real	3525	581
	Fake	570	3328

Fig. 5. Confusion matrix for performance of system

VI. TRAINING AND TESTING THE DEEP CNN

The model has been trained and tested on a dataset collectively containing 10000 images of 500 real, 500 fake and 2000 real and 2000 fake notes. The dataset included 40000 images in .jpg format. The dataset was divided into two sets – the training dataset and the testing dataset. The dataset is divided in 80:20 ratios. The training dataset consisted of about 32000 images of the 500 real, 500 fake, 2000 real, 2000 fake and the testing dataset consisted of about 8000 images. Training took around 10 hours for the entire dataset. The proposed methodology for finding of counterfeit note is grounded on CNN architecture. The performance of the system is depicted in Figure 5. For calculating confusion matrix, the model is tested 8000 times. 6777 times out of 8000, the system predicts the result correctly.

VII. RESULTS

The testing accuracy obtained was about 85.6%.The training and the validation accuracy were 98.57% and 96.55% respectively. Recall is 86% and Precision is 85.8% A snapshot of the tested images (result) is taken (Refer Figure 6). The images are pre-processed and shrunk into a size of 80 by 80 pixels as per our architecture requirement. The 500 and the 2000 rupee notes cover of about 85-90% of the entire image. The results can be improved by applying edge detection techniques and the cropped image can be passed to the model.

VIII. CONCLUSION

Deep learning has gained tremendous success in image classification tasks. Our architecture which is based on Deep CNN works as feature extractor eliminating the need to apply image processing technique and manually checking the presence of security features in the note. The generated data-set has successfully helped conduct experiments and tried to mimic the real-world scenario. The application built will be useful to any common person to detect a counterfeit note. Future scope includes trying out new Deep CNN architectures to increase the accuracy of the model. Increasing the data-set, so that the model gets trained better and produce better results.

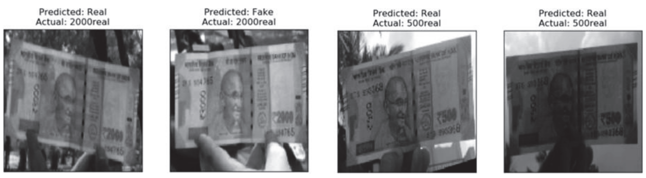

Fig. 6. Results obtained after testing the model on the testing dataset containing 8000 images

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