Recognition of Fake Currency Note using Convolutional Neural Networks

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Abstract: In this paper, the Automatic Fake Currency Recognition System (AFCRS) is designed to detect the counterfeit paper currency to check whether it is fake or original. The existing counterfeit problem due to demonetization affects the banking system and also in other fields. A new approach of Convolution Neural Network towards identification of fake currency notes through their images is examined in this paper which is comparatively better than previous image processing techniques. This method is based on Deep Learning, which has seen tremendous success in image classification tasks in recent times. This technique can help both people and machine in identifying a fake currency note in real time through an image of the same. The proposed system, AFCRS can also be deployed as an application in the smartphone which can help the society to distinguish between the fake and original currency notes. The accuracy in the proposed system can be increased through the original fake notes, where as the proposed system contains the images from children’s bank churan label.


I. INTRODUCTION

Automatic recognition of fake Indian currency is very important in major domains like banking nowadays. This system is used to detect whether the currency is fake or original through the auto mated system which is through convolution neural network, in deep learning. Deep learning excels in the task of recognition and classification of images over a large data sets, which is also primarily used in object category recognition. In the recent demonetization drive may be a step towards eradication of corruption and black money, but it fails to address the problem of counterfeit currency. A deep neural network (Figure-1) is a computational model that works in a similar fashion to the neurons in the human brain. Each neuron takes an input, performs some operations then passes its output to the following neuron that is to its hidden layer.

Identifying a fake currency note by mere visual inspection is still a difficult task. An average individual is not fully aware of all the security features present in a currency note and thus remains vulnerable to fraud. Equipping an algorithm with low cost applications which can identify a currency note as fake through an image is one promising direction towards solving this problem. Future works can also be done by implementing the same algorithm in smart-phones.

II. RESEARCH METHOD

It is possible for any person to print counterfeit bank notes simply by using a computer and a laser printer at house. Therefore, this issue after demonetization had become more such that it can be distinguished via automatic machines through various techniques are listed below. [6, 9, 15]

A. Techniques


B. Software Models for Paper Currency

The technique which is presented by Mirza and Nanda in the year 2012 tells that they extracted 3 features (identification mask, security thread, watermark) using edge based segmentation with the help of SOBEL operator. [8]

In the year 2012, Sharma.J et.al proposed an algorithm based on LBP (local binary patterns) which produced good performance for images with low noise with 99% accuracy. [14]

Mobile currency recognition system using SIFT to recognize partial images was proposed by Paisios et.al in the year 2012 states that the system is evaluated using limited sample set with different state which are folded, incomplete or rotated. They used KNN algorithm which has an accuracy 75% for the first model and 93% for the second model. [12]

Sargano et.al proposed an algorithm feed forward Back Propagation neural network used for classification which takes less time compared to other algorithms in the year 2013. [13]

In the year 2014 Da-Costa developed a bank note recognition system to recognize multiple banknotes in different perspective views and scales. He used feature detection, description and matching which are used to enhance the confidence in recognizing results. But the proposed model is not suitable for smartphone due to high computation power. Whereas the results are robust to handle the folded and wrinkled notes. [3]

Considering the mentioned literature survey, we should take an algorithm which takes less time, maintains high accuracy, which can be suitable for smart-phones and should also work with large data sets. According to my survey, CNN algorithm is the one which satisfies all the conditions by omitting the limitations which are in the above related techniques and papers. The advantage of CNN over the image processing technique is that, Convolution neural networks (CNN s) are a specialized kind of neural network for processing in-put data that has an inherent grid-like topology. Generally, the input data to a CNN will have natural structure to it such that nearby entries are correlated. Examples of this type of data are 1-D audio time series data and 2-D images. The more formal definition of a CNN is a neural network that uses convolution in place of general matrix multiplication in at least one of its layers. Convolution of two discrete vectors, x[n] and w[n], is defined as follows: (eq : 1)

\[(x*w)[n]= \sigma(\infty_{k=-\infty}^{k} x[k] w[n-k])\]

A CNN attempts to find the most relevant patterns that help determine how to accomplish the given task. Whereas the disadvantages of image processing are, initial cost can be high depending on the system used. And CCD or digital cameras that are used for digital image processing have some disadvantages like: Memory card problems, higher cost, Battery consumption.

III. THEORY AND EXPERIMENTATION

In order to implement the proposed solution of finding Counterfeit notes, we simulate the operations using CNN with the help of python language.

A. Proposed Solution

We will be building a convolutional neural network according to proposed algorithm which will be trained on the given fake and original currency data set, and later be able to predict whether the given currency image is fake or original. In this AFCRS we will be solving an image classification problem, where our goal will be to tell which class the input image belongs to. The way we are going to achieve it is by training an artificial neural network on image data set of currency and make the NN (Neural Network) to predict which class the image belongs to, when it sees an image having fake note or original note the next time. Convolutional neural networks (CNN’s) are nowadays widely used in pattern-recognition and image-recognition problems. They have many advantages compared to other techniques. Typically, Convolution neural networks use approximately 5 to 25 distinct layers of pattern recognition. They take raw data, without the need for an initial separate pre-processing or feature extraction stage: in a CNN, the feature extraction and classification occur naturally within a single framework. This is a major advantage when compared to other image processing techniques, while they need lot of computations only for pre-processing step.

B. Architecture of CNN

For our experiment we have used the python libraries like Theano and TensorFlow for implementing and training the deep learning model. There are many pre-trained models available on the internet like Le Net, VGG Net, Alex Net, ZF Net, Google Net/Inception, ResNet[4].
About VGG Net (Figure 2), it is better because it consists of 16 layers with learnable parameters, i.e. weights and biases. The pooling layers don’t count as they do not learn anything. To reduce the number of parameters in such very deep networks, small 3x3 filters are used in all convolutional layers with the convolution stride set to 1. At the end of the network are three fully-connected layers. The VGG networks use multiple 3x3 convolutional layers to represent complex features. Therefore, here we chose VGG Net architecture similar to Alex Net for our network which is going to produce minimum error rate and is in top 5 error rate architectures ILSVRC (ImageNet Large Scale Visual Recognition Competition) 2014 competition.

![Figure 2: Output screenshot of VGG Net model](image)

Figure 2: Output screenshot of VGG Net model summary generated from the experimental setup.

C. Data-set Generation

We generated a data-set of paper currency. This data-set has been created for this specific purpose. The image have been collected from various google sources and children’s bank of India with Churan label. This data-set is segregated into two types, original notes and fake notes (Figure 3). In this AFCRS we have used 75% of the images in the data set for the purpose of training and the rest 25% of the images for the purpose of testing.

Then we give the training images as input to our model and train the model. While generating the data set, we supposed that the old currency notes which are used before demonetization as fake currency because, they are legally banned and if they are supposed as original currency, then it will become very difficult while addressing the problems related to banking sector.

![Figure 3: Fake and Original 2000 rupee note](image)

Figure 3: Fake and Original 2000 rupee note

D. Methodology

In the coding part, we are going to use Keras deep learning library in python to build our CNN (Convolutional Neural Network). We should install the TensorFlow and Theano which works on the back end of Keras. Tensorflow is an open source software library for data flow programming across a range of tasks. It is a symbolic math library, and is also used for machine learning applications such as neural networks. Theano is a Python library and optimizing compiler for manipulating and evaluating mathematical expressions, especially matrix-valued ones.

In Theano, computations are expressed using a NumPy-esque syntax and compiled to run efficiently on either CPU or GPU architectures.

After installing the required libraries, we train our model as discussed above. After training and testing the model, we set an epoch value which increases the accuracy of the AFCRS upon increasing the value of epochs.

I. Pre-processing

The simplest way to get the data without over-fitting and under fitting is to pre-process the data-set. The main aim behind the data pre-processing is that to add a value to the base value which is the data-set generated. The main advantage of data pre-processing is to get a better training-set. For these purposes, we use Keras library for pre-processing the images. The VGG-16 model that we use in our experiments (AFCRS) it requires an input image shape of 64x 64 x 3, where 3 refers to the R, G, B (red, green, blue) components of a colored image and the image must be 64 x 64 pixels in size. We then apply the following three types of image pre-processing for the original datasets, and we also choose our first filter beginning with 64.

a) Image Re-scaling

We need to re-scale the image to make the model data in a standard format so that the
training is improved, accurate, and faster. We have re-scaling factor in keras. To apply this factor, we need to import the library from keras pre-processing as "ImageDataGenerator". If the re-scaling factor is none or 0, no re-scaling is applied, otherwise we multiply the data by the value provided. This is done after applying all other transformations. For our model AFCRS, we use a re-scaling factor as: rescale=1./255 for both training and testing data-sets.

b) Image Shearing

We need to shear the image to make the training data improved, accurate. We also have shear range factor in keras. This is to be imported from the keras pre-processing library. For our model AFCRS, we use a shearing range as shear_range=0.2. Shear range is generally a Shear angle in counter-clockwise direction in degrees, which is also known as shear intensity.

c) Perspective Transformations

Applied perspective transformations on training data to zoom in the range of zoom_range=0.2 to get the accurate results by learning in an accurate manner. Zoom range is a float or lower, upper range for random zoom. This is also done by importing a library from keras pre-processing.

II. Training the CNN

Here, after choosing the VGGNet for our model AFCRS, we fine-tuned the VGGNet [4], which is a pre-trained network. This speeds up the training process, since there are fewer layers to actually train. To train the neural network, it is actually better to start with a bad performing neural network and bring up the neural network with high accuracy. In terms of loss function, we want our loss function to be too much lower in the end of training. This indicates that our neural network has high learning rate and accuracy. The problem of training the network is equivalent to generate the loss function with minimal error rate. It is important and even efficient to minimize the loss because, it turns out that loss is much easier function to optimize.

Even if there are a lot of algorithms that activation functions and optimization functions, we choose ReLU (Rectifier linear unit) as our activation function, and we can choose ‘adam’ as our optimization function because, it improves neural networks by speeding up training. And also computational step of a ReLU is easy. To recognize the given currency note as fake or original, we must see the accuracy of the VGG-16 model fine-tuned with the generated data-set. It was approximately 55% on the corresponding test set, though our data-set was very small and limited to 200 images, result is still very encouraging. If we increase our image data-set through real-world samples can make the model more accurately trained which may generalize our results beyond 80% accuracy which is a good sign for prediction of results. Despite the perfect score, the result might be attributed to over-fitting on the data-set, as the training and test sets were very similar. Therefore, after pre-processing, we must analyze the loss and accuracy trends of our model, AFCRS by changing the batch sizes and epochs. There are basically 2 cases in deep learning regarding the loss and accuracy values.

IV. RESULTS AND ANALYSIS

Loss trends are generally analysed with respect to Training Loss (TL) and Validation Loss (VL). Accuracy trends are generally analysed with respect to Training Accuracy (TA) and Validation Accuracy (VA).

A. Under Fitting

The model is said to be under-fitted only in the case when training loss is greater than validation loss (TL>VL), and when training accuracy is much lower than validation accuracy (TA<VA).

B. Over Fitting

Over-fitting generally refers to a model that models the training data too well. It can be recognized when the training loss is much lower than the validation loss (TL<VL), and when the training accuracy is slightly greater than the validation accuracy (TA>VA). Therefore, we can say from above images (Figure 4, Figure 5) that the model got over-fitted as TL<VL and TA>VA.

![Figure 4: Screenshot of VGG 16 Loss trends (before pre-processing).](image-url)
Through the graphs (Figure 6, Figure 7) we came to a conclusion that our model, AFCRS is perfectly fitted when compared to the images before pre-processing (Figure 4, Figure 5). But, we need to improve our accuracy and decrease the loss values which can be done by increasing the batch size of the model from 16 to 32. (Figure 8, Figure 9)

C. Recognition of currency

After knowing the fitted model from the above analysis, we now need to recognize the currency which is shown in below sample figures (Figure 10, Figure 11) which were the screenshots taken from our experimented model, AFCRS. Through these analysis, It is clearly seen the distinguishing between the fake and original currency note. So, it is therefore advisable to deploy the same in mobile as an application which is a mere advantage for society.

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V. CONCLUSION

In this paper, we proposed a model which demonstrates the feasibility of using CNN with the VGG 16 architecture. Although the generated data set was small and did not represent the real world scenario of fake currency data-set, it was very helpful throughout the experiment. The process of detection of fake note is quick and easy under the trained model. By this we can also assure that under the real and large data set, the model AFCRS can be well-trained and also provides accurate results, which can help the people in recognizing the currency note whether it is fake or original. Future research may include deployment of the model in a smartphone as an application and make society and people more comfortable in recognizing the counterfeit currency. This model can also be compared with various architectures of CNN which may have low error rate than the present model and can be combined by applying image pre-processing techniques like and edge-detection to crop the currency note out of an image which will present better results.

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