International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-8 Issue-5, March 2019

Recognition of Fake Currency Note using Convolutional Neural Networks

Navya Krishna G, Sai Pooja G, Naga Sri Ram B, Yamini Radha V, Rajarajeswari P

***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 effects 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.*

***Index Terms:** Deep Learning, Convolutional Neural Network, Counterfeit paper currency, Automatic recognition, Currency, Image Processing.*

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, per- forms 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.

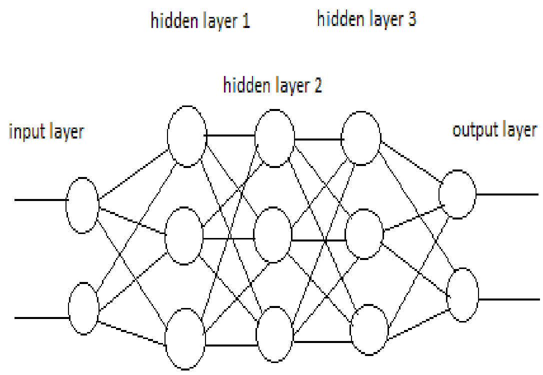

Figure 1: A Deep Neural Network

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

The paper "ANN based currency recognition system using compressed gray scale and application for SriLankan currency notes" [7] , presented by D.A.K.S. Gunaratna, N.D.Kodikara and H.L. Premaratna introduced a technique of Image Acquisition pre-processing through gray scale conversion, image segmentation, edge detection and PCA techniques in the year 2008. The paper "Bangladeshi bank note recognition by neural network with axis symmetrical marks" [2], presented by N. Jahangir, A.R. chowdary introduced a neural network based recognition scheme by back propagation algorithm using multi-layer perceptron in the year 2007.

Manuscript published on 30 March 2019.
***Correspondence Author(s)**
Navya Krishna G, CSE, Koneru Lakshmaiah Education Foundation , Guntur,India.
Sai Pooja G, CSE, Koneru Lakshmaiah Education Foundation , Guntur,India.
Naga Sri Ram B, CSE, Koneru Lakshmaiah Education Foundation , Guntur,India.
Yamini Radha V, CSE, Koneru Lakshmaiah Education Foundation , Guntur,India.
Rajarajeswari P, CSE, Koneru Lakshmaiah Education Foundation , Guntur,India

The paper "Multiple kinds of paper currency recognition using neural network and application for euro currency" [10] proposed by F. Takeda, T. Nishikage introduced the enhanced neuro- recognition system to increase number of recognition patterns using sensors in the year 2000. The review presented by A. Frosni, M. Gori and P. Priami in the year 1996 through a paper "A neural network model for paper currency recognition and verification" [5] classifies and verifies through a model called multi-layered perceptrons. The paper which is presented by F. Takeda, S. Omatu "High speed currency recognition by neural networks" [11] in the year 1995 tells that how the recognition is done by an ordinary method of neural networks that is through only one hidden layer, input layer and an output layer. The review presented by M. Fukumi, N. Akamastu in the year 1996 through a paper "A method to design a neural network pattern recognition system using a genetic algorithm with partial fitness and deterministic mutation" [1] uses the genetic algorithm for recognition system. These are the few techniques related to Detecting and Recognition the fake paper currency.

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 Propogation 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)

$$(x^{*}w)[n] = \text{sigma } (-\infty_{\text{to } k}) \Big[x[k]\ w\ [n-k] \Big]$$

eq:1

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.

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

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.

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 64, 64, 64)	1792
conv2d_2 (Conv2D)	(None, 62, 62, 64)	36928
max_pooling2d_1 (MaxPooling2	(None, 31, 31, 64)	0
dropout_1 (Dropout)	(None, 31, 31, 64)	0
conv2d_3 (Conv2D)	(None, 31, 31, 128)	73856
conv2d_4 (Conv2D)	(None, 29, 29, 128)	147584
max_pooling2d_2 (MaxPooling2	(None, 14, 14, 128)	0
dropout_2 (Dropout)	(None, 14, 14, 128)	0
conv2d_5 (Conv2D)	(None, 14, 14, 256)	295168
conv2d_6 (Conv2D)	(None, 12, 12, 256)	590080
conv2d_7 (Conv2D)	(None, 10, 10, 256)	590080
max_pooling2d_3 (MaxPooling2	(None, 5, 5, 256)	0
dropout_3 (Dropout)	(None, 5, 5, 256)	0
conv2d_8 (Conv2D)	(None, 5, 5, 512)	1180160
conv2d_9 (Conv2D)	(None, 3, 3, 512)	2359808
max_pooling2d_4 (MaxPooling2	(None, 1, 1, 512)	0
dropout_4 (Dropout)	(None, 1, 1, 512)	0
flatten_1 (Flatten)	(None, 512)	0
dense_1 (Dense)	(None, 512)	262656
dropout_5 (Dropout)	(None, 512)	0
dense_2 (Dense)	(None, 2)	1026

Total params: 5,539,138
Trainable params: 5,539,138
Non-trainable params: 0

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

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 li- brary, 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-esquare 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 in- creasing 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

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

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 net- work 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 neu- ral 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 ac- curacy 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.**

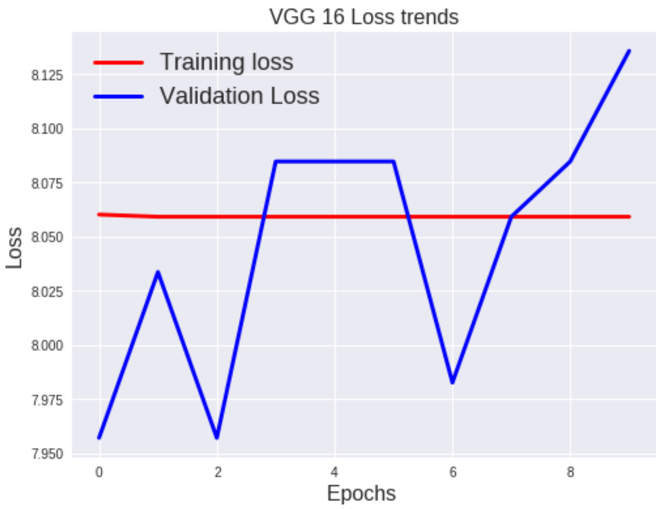

Figure 4: Screenshot of VGG 16 Loss trends (before pre-processing).

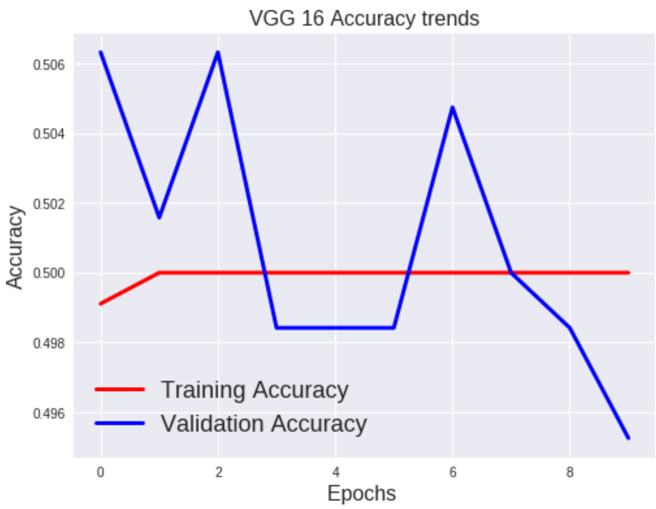

Figure 5: Screenshot of VGG 16 Accuracy trends (before pre-processing).

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

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)

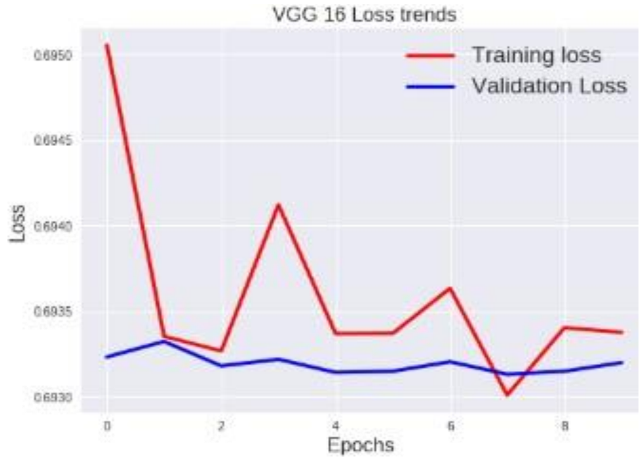

Figure 6: Screenshot of VGG 16 Loss trends when batch size is 16 (after pre-processing).

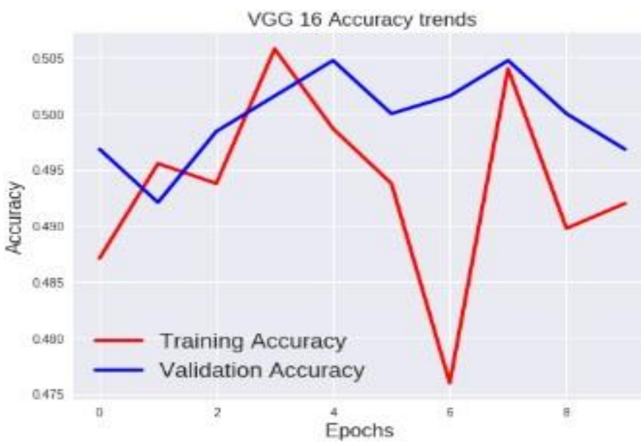

Figure 7: Screenshot of VGG 16 Accuracy trends when batch size is 16 (after pre-processing).

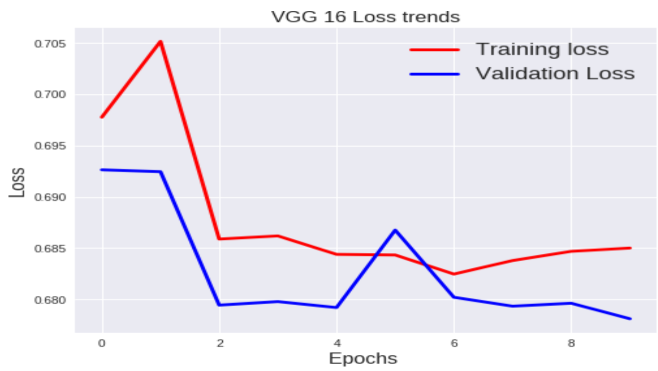

Figure 8: Screenshot of VGG 16 Loss trends when batch size is 32 (after pre-processing).

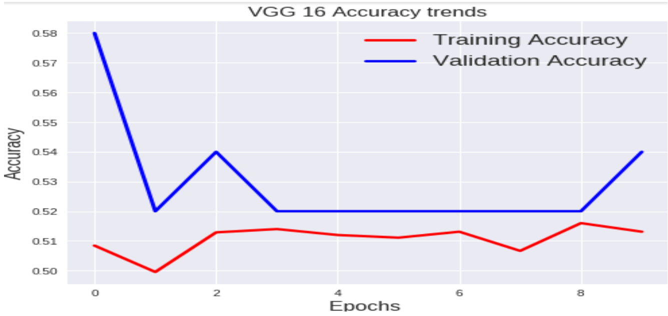

Figure 9: Screenshot of VGG 16 Accuracy trends when batch size is 32 (after pre-processing).

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.

ACKNOWLEDGEMENTS

I thank my co-authors, university and departmental in-charges for supporting me through-out the project by conducting sessions for reviews and guiding us through their valuable suggestions continuously.

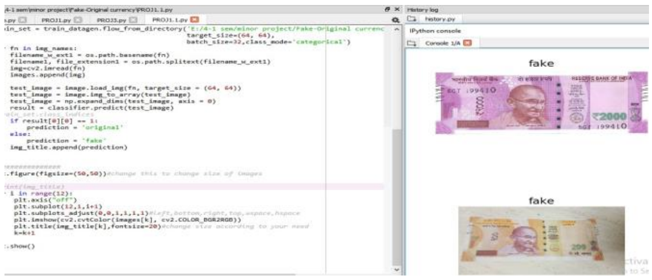

Figure 10: Screenshot of experimented model for recognizing fake currency.

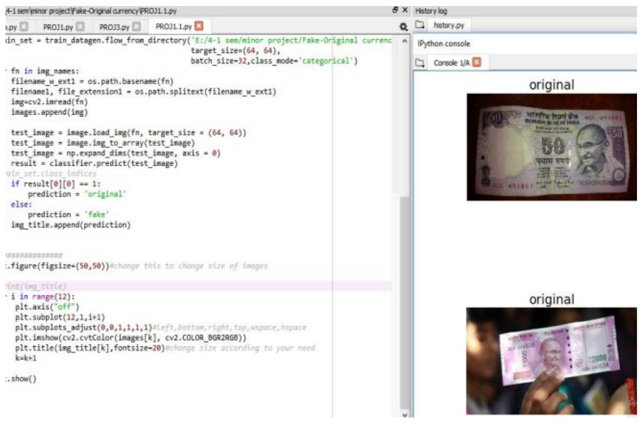

Figure 11: Screenshot of experimented model for recognizing original currency.

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

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 smart phone 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.

REFERENCES

1. N. Akamatsu, M. Fukumi, A method to design a neural pattern recognition system by using a genetic algorithm with partial fitness and a deterministic mutation (1996).
2. A. Chowdhury, N. Jahangir, Bangladeshi banknote recognition by neural network with axis symmetrical masks in masks, in: 10th international conference on computer and information technology.
3. Da-costa, Multiview banknote recognition with component and shape analysis (2014).
4. S. Das, CNN Architectures: LeNet, AlexNet, VGG, GoogLeNet, ResNet and more, 2017.
5. P.P.A. Frosini, A neural network based model for paper currency recognition and verification, IEEE Transactions on Neural Networks 7 (1996). 1482–1490.
6. P. Gidveer, S.R. Darade, Automatic Recognition of Fake Indian Currency Note, International Conference on Electrical Power and Energy Systems (ICEPES), Bhopal, India, pp. 290–294.
7. D.A.K.S. Gunaratna, N.D. Kodikara, Premaratne, ANN Based Currency Recognition System using Compressed Gray Scale and Application for Sri Lankan Currency Notes - SLCRec, World Academy of Science, Engineering and Technology International Journal of Computer and Information Engineering 2 (2008) 2957–2962.
8. R. Mirza, V. Nanda, Design and Implementation of Indian Paper Currency Authentication System Based on Feature Extraction by Edge Based Segmentation Using Sobel, Operator, International Journal of Engineering Research and Development 3 (2012) 41–46.
9. P.R. Nagpure, T.Ghotkar, S. Shetty, Recognition and Fake Note Detection, International Journal of Innovative Research in Computer and Communication Engineering Vol 4 (March 2016).
10. T. Nishikage, F. Takeda, Multiple kinds of paper cur- rency recognition using neural network and applica- tion for Euro currency (2000) 27–47.
11. S. Omatu, F. Takeda, High speed paper currency recognition by neural networks (1995) 73–77.
12. Paisios, Currency recognition using a smartphone: Comparison between color SIFT and gray scale SIFT algorithms (2012).
13. M. Sarfraz, A. Sargano, Robust Features and Paper Currency Recognition, in: The 6th International Conference on Information Technology Cite this pub- lication.
14. J. S.Dewan, Extended Local Binary Pattern for Face Recognition, Technology ICAET, 2015.
15. V.Vashishtha, M.Sadim, A Paper Currency Recogni- tion System Using Image Processing To Improve the Reliability with PCA Method, International Journal of Engineering Science & (2015).

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)