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Identification of Fake Indian Currency using Convolutional Neural Network

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***Abstract*—The progression of shading printing innovation has expanded the rate of Fake currency copying notes on a large scale. Albeit electronic monetary exchanges are turning out to be more popular and the utilization of paper cash has been diminishing as of late, banknotes still remain in distribution attributable to their dependability and straight forwardness in use. Few years ago, the printing should be possible in a printing-houses, yet presently anybody can print a money paper with most extreme exactness utilizing a straightforward laser printer. As an outcome, the issue of duplicate currency rather than the authentic ones has been increases generally. India had reviled the problems like defilement and dark cash and fake of money notes is likewise a big issue to it. To handle this problem, a deep learning-based framework is proposed to identify the fake Indian currency. The MATLAB tool has been used to identify the fake currency. The outcome will classify whether the Indian currency note is Real or Fake.**

Keywords—Indian Currency, Convolutional Neural network, Alexnet, Resnet50, Darknet53, Googlenet

I. INTRODUCTION

Counterfeit currency is a major issue around the world, it influencing the economy of various countries. Therefore, fake currency is not approved by the government. In India Reserve Bank of India is only give the approval to banks for generating the currency. In India many of the people have been working on daily basis, hence workers, farmers and uneducated people facing the problems with the counterfeit currency. They are unable to identify the fake currency. In order to overcome these problems researches proposed the various algorithms with development of image processing methods. The image processing algorithms such as recognition, identification of denomination, counterfeit detection and currency classification. These are used in automatic counting machines, vending machines and automatic transactions. But counterfeit detection and classification is challenging issue in many applications.

The conventional methods based on colour, size, texture and shape identify the fake currency. Edge detection, Watermarking, feature extraction, segmentation methods have been used to detect the fake currency. The major steps involved in the process of identification and recognition of fake currency is creating database of particular country, converting RGB to grayscale image, segmentation is used to segment the logo, currency value, number and signature of the governor. In the conventional methods feature extraction is major issue to detect the fake currency and these are also providing the less accuracy. To overcome this problem deep learning with convolutional neural networks (CNN) came into the picture. In this paper four predefined networks i.e Alexnet, Resnet50, Darknet53 and Googlenet have been used to detect the fake Indian currency. In order to detect fake Indian currency large database with different value currency under various angles and illumination conditions required.

In this paper Section II gives the related work to Indian fake currency detection. In Section III discussed about Indian currency dataset. Section IV describes the proposed method and Section V gives the brief discussion about the CNN. The experimental results and conclusions have been reported in Sections V and VI, respectively.

II. RELATED WORK

There are many research papers which discuss about Fake Currency Detection by considering the Feature Extraction Method. J. Lee et.al [1] have discussed Banknote acknowledgment is an interaction step in which the category, bearing, and side of the info banknote are characterized. The justification ordering bearing and side notwithstanding section is that the situation of a district of revenue inside a banknote, which is utilized to execute the next cycle (chronic number acknowledgment, fake banknote identification, and wellness grouping), shifts as indicated by the course and side of the banknote. D. Galeana Pérez et.al [2] Manual testing of notes in exchanges is exceptionally tedious and befuddling process and furthermore there is a shot at tearing while at the same time dealing with notes. Thusly, programmed strategies for monetary order acknowledgment are needed in numerous applications like programmed selling merchandise. In planning of this framework one testing case is to plan framework that is extraction of attributes from money 3 picture for exactness of the mechanized framework. B. Sai Prasanthi et.al [3] Computerized distinguishing counterfeit cash framework can be very assistance full to banking or other business such countless creators work on this innovation according to his viewpoint counterfeit money recognition is vital undertaking in human existence. India is likewise one of them. Julia Grace et.al [4] The printing house can make fake paper cash, yet it is feasible for any individual to print fake monetary orders basically by utilizing a PC and a laser printer at house. Yeh, Chi-Yuan et.al [5] proposed a framework dependent on various bit support vector machines for fake banknote acknowledgment. A help Support Vector Machine (SVM) to limit bogus rates is created. Every banknote is separated into parcels and the luminance histograms of the segments are taken as the contribution of the framework. Each parcel is related with its own bits. M. Hida et.al [6] Fake coins were researched utilizing X-beam fluorescence (XRF) for a quantitative examination with practically no pre-treatment and by a metallic magnifying lens for perception of their microstructures. Copper, nickel, iron, zinc, manganese, chromium, cobalt and lead were recognized by XRF. Tuyen Danh Pham et.al [7]

Programmed acknowledgment of phony banknotes is a significant assignment in useful banknote taking care of. Exploration on this assignment has for the most part elaborate techniques applied to programmed arranging machines with different imaging sensors or that utilization specific sensors for catching banknote pictures in different light frequencies. K.-H. Lee et.al [8] propose a picture division technique for programmed paper-cash assessment framework. The UV (bright) designs installed in the paper cash ought to be sectioned to decide if the cash is real or not. A. Bruna et.al [9] It depicts both equipment and programming parts to distinguish fakes of Euro banknotes. The proposed framework is additionally ready to perceive the banknote esteems. In an unexpected way than other best in class strategies, the proposed approach utilizes banknote pictures obtained with a close to infrared camera to perform acknowledgment and verification. This permits one to assemble a framework that can adequately manage genuine phonies, which are generally not perceptible with noticeable light. Yongjiao Liu et.al [10] Acknowledgment for new and old cash is a critical capacity of the paper money sorter. Step by step instructions to segregate unsuitableness banknotes which turned out to be harsh and fluffy, even be harmed is a significant errand in monetary establishment. Not the same as conventional wellness banknote acknowledgment dependent on extricating highlight physically, a strategy dependent on convolutional neural organization was proposed to distinguish wellness banknotes. Milan Tripathi [11] have been proposed a CNN model for fruit classification using Densnet, Vgg16, Vgg19 and InceptionV3. Out of four predefined networks Densenet achieves 100% accuracy. Joy Iong et.al [12] have been proposed deep convolutional neural network for financial fraud detection and achieves 99% accuracy.

III. DATASET

The dataset has been created using the mobile camera and scanner. It consists of total 247 images which consists of the 121 Fake Indian currency and 126 are the real Indian currency. The Fake Indian Currency is created using scanner and real Indian currency is created using mobile camera. By using mobile camera, both side of currency is captured. With the captured currency, the scanner is used to create the fake Indian currency and printed on plain paper using printer. As a result, the number of images in each type of currency of 10, 20,50, 100, 200 and 1000 currency. The sample real and fake currency images are shown in Fig.1 and Fig.2.

Fig.1 Real Indian Currency Data set

Fig.2 Fake Indian Currency Data set

IV. PROPOSED DESIGN

The proposed method block diagram is as shown in Fig. 3.

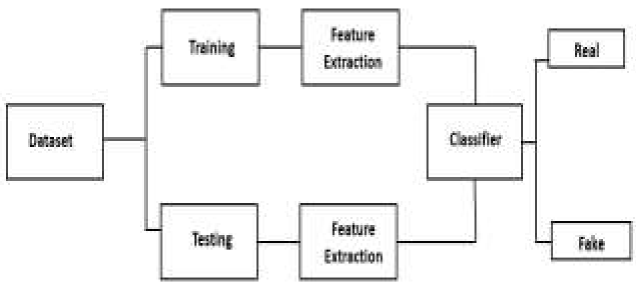

Fig. 3. Block Diagram of Proposed Method

The following steps are the brief description how the method works,

Step1: The dataset consists of two classes namely Original and Fake Indian Note Currency, it can be split into 80% training set and 20% testing set.
Step2: The training set and testing set features are extracted using predefined convolutional neural networks (CNN). In this paper four networks i.e Alexnet, Resnet, Googlenet, Darknet53 have been used for extracting the features.
Step 3: After extracting the features using CNN classification is carried out using Support Vector Machine (SVM), whether the test image is real currency or fake currency.
Step 4: Accuracy is calculated using confusion matrix for four predefined networks.

V. CONVOLUTIONAL NEURAL NETWORKS (CNN)

In this paper four predefined convolutional neural networks have been used to extract the features of real and fake Indian currency. The Alexnet [13], Darknet53[14], Resnet50[15], and Googlenet [16] architecture is shown in Fig.4, Fig.5, Fig.6, Fig.7and Fig.8. Each predefined network mainly consists of the convolutional layer, pooling layer, ReLu layer, fully connected layer and softmax layer.

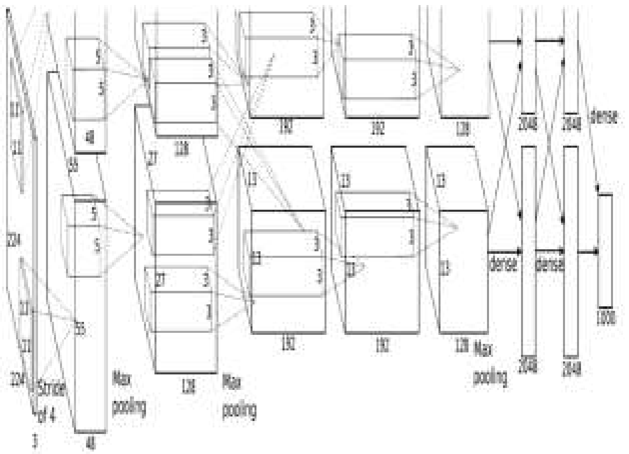

Fig. 4. Architecture of Alexnet [13]

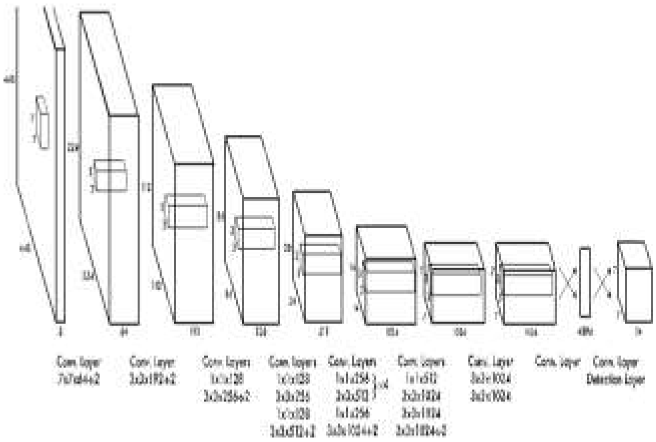

Fig. 7. Architecture of darknet53 [14]

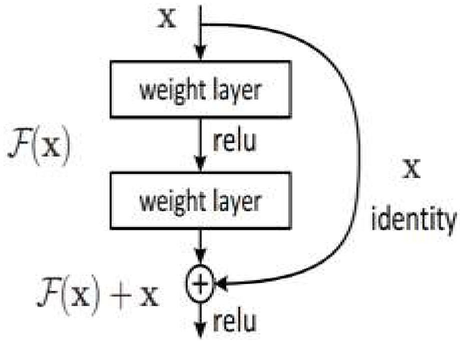

Fig. 6. Residual learning: a building block [15]

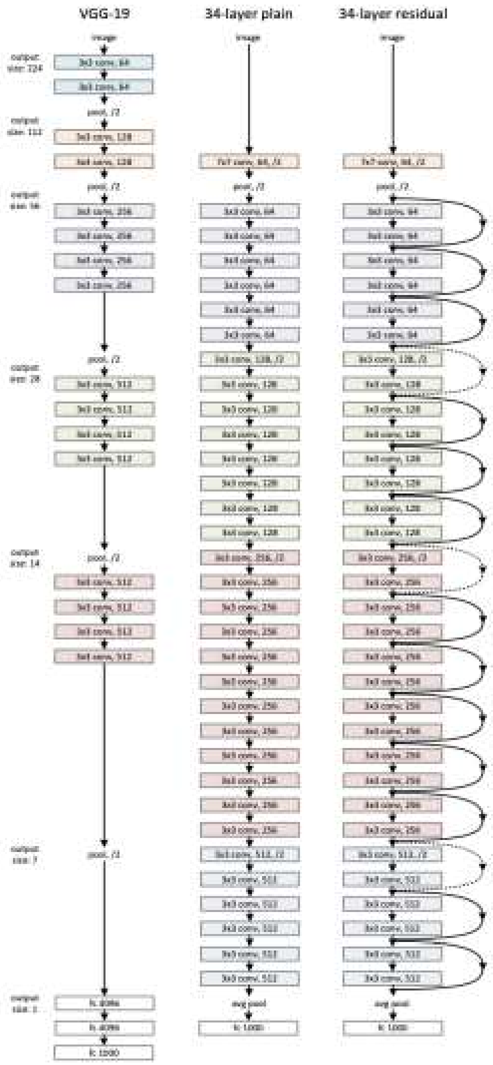

Fig. 5. Examples of network Architectures [15]

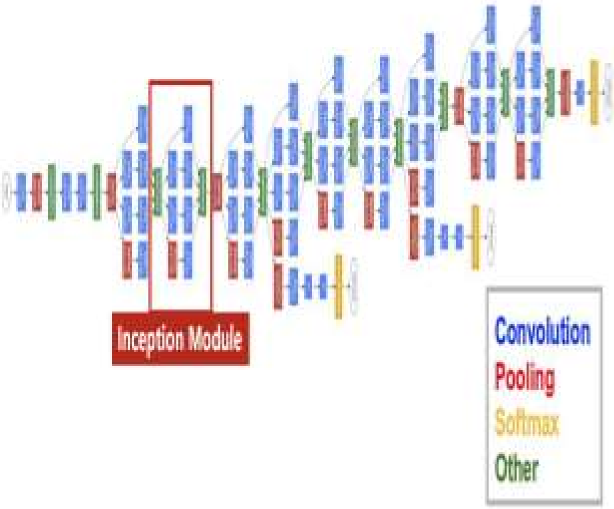

Fig. 8. Architecture of Googlenet [16]

VI. EXPERIMENTAL RESULTS

The training and testing performance is evaluated using MATLAB on desktop computer using the following specifications 11^{th} generation Intel Core i5 Processor, 512GB SSD, 8GB RAM, Windows 10 + MS Office, 2GB NVIDIA GeForce MX330 Graphics. Four predefined CNN architectures namely Alexnet, Googlenet, Daknet53, Resnet50 have been used for testing the performance of the created dataset. Before extracting the training features and testing features data augmentation was performed on the training images and testing images. In data augmentation three operations are considered namely flipping, rotating and scaling. The four predefined CNN networks average accuracy have been compared. Fig.9, Fig.10, Fig.11 and Fig.12 shows the predicted class and confusion matrix using Resnet50, Darknet53, Alexnet, Googlenet. In Table I gives the True Positive, True Negative, False positive, False Negative and Accuracy values for four predefined networks. The Table II shows the Precision, Recall rate, F-Measure, Specificity and Youden Index for four predefined networks. The Resnet 50 achieves highest accuracy i.e 80.94% compared with the Alexnet, Darknet53 and Googlenet. The Darknet53 achieves good Precision rate 77.57%. The Resnet50 and Darknet53 obtain 87.62% Recall Rate. Interms of F-Measure Resnet50 got 0.99. The Specificity of Googlenet is 89.10%. The Resnet50 achieves 61.87% Youden Index. The Precision, Recall rate, F-Measure, Accuracy and Specificity formulae have been given below.

$$Precision = \frac{TP}{TP + FP}$$

(2)

$$Recall = \frac{TP}{TP + FN}$$

(3)

$$F - Measure = \frac{2 \times Precision \times Recall}{Precesion + Recall}$$

(4)

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP}$$

(5)

$$Specificity = \frac{TN}{TN + FP}$$

(6)

$$Youden\,Index = Sensitivity + Specificity - 100$$

(7)

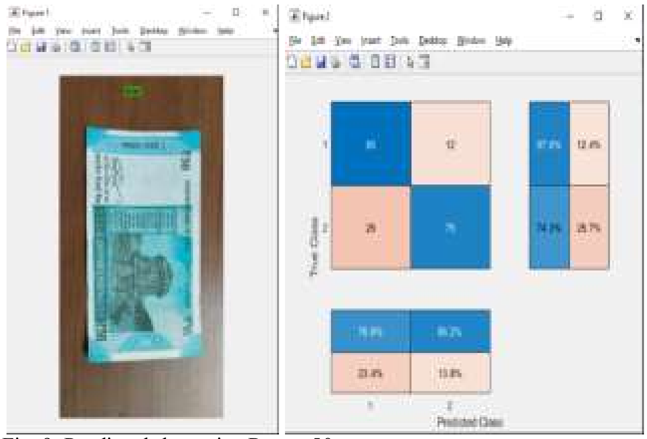

Fig. 9. Predicted class using Resnet50

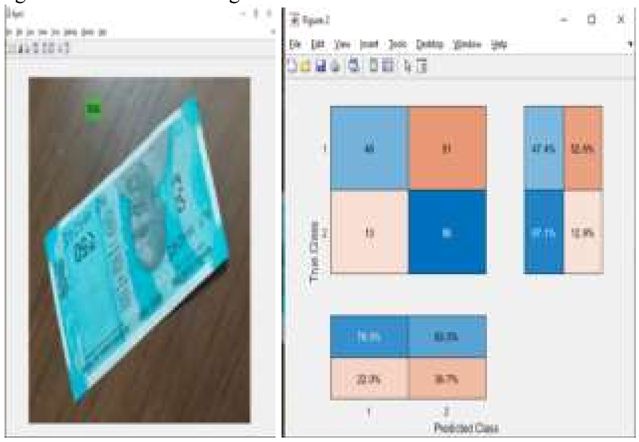

Fig. 10. Predicted class using Darknet53

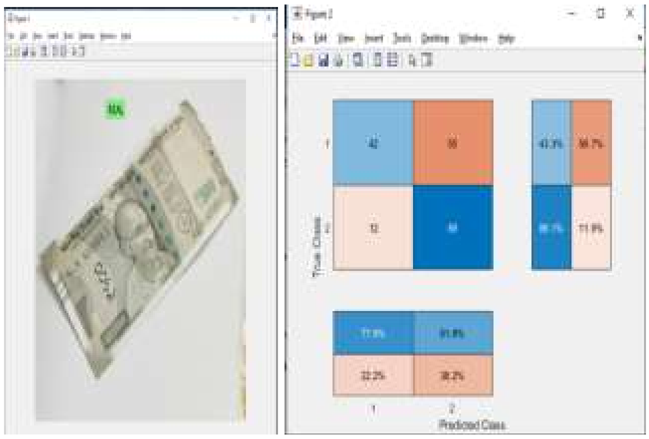

Fig. 11. Predicted class using Alexnet

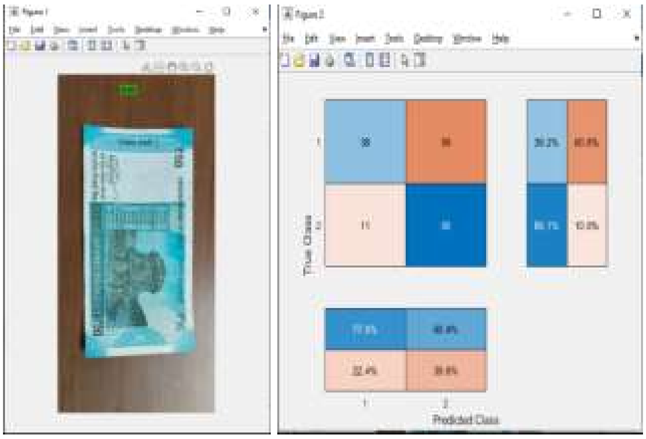

Fig. 12. Predicted class using Googlenet

TABLE I. TP,FP,FN,TN AND ACCURACY COMPARISON OF FOUR PREDEFINED NETWORKS

NETWORK	True Positive (TP)	False Positive (FP)	False Negative (FN)	True Negative (TN)	ACCURACY
Darknet53	46	13	51	88	72.04
Alexnet	42	12	55	89	65.15
Resnet50	85	26	12	75	80.94
Googlenet	38	11	59	90	64.64

TABLE II. PRECION, RECALL, F-MEASURE, SPECIFICITY AND YOUDEN INDEX OF FOUR PREDEFINED NETWORKS

Network	Precision	Recall	F-Measure	Specificity	Youden Index
Darknet53	77.57	87.62	0.57	74.25	29.6
Alexnet	80.76	43.29	0.56	88.11	31.4
Resnet50	76.57	87.62	0.99	74.25	61.87
Googlenet	77.55	39.17	0.52	89.10	28.27

VII. CONCLUSION

Day by day the rate of fake notes in the market are increasing rapidly. Currently there are various technologies have been used to determine whether the note is real or fake currency. In this paper, a convolutional neural networks for detecting the fake Indian currency has been proposed. Four Predefined networks i.e Alexnet, Resnet50, Darknet53 and Googlenet have been used in CNN to verify the accuracy of created dataset. The results showed that the four predefined networks are good at one parameter and compromising on the other parameters. To overcome this problem in future dataset verification will be done using novel CNN architecture to obtain the better results by considering all parameters.

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