Forged Multinational Currency Identification and Detection System using Deep Learning Algorithm

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ABSTRACT

Now a days as many counterfeit banknotes are manufactured and circulated in global market, which results in significant damage and harm to society. Recognizing the currency's originality is a very difficult task to general person. Because of advancement in generating highly accurate fake currency. There are several techniques available, such as automatic sorting of banknotes in payment facilities, automated payment machines or sales machines, which consists of several tasks such as identification of banknote type, classification of recirculation fitness and detection of fake banknotes. Banknote identification is the most important approach, based on an image processing system. There are many techniques used in the classification of banknotes by different countries that has been conducted experiments on separate image data sets of each country. Deep learning is a machine learning technique which analyzes & learns the features of the original note. Using the neural networks, the most important aspect is to find more essential features. In the age of big data, in which vast amounts of data must be processed for any application in the real world, the superior techniques are deep learning. In this study, banknotes from various countries are examined by extracting their minute features in carefully and analyzing them using deep learning. Proposed system recommended a Convolutional Neural Network algorithm to detect Forged banknote using dataset of multiple country currency. This approach is chosen to achieve high accuracy with good performance with respect to loss and accuracy in training and validation in terms of huge dataset. So it helps individuals to avoid personal economic damage caused by counterfeiters.

Keywords

Deep Learning, Currency Recognition, Currency Identification

1. INTRODUCTION

Now everybody works online because of their busy lives, no one is bothered to visit a bank as majority of financial transaction are performed using various ways introduced on internet. The rise in electronic and digital financial transactions resulting in a decline use of physical currency, still transactions involving banknotes is the universal means of exchange or general circulation in order to facilitate the sale and distribution of goods in both everyday life and largescale commerce. Currency within the system of market economy Automated machines include many techniques in these transactions and have the ability to handle multiple tasks, including the identification of banknotes, fitness verification, counterfeit detection and serial number recognition. Problems arise when banknotes used in systems like automated teller machines (ATMs) and vending machines cannot be recognized because of higher than average spoilage levels.

Currency reputation is critical as a means of economic activity as it destroys not only personal property but also national creditworthiness. Cases that have recently been falsified are increasing rapidly in forgery cases. Counterfeiting crime is not just one country's concern. Hence detecting counterfeit is important for economic and social soundness.

The development of automated systems for recognizing currencies has developed day by day. In many areas such as the banking system, railway ticket counter, shopping mall, currency exchange service etc., cost-effective solution and efficient currency recognition system is considered as important. Banknotes are used to carry out finance operations. The various technological advances and new equipment in the field of scanners and printing machines have led the miscreants to make high accurate copies of banknotes. It is very difficult for human eyes to differentiate between fake and genuine because they are designed with great precision to look like a genuine note and counterfeiters are prone to making such fake currencies, and appear to have overwhelmed the network. This scenario enforced there is a requirement of a proper technique that helps to result properly with lot of training data to achieve high accuracy. Proposed system helps to common people to deal with this scenario easily using image of currency. Mainly this paper focused on multiple countries with different denominations of that country. Performance of system can be monitored with the help of precision and time. The primary objective is to focus on minute parameter which helps to classify between genuine or fake banknotes and introduce a straightforward and competent approach.

2. LITURATURE SURVEY

A lot study is introduced by various researchers in classification and identification of banknotes of different countries and also conducted various experiment on image dataset of each country.

Achal Kamble et al [1] proposed a new method for the identification of fake Indian documents by making use of image processing techniques. Author working on currency image is the one represented in the space of dissimilarity, that dimensional testing of the disparity between the picture being considered and a prototype. They have obtained the dissimilarity between two images; detecting and defining the local key points on each image.

Tushar Agasti et al [2] introduced a new method for detecting Indian currency notes using image processing. Feature extraction includes features such as serial number, protective string, identification mark, portrait of Mahatma Gandhi. Proposed method also extracts functionality, even if the note has scrawl on it. Monali Patil et al [3] is introducing a new approach to detecting fraud on Indian Notes. First, take the image input and pre-process the image after pre-processing, and apply algorithm to extract the image's inner and outer edges. Clustering is achieved using the k-means algorithm, comparing the features of the image and classifying it as original or fake using SVM algorithms. Experimental results show that using SVM Algorithm has better accuracy performance than using the CNN Algorithm for Indian Currency.

Gai et al [4] introduced method which uses quaternion wavelet transform and generalized Gaussian density. These techniques are used to extract the function and Neural Network is used to classify banknote in China, Europe and United State.

A distance based Euclidean banknote system is proposed by Bhurke et al [5] Developed strong GUI for different country including India, Saudi Arabia, Australia, etc.

Based on above literature survey, we analyzed that we should concentrate on precision and time to hand huge data set of multiple country with different denominations of each country.

3. PROPOSED METHODOLOGY

General flow of proposed system for banknote recognition is as shown in following figure 1 Following are the steps used to perform analysis.

- Step 1: Take Input as Inage of front view and back view of banknote.
- Step 2: Perform preprocessing on image to rescale size, Shearing and transformation to zoom.
- Step 3: Transfer processed image to pre-trained CNN.
- Step 4: Categorize Image into genuine and fake banknote and determine denomination.

Firstly dataset of various countries are generated which includes India, Bhutan, and Saudi Arabia initially. Dataset is generated from various sources of internet, Churan Bank, Children Bank of India etc. These images are collected for both front side view and back side view of banknotes. After dataset generation it is categorized into two parts as genuine and fake for the purpose if training [6].



Fig 1: General Flow of Proposed System

Pre-processing of images is implemented to strengthen and intensify certain extracted image characteristics important for future analysis and processing. Using median filter, noise from image is eliminated from the separated image. Median filter is effectively based on a moving window over the entire image and measuring the resulting pixel value as the median value of the present window's brightness value. Restore the resulting smoothed picture canals. Another pre-processing implemented is to normalize the scale of different currency notes with the same aspect ratio retained. The aspect ratio may be defined as the ratio of note width to note height. Complete image size the aspect ratio of the note of a given denomination is independent of the distance from which the photograph was taken [7]-[8].

Alex Net architecture inspired the CNN used in proposed method. Alex Net consists of eight layers. Top five layers are convolutional layer where some of them are accompanied by max-pooling layer. Bottom three layers are fully connected layers. Here ReLu is used as a activation features to get improved training efficiency over tanh and sigmoid [3]. The main advantage of using ReLu is there is a decreased risk of gradient loss. In Convolutinal layer feature extraction is done in several filters with different sizes followed by pooling and in fully connected layer classification is done with number of nodes at each layer. So technically this architecture is used for training and testing purpose where each input image pass through series of layers with different size filters, pooling and fully connected layers series. Filter coefficient of convolution layer and weights of fully connected layers are learned from training data of images of banknotes. In network training phase full network models trained coefficient and weight in memory for the purpose of testing. Finally in proposed method, as an output banknote is classified as either genuine or fake according to origin of country and denomination using fully connected layers of trained convolutional network model [9]-[10].

4. PRAPOSED IMPLEMENTATION

In this study the currencies of Indian, American, Saudi Arabia, and Bhutan are studied and established. For front view and back view, the features of those four currencies of different types are extracted. Segmentation of images in the RGB, HSV and YCbCr Color regions provides the best comparison of hidden features of all currencies. Following Steps are performed which passes through series of layers as shown in Figure 2.



Fig 2: Convolution Neural Network Architecture

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- A. Take input image of front side and back side of the currency.
- B. In pre-processing phase Images are converted into RGB, HSV and YCbCr formats.
- C. Feature extraction on both images is compared with existing data features of currency which have been already stored in the database.

Image is preprocessed by using our deep learning algorithm.

- Segments of currency as an input.
- Set different weights (As Deep learning is work on different layers and it need to set weight for each layer).
- Calculated, Hidden layer by the formula.
 - input_of_hidden_layer1 = values of original currency features-inputted currency feature ;.....(1)

output_of_hidden_layer1=weight1 input_of_hidden_layer1.....(2)

• Using above formula we have calculated 3 layers and using following formula we have calculated error function which helps to take the final decision.

 $Error fun = abs(\sum(output_of_hidden_layer3))....(3)$

• With the help of values of original features of

currency and error function comparison decision is taken place

Attributes of paper currencies that are used by citizens to distinguish various banknote denominations are employed in the proposed system. For their identification, the specifics of the picture and the exact characteristics of banknotes, rather they find the common characteristics of banknotes such as the size, background color (the basic color), and the texture present on banknotes. Thus we are introducing some other way or traditional currency detection features [11,12].

5. RESULTS

The experiments were performed to identify the Indian, American, Bhutan and Saudi Arabia's fake currency notes. The images and then features were extracted from the acquired images using the proposed technique.

The identification between real image and fake currency image was done on the basis of dissimilarity and discontinuity between them. The extracted features were used for fake currency detection. The decision weather a note is fake or real was made by comparing the values of Original note and error function which have been implemented. Here some images of currencies of different countries has been collected and their features that have been considered for the identification and detection of fake note. Every note is converted into three different types of color image such as RGB, HSV, and YCbCr.



Fig 3: Different feature Segments Indian Currency 2000

As shown in above Figure 3 eight segments features of each type of color image have been considered for detecting the Indian currency 2000.

MR1	MG1	MB1	MM1	SD1	Corr1
178.58673	104.00663	122.88265	135.15867	39.074955	0.9613636
195.04688	182.56275	204.10935	193.90633	80.844159	0.9980157
223.10833	192.60095	220.51286	212.07405	40.778547	0.9846653
196.91354	150.45472	204.04762	183.80529	43.653317	0.9835227
210.60651	145.06523	177.7786	177.81678	45.993545	0.9804845
141.64178	104.69193	129.81639	125.38337	77.063507	0.9945765
216.02963	212.14014	213.91541	214.0284	80.422073	0.9982264
203.58661	158.73637	198.65435	186.99244	41.158766	0.9799201
195.69	156.28234	183.96465	178.64567	56.123609	0.9850968
MR2	MG2	MB2	MM2	SD2	Corr2
0.9574155	0.4245317	0.7003401	0.6940958	0.2263526	0.9517122
0.7293997	0.2157469	0.8051186	0.5834217	0.3556505	0.9825243
0.8391649	0.1558001	0.8848693	0.6266114	0.3457881	0.9768316
0.8102322	0.2724594	0.8007331	0.6278082	0.2687705	0.9749145
0.9078032	0.3258784	0.8294085	0.6876967	0.2739342	0.9911289
0.8475181	0.385639	0.5564682	0.5965418	0.3094041	0.9784295
0.4184915	0.0931764	0.8482217	0.4532965	0.4478486	0.9791143
0.8372695	0.238536	0.8024577	0.6260877	0.293375	0.9695442
0.7934118	0.263971	0.7784521	0.611945	0.3151405	0.9755249
MR3	MG3	MB3	MM3	SD3	Corr3
126.32075	125.22415	159,41514	136.98668	19.583366	0.8901399
178.10127	135.61969	131.94164	148.5542	43.944808	0.9959523
191.9781	135.73619	139,41881	155.71103	32.277513	0.9290347
162.39029	144.64482	144.57796	150.53769	20.308719	0.941935
160.61684	132.65453	154.45179	149.24105	22.11374	0.9700315
117.85098	133.55147	142.43053	131.27766	39.955349	0.9621166
199.32605	128.17252	129.57921	152.35926	52.155343	0.9876469
167.74965	138.88748	144.84197	150.49303	23.19323	0.8748563
163.04174	134.31136	143.33213	146.89508	31.691508	0.9439641

Fig 4: Data Table of original Indian Note 2000 Here, mean of each values are shown in Figure 4 and 5

MR1,MG1,MB1,MM1 SD1 and Corr1 (Mean Red, Mean

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Green, Mean Blue, Mean of Mean RGB, Standard Deviation and Correlation of RGB Image) have calculated for the processing of image on Indian currency 2000 rupees note. Same way calculated this for YCbCr and HSV image also.

MR1	MG1	MB1	MM1	SD1	Corr1
146.1898	57.945918	58.35068	87.495465	66.816878	0.0065474
239.40014	221.06629	221.17875	227.21506	23.804585	-0.0531377
237.80071	222.05381	220.74405	226.86619	8.0656407	-0.1042158
206.31447	154.7606	166.21961	175.76489	52.293003	0.2625157
192.09562	108.46571	117.58194	139.38109	65.870037	0.5305986
157.70207	86.37334	97.937063	114.00416	74.812894	0.0238581
214.49295	212.89857	202.86643	210.08598	59.662681	0.0708941
200.96557	136.14284	152.98835	163.36559	68.098856	0.3127183
199.37017	149.96338	154.73336	168.0223	52.428072	0.1312223
MR2	MG2	MB2	MM2	SD2	Corr2
0.2857111	0.6783843	0.5732933	0.5124629	0.3393087	0.09028
0.4970677	0.0799768	0.9388241	0.5052895	0.4538967	0.0658168
0.0172601	0.0717777	0.9325518	0.3405299	0.4217212	0.0216746
0.8644332	0.2807381	0.8091379	0.6514364	0.3419953	0.4577126
0.7950267	0.4782928	0.7533167	0.6755454	0.3028273	0.4265379
0.939082	0.540748	0.6184395	0.6994232	0.295653	0.0871839
0.1506254	0.0875247	0.844696	0.3609487	0.3772939	-0.0144631
0.6690241	0.376172	0.7881003	0.6110988	0.3509507	0.5199561
0.5272788	0.3242018	0.7822949	0.5445918	0.3604559	0.2068374
MR3	MG3	MB3	MM3	SD3	Corr3
88.464796	115.01735	166.70442	123.39552	41.967708	0.0257869
210.55694	125.19108	136.16062	157.30288	39.486557	-0.0457038
210.61548	125.44071	135.00762	157.02127	38.116348	0.0142072
163.24594	125.41662	149.7789	146.14715	30.054621	0.1176694
131.51909	119.61288	164.06653	138.3995	33.675969	0.530166
109.62867	122.51493	158.49368	130.21243	40.207356	0.0449528
198.26762	123.07885	129.32354	150.22334	45.113074	0.0667236
151.20647	125.87364	155.22897	144.10303	35.949774	0.2107191
157.93813	122.76826	149.34554	143.35064	38.071426	0.1205651

Fig 5: Data Table of Fake Indian Note 2000

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Fig 6: Different feature Segments Bhutan Currency

As shown in above Figure 6 eight segments features of each type of color image have been considered for detecting the Bhutan currency.

MR1	MG1	MB1	MM1	SD1	Corr1
138.30102	148.0043	152.97226	146.42586	51.445079	0.9948078
155.33293	162.79661	168.4468	162.19211	61.385866	0.99606
113.67898	125.84739	136.06492	125.1971	48.373529	0.9907734
142.59035	146.1875	136.48268	141.75351	72.589403	0.9971904
160.32399	157.39998	142.43283	153.3856	78.703277	0.9979759
131.03292	139.61853	150.85536	140.50227	68.493061	0.9974056
182.99961	161.65765	143.02073	162.55933	60.517242	0.9955494
156.25529	166.24388	171.17458	164.55791	60.246289	0.9953973
1180.5151	1207.7558	1201.4502	1196.5737	501.75375	7.9651598
MR2	MG2	MB2	MM2	SD2	Corr2
0.5421139	0.1279367	0.6022634	0.4241047	0.254194	0.9893667
0.4889168	0.1388797	0.6691012	0.4322992	0.2859596	0.9866141
0.4989198	0.2118067	0.5454226	0.4187164	0.2170473	0.9891
0.2275798	0.1279058	0.5734368	0.3096408	0.2808309	0.9661385
0.1471735	0.1925787	0.6300651	0.3232724	0.3089862	0.9754655
0.5485171	0.2171556	0.5965011	0.4540579	0.2661683	0.989898
0.2306094	0.2834234	0.738168	0.4174003	0.3164511	0.9882401
0.4987469	0.1315092	0.6791181	0.436458	0.2843304	0.9797053
3.1825771	1.4311956	5.0340763	3.2159497	2.2139678	7.8645282
MR3	MG3	MB3	ммз	SD3	Corr3
141.10698	131.67586	123.44531	132.07605	26.802261	0.9717149
154.44782	131.55934	124.36677	136.79131	33.588241	0.9781196
121.95696	134.33049	121.86156	126.04967	24.341085	0.958139
139.67697	124.37823	127.03091	130.36204	36.767592	0.9844172
150.46436	121.07533	130.3213	133.95366	40.871235	0.9892883
134.80421	134.13257	123.45874	130.79851	34.980099	0.9854062
158.49375	116.63359	138.68219	137.93651	34.099488	0.9816732
156.69133	131.62111	123.30069	137.20438	33.218867	0.9769823
1157.6424	1025.4065	1012.4675	1065.1721	264.66887	7.8257407

Fig 7: Data set of original currency of Bhutan

MR1	MG1	MB1	MM1	SD1	Corr1
138.71221	142.51818	147.47465	142.90168	58.543773	0.0343695
179.50677	176.23999	176.38125	177.376	66.234789	0.2896358
121.65754	126.14439	137.12067	128.30753	62.486935	0.2199479
149.96739	146.92442	141.98471	146.29218	80.760568	0.0228248
177.67141	162.15155	152.64118	164.15471	81.17572	0.7152342
141.13828	141.98134	144.17164	142.43042	72.034172	-0.064191
206.48338	172.64952	152.33647	177.15646	69.318202	0.4813872
176.66872	175.25824	175.0258	175.65092	70.415167	0.2653052
1291.8057	1243.8676	1227.1364	1254.2699	560.96933	1.9645141
MR2	MG2	MB2	MM2	SD2	Corr2
0.5590586	0.098286	0.5789791	0.4121079	0.2831517	0.1684083
0.321928	0.0842817	0.719597	0.3752689	0.3578204	0.4941908
0.4633799	0.1894235	0.5474295	0.4000776	0.2729258	0.7566413
0.1000563	0.1407784	0.588579	0.2764712	0.3211468	-0.01122
0.0634284	0.2358675	0.6967513	0.3320158	0.3505873	0.2884802
0.4095196	0.1346167	0.5747611	0.3729658	0.3206041	0.1640008
0.2186742	0.2964542	0.8132984	0.4428089	0.3767156	0.6378955
0.3609551	0.0788355	0.7039859	0.3812588	0.3591812	0.4298405
2.4970002	1.2585434	5.2233814	2.992975	2.6421329	2.9282377
MR3	MG3	MB3	ммз	SD3	Corr3
137.90242	130.69436	126.05022	131.549	29.507992	0.0204631
168.21693	127.67439	129.39537	141.76223	38.171007	0.1814327
124.26182	133.45469	125.22239	127.6463	31.104549	0.2752669
142.48505	125.33356	129.71162	132.51008	40.791793	0.0240451
158.31395	121.53885	135.44464	138.43248	42.886907	0.7192594
137.93942	129.07133	127.48266	131.49781	36.184483	-0.061203
170.97741	114.08405	144.32195	143.1278	40.61997	0.5300772
166.85809	127.70632	128.66042	141.07494	39.596374	0.2276081
1206.9551	1009.5575	1046.2893	1087.6006	298.86307	1.9169496

Fig 8: Data set of Fake currency of Bhutan

Here, mean of each values are shown in Figure 7 and 8 MR1,MG1,MB1,MM1 SD1 and Corr1 (Mean Red, Mean Green, Mean Blue, Mean of Mean RGB, Standard Deviation and Correlation of RGB Image) have calculated for the processing of image on Bhutan currency. Same way calculated this for YCbCr and HSV image also.

6. CONCLUSION

In this Research, on bank note identification and detection technique using deep learning is considered. Also focused Bank note of various countries by extracting its features in depth and analyze it using deep learning based algorithm and also recommend that this technique can be used to detect forged bank note by persons to avoid personal monetary damages.

Proposed method is tested by giving duplicate as well as original note as input. through this results are tested for both the cases i.e. front view and back view and it properly works. Proposed system used MATLAB tool on the basis deep learning process of automatic recognition of fake and genuine Indian and Foreign currencies. Proposed system is cost effective and efficient system than the existing one.

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