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DEEP LEARNING TECHNIQUES FOR THE CATEGORY OF INDIAN CURRENCY

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Abstract

The use of machines has replaced human labor in almost every industry due to technological advancements and development. Several areas of banking and automated sales systems may benefit from currency paper recognition. Accurately identifying paper currency notes is a must in today's age of automated current repeating systems. Unfortunately, as currency notes get worn and damaged, machines typically struggle to detect and recognize them in circulation. Predicting and analyzing real money notes is challenging for visually impaired persons without any technical help or aid. With the use of these models, the identification accuracy of currency notes has been improved and strengthened throughout time. All of our research techniques are up to par and producing the expected results. This study offers an analysis of the Indian paper currency and suggests a model that may identify the currencies with more accuracy. With the help of CNN model technique's Deep Learning approach, currency identification analysis has become more accurate, faster, and more efficient. What's more, the method is fully automated, requires no human participation, and is minimally difficult. This article outlines a two-pronged approach: first, using Keras to train a DL model; second, using Heroku to host a Flask-based web app. For the purpose of distinguishing between various denominations, our suggested algorithm design and experimentally based findings are helpful for those who are visually impaired.

Index Terms—Currency Prediction, Currency Analysis, Deep Learning, Keras, Convolution Neural Network (CNN), Heroku

INTRODUCTION

Seeing and confirming currency, especially banknotes, relied only on visual inspection in the

past. Our visual field is limited, and even without special technology, it's easy for humans to distinguish between certified currency and counterfeit. The increasing sophistication of counterfeiting technology makes it more difficult to distinguish between counterfeit and genuine currency, even if UV-based recognition technology is currently in use [17]. Lovely Professional University of Computer Science and Engineering in Delhi, India Pavan Reddy at Gmail Our system's primary goal is to help regular people identify different types of currencies with fast, reliable answers. With our model tuned to identify unique properties of Indian cash, we can identify counterfeit notes with ease. On a larger scale, our contribution to the new development era is an evaluation of the major feasibility of various deep learning techniques. We also hosted a flask web on heroku to recognize different currency notes using conventional machine learning strategies. Novel identification procedures are now being developed by examining special security facts of the much-planned money, thanks to the enhancement of image handling strategies. The trend is towards data-driven processes in particular. This demonstrates the need for more readily available information. This is how money acknowledgment methods use data growth via the use of techniques like image enhancement, shading analysis, and similar approaches. All throughout the globe, people are using different kinds of money, and those different kinds of money seem to have different features. Consider factors such as paper size, discernible proof impressions, color, design, and a plethora of others. Workers at places like cash trading offices have it especially tough when it comes to the task of distinguishing between the different monetary standards. It is a laborious task that may lead to incorrect identification if the pictures for each of the money kinds are not recognized. Furthermore, due to developments in image technology for filtering and printing, counterfeit banknotes are now easier to create and almost impossible to detect. Consequently, a highly effective and exact automated system for

recognizing the provided funds is very necessary. In order to recognize paper currency, all of the visible features play an important role. The most optimal way, according to previous studies, is to recognise a note and identify its recognizable components. Part Two.

RELATEDWORKS

Recognizing counterfeit cash is the long-term goal of currency recognition systems. When picking between currencies that are based on reality and those that are based on sham, security-based currency features are the real deal. Watermarks, sleep-based images, security-oriented thread, and optically suggested changeable ink were the basic security-oriented highlights. In the past, many have looked to deep learning networks for help with paper currency classification and identification, but few have succeeded beyond utilizing image processing methodologies and OpenCV based techniques to solve the fundamental functionality problem of currency recognition. In prior studies and research, such as Bag of Desirable Words, Histogram diagrammatic view of Oriented Gradients, Color based Comparison with delta-E metric method, and Template Based Matching, the overall accuracy was 100%. Additionally, it employed additional parameters for central numeral detection, which yielded an accuracy of 97.2%, TP rate of 95.11%, and FP rate of 0.097% [2]. Aids for the visually impaired and the blind allow these persons to live more independently and with greater quality of life. Using DTC and KNN to fine-tune the model, another group of researchers—N. A. Jasmin Sufri, N. A. Rahmad, M. A. As'ari, N. A. Zakaria, M. N. Jamaludin, L. H. Ismail, and N. H. Mah mood—achieved a 99.7 percent accuracy rate when classifying Malaysian ringgit banknotes [6]. A SURF-implied method for robust and efficient component-based banknote recognition systems Characteristics that allow for the formalization of banknote images in order to identify points of interest and which might be helpful in the matching process between descriptors and references based on banknote photographs [1]. The suggested system for recognizing denomination notes in Indian currency uses a number of machine learning techniques, including a deep learning approach, to select the most interactive and prominent features based on the distribution of the currency in numerical form, the national emblem, the identification mark, and the

main color band. When sorting databases using three different region-based regions, SVM and BC both provide efficient, desirable, and static-based performance (99.7 percent) compared to KNN technique and DTC [6]. Though it failed miserably when presented with a fresh database with a contrasting orientation, Alexnet achieved perfect accuracy when presented with a database based on the same orientation. Previous research on sensor-based architectural systems has relied on a wide variety of electrically-based components, and the anticipated outcomes have not been experimentally correct, all because of the limitations of sensor utilization. Using picture size and orientation analysis, our system builds currency classifiers, which are then released online using the Heroku API.



Fig. 1. Dataset additional with the model hosted and gives a better accuracy of 99.07%.

PROPOSED METHODOLOGY

For this study to be carried out as planned, the CNN-equipped model must be used. In order to accomplish the objective of Indian paper money. The purpose of data augmentation is to provide the relevant inferred model with more accurate data points. The

Convolutional Neural Network (CNN) technique is an improved algorithm for image classification that uses Deep Learning. It grasps the distinctive shape of images, assigns weights and biases the nature to different parts of the image representation, and helps identify photos among a multitude of diverse photographs.

SUMMARY OF THE DATASET

Images of Indian currency notes (in seven different categories) totaling 377 were culled from Google Images and Shutterstock Photo & Video. For example, in order to identify the kind of Indian note in a photo or for usage in real-time applications, the model is trained to estimate what proportion of images correspond to each class. The photographs in this dataset, which serves as a data set for image classification, do not adhere to a certain resolution; rather, they may display varying aspect ratios representing seven various varieties of Indian currency notes. As a means to improve the outcome, we have decided to use actual currency as our data source. That is, ten, twenty, fifty, hundred, two, hundred, five hundred, and two thousand rupee notes are all recognized as denominations of money in India. For more accurate forecasts, make sure the money is shot in well-lit settings, both front and rear.

A. DATA GROUPING 1) The dataset is divided into three parts: the training set, the testing set, and the validation set. However, the methods used by deep learning seem to be insufficient with this large quantity of data. To combat overfitting, we have used data augmentation on the original data and created new data using this method; however, this isn't enough to achieve better robust training-based results, as our expanded examples are still very similar. 2) The most entropic constraint of our model-based system as the amount of data it is allowed to store should be the primary focus for countering overfitting. The use of more provisions might make a data-depot model more accurate, but it also increases the likelihood that it will start storing aspects that aren't relevant to the problem at hand. In the meantime, a model with limited feature storage should focus on the most important provisions in the data; they should be based on processes that are more likely to be actually significant and on theories that are better formulated. 3) For this, we have developed a five-step process that incorporates random orientation for clipping or enlarging, arbitrary

rotation, and random fitted color-based correction, as well as dashing to uniform size. As with data-based augmentation, dropout starts with reducing overfitting by preventing a fine-tuned layer from monitoring twice the identical real-similar patterns.

Section C.: Return on Investment Abstract Our model technique makes use of Convolutional Neural Networks (CNNs):

- When compared to other image-oriented classification methods, CNN makes very less use of computation-based pre-processing functions. One notable advantage of using CNN in feature-based inferred design is that it is not limited by prior-based focus knowledge or reduced human effort. We do a number of activities in our study sector, including:
- detecting borders, isolating the ROI, calculating, and detecting color characteristics. We additionally track the aspect ratio of all the money denominations depending on that theme's unique boundaries, as well as the primary equipped target image's aspect ratio, which remains constant regardless of lighting conditions.

Section D: The Methodology of the Suggested Algorithm: A Step-by-Step Guide to the CNN Method:

- The numerical values of Indian currency notes are considered for application at the advanced system-oriented training level.

Taking into consideration the convolutional implied layer that is created and produced as a result, the optimal graded based filters and feature equipped maps are applied to every single picture.

- To ensure that the model's integrated based images are linear, the Rectifier tuned function is used.
- The unification procedural step receives the generated spark images at this stage, and it provides the'spatial oriented invariance' resources to this specific CNN model, which in turn produces the collective based feature map.
- To prevent several incoming neurons from converging for the same indicated weights, a defined-based suitable Dropout layer is applied.
- Doing the same thing twice more depending on that
- The characteristics are mapped collectively before being input into the corresponding neural network based model.
- To increase the speeding implied time, the Dense based layer is introduced at the final procedural step.

function provided by the RELU layer, which is based on non-saturation.

$$(z) = \max(0, z). \quad (2)$$

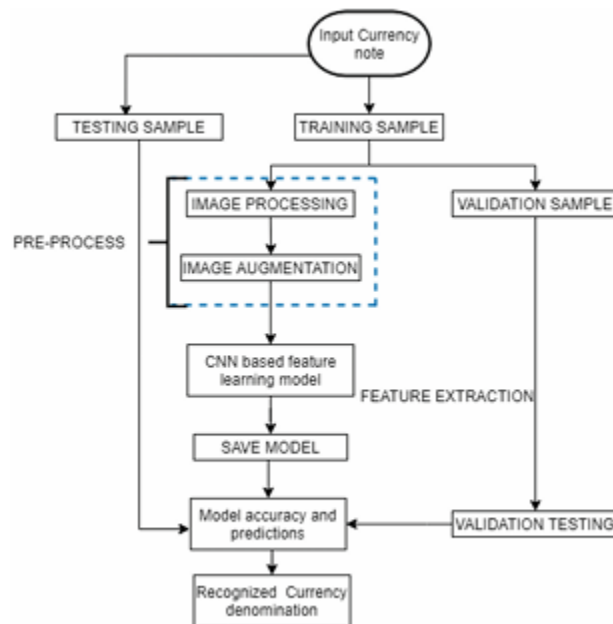


Fig. 2. Flowchart of proposed architecture

An input-driven layer, an output-driven layer, and a multitude of hidden-based layers are all components of a CNN-based model's multi-layered functionality. In most cases, a series of convolutional-driven layers comprises the hidden-based layers. a) DETAILS OF THE CONVOLUTIONARY LAYER-BASED MODEL APPROACH: • This layer handles the incoming data and sends its output to the layer below it that handles the exiting data. In the first section of the main Convolutional Based Layer, the core kernel is responsible for performing the convolution based root operation. In order to keep tabs on low-level sharp-oriented features including color implication, orientation, and edges, the primary first-handed convolutional layer is responsible.

$$\text{conv}(A, B)x, y = \sum_{i=1}^{n_p} \sum_{j=1}^{n_q} \sum_{k=1}^{n_R} B_{i,j,k} A_{x+i-1, y+j-1, k} \quad (1)$$

High-Level Versatile Leveraging Features: The entire architecture of the intended system is regulated to the features with a high grasp of photos and pictures in the specific dataset by adding more convolutional based layers. What follows is an activation-triggered

By leveraging the corresponding negative records and values down to a specific base value of 0, this basic layer aids in retrieving them from the activation-oriented featured map. It then analyses the incremental ratio of the non-linear based resources and properties of the comprehensive based network matrix of the core convolution layer, taking into consideration the basic layered decision function. • A layer for pooling: This foundational layer reduces the complexity of the data matrix by combining the results of the neuron-based clusters matrix in one layer with the one objected neuron in the aligned layer below it. In order to smooth out the initial computations, convolutional oriented networks may take in pooling sharp layers that are either universally or locally based. In local object pooling, tiny lined groups—usually 2*2 in size—are integrated, and then all the universal neurons' analysis functions of the convolutional layer matrices are applied downstream. Furthermore, by using the functions of average or maximum basic cost, respectively, followed by every neuron that is cluster minimized at the edge preceding layer, fusing may correspondingly provide an average or central max.

$$(n_p - f + 1)/sX(n_q - f + 1)/sXn_r \quad (3)$$

- > n_p - height of feature map
- > n_q - width of feature map
- > n_r - number of channels in the feature map
- > f - size of filter

The structure's size is around 2*2, making it acceptable in bulk situations, according to the maxpooling orientate shape. However, without a doubt, the massive input volumes would need a 4*4 matrix or larger merging at the lowest level layers. In addition, picking the enormous, massively based forms would likely drastically reduce the lead signal's direction of dimension, leading to substantial data edge loss. The most effective performance-based pooling windows are those that do not overlap. Firstly, the elemental resultant matrix is leveled into the basic desired layout of the deep vector shaped configuration. Then, it is moved to this engraved layer, which is analogous to a series of neural networks. This process is called the fully

dimensionally connected base layer. The corrected vector (x1, x2,...) will sit atop the sharp feature cross map based matrix in the figure given above. We combined all of the basic characteristics into a model using the idea of completely ordered linked derived oriented layers. Classify and differentiate the outputs at the end by using the activation lower function.

$$\dim(\text{image}) = (n_P, n_Q, n_R) \quad (4)$$

where: n_P = size of height
 n_Q = size of width
 n_R = number of channels used in convolution layer

$$\dim(\text{filter}) = (f, f, n_R)$$

$$\dim(\text{conv}(N, M, O)) = \left(\left\lfloor \frac{n_P + 2p - f}{s} + 1 \right\rfloor, \left\lfloor \frac{n_Q + 2p - f}{s} + 1 \right\rfloor \right); s$$

$$0 = (n_P + 2p - f, n_Q + 2p - f); s = 0$$

Where $\lfloor X \rfloor$ is the floor function of X .

RESULTS

Improved predictions and protection against overfitting are the results of fine-tuning the model using validation accuracy and losses as metrics. The procedures performed before to and subsequent to generalizing the various dataset characteristics are shown by the loss function graph in the subfigure. After 20 iterations on the testing dataset, this approach-based model yields a validation-oriented accuracy ranging from 0.87 to 0.94 and a validation loss of 0.09. Once the optimal parameters for the CNN model were identified, the model underwent fine-tuning, and after a few rounds, it achieved a testing dataset accuracy of 99.16%. Consequently, 99.1428% was the ideal accuracy for the hidden data. Below is the confusion matrix that shows how well the model performed while using an approach based on all potential entities in both the horizontal and vertical dimensions. The projected matrix entities' outcomes are emphasized by the columns-based architectural model, while the real variables' entities are provided by the basic rows. All characteristics along the leading-based diagonal (the one that

TABLE I EXPERIMENTAL RESULTS

Epochs	loss	accuracy	val_loss	val_accuracy
0	0.062005	0.975	0.376469	0.875886
1	0.179403	0.930556	0.700707	0.812057
2	0.518005	0.858333	0.289787	0.914894
3	0.052366	0.980556	0.099415	0.960993
4	0.063533	0.986111	0.23844	0.911348
5	0.11448	0.958333	0.758479	0.783688
6	0.665984	0.808333	0.529858	0.808511
7	0.116055	0.952778	0.222358	0.943262
8	0.041547	0.994444	0.103608	0.957447
9	0.041602	0.986111	0.125209	0.946809
10	0.023229	0.991667	0.124574	0.946809

The proper projected elemental categorization for every type of corresponding Indian banknote denominations (INR10/-,20/-,50/-,100/-,500/-, 2000/-) begins from the position on the top left matrix and travels down to the position on the bottom right.

		True Classes						
		10	20	50	100	200	500	2000
Predicted Classes	10	49	0	0	1	0	0	0
	20	0	49	0	0	1	0	0
	50	0	0	50	0	0	0	0
	100	1	0	0	49	0	0	0
	200	0	0	0	0	50	0	0
	500	0	0	0	0	0	50	0
	2000	0	0	0	0	0	0	50

Fig. 3. Confusion Matrix

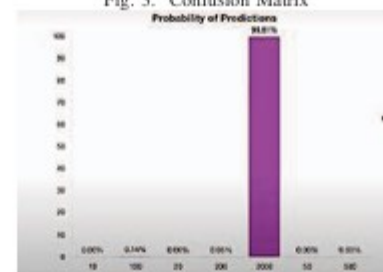


Fig.4. Predictedclass

Through a series of previous proposed models

Our suggested technique provides better and more promising outcomes while reducing overall time in this sector, which works on several deep learning models such as densenet, imagenet, resnet, VGG16 [4], and others. This is due to the fact that these models reach a saturation point beyond which further improvement is impossible. In addition, these architectures may provide incorrect predictions due to

the decay of denominations, leading to an increase in false positives. The solution to this problem is quite simple: at the activation layer, which classifies the image data, it is compared with the training dataset, and the similarity index is represented as a bar graph. With this extra parameter, the model is able to identify the picture more accurately and make more trustworthy predictions, which in turn enhances the likelihood

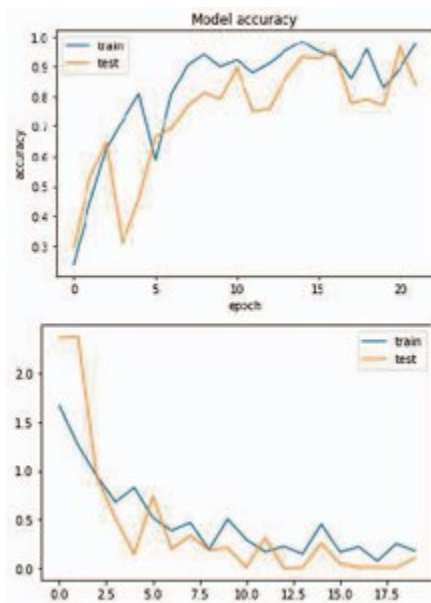


Fig.5.
AccuracyvsEpoch&LossvsEpochbeforeparamete
roptimisation

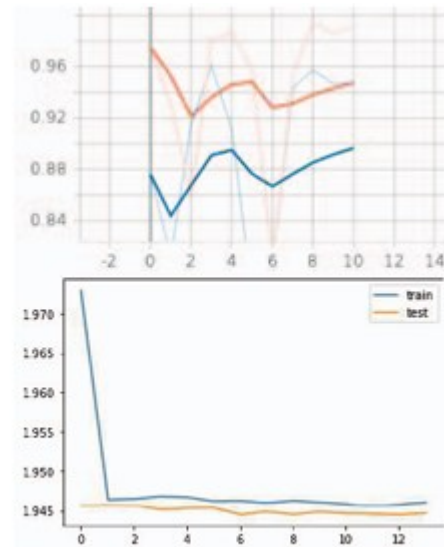


Fig.6.
AccuracyvsEpoch&LossvsEpochafterparamete
roptimisation
offindinggoldcounterfeitchurrencywhichmaycircul
atewithin themarkets.

CONCLUSION

This study is built on an architectural algorithm design and uses a vision-based technique to identify and categorize various features of Indian cash, such as fresh notes, old notes with wrinkles, and so on. In order to maximise the impact of our experiments, we trained a convolutional neural network (CNN) model.

TABLEII COMPARATIVEANALYSIS

Ref. No.	Currency origin	Methodology of feature matrix recognition used	Accuracy obtained
[10]	Thai land	backpropagation neural network and Correlation based mapping	99
[11]	China	Three layer BPNN	92-98
[12]	India	Visual bag of words	96.7
[13]	Multiple currencies	Image histogram for color and markov chain for analysis of texture	95
[14]	India	PCA based validation by WEKA classifier	100
[15]	USA	PCA based Eigen faces	99.8
[16]	USA	Feature extraction using PCA and recognition through K-Means	99.994
[2]	India	Bag of words , Histograms Of Oriented Gradients,Color Comparison using Delta-E metric	92-100
Ours	India	Our Approach	97-99.4

precise by extracting characteristics from the picture collection layer by layer. The training accuracy on the data is found to be 99.86%, while the testing accuracy is 99.14%. Which, when compared to earlier efforts, yields ideal outcomes from time-consuming techniques like denseneural networks, ANN VGG16, VGG19, etc., where the scope of progress becomes inactive after certain iterations when the models saturate. Our team has decided to construct and host the model on Heroku as a Flask web app. The user has the option to either choose an image from their device or take a picture using the built-in camera. Amazon S3 Bucket stores the submitted images for prediction purposes. On the back end, we used sentry to capture the exception and CSRF token to safeguard against CSRF attacks. A bar chart with a similarity index is used to illustrate the predictions when the picture is uploaded.



Fig.7. Working Model

FUTURESCOPE

Improving the architecture's main metrics, discovering outliers in the model, keeping up with the newest technologies used to make false notes, and increasing the model's learning potential for improved prediction all need significant volumes of datasets comprising both new varieties of fake and legitimate banknotes.

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