Fake Currency Identification Using CNN

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ABSTRACT

The livelihood of the populace and the nation's economy are now seriously threatened by counterfeiting of money. Although there are fake cash detectors, and are only used in banks and corporate offices, leaving the general public and small companies at risk. In order to detect and invalidate fraudulent Indian currency,will develop a software-based system in this project using cutting-edge image processing and computer vision techniques. First,will analyse the many security characteristics of Indian currency. This currency authentication system was created entirely in the Jupyter Notebook environment using the Python programming language. With the help of a real-time photograph, our project will identify Indian banknotes. The history of our issue is the use of image processing technologies to check the legitimacy of money notes. The software analyses note properties to identify counterfeit money. Accuracy and speed are two metrics that can be used to assess this software's success rate.

***Keywords*— Currency authentication, Replicating currencies**

I. INTRODUCTION

Reproducing money refers to the illicit production of real money, therefore counterfeit money is fictitious money that has not been approved by the government. The RBI is the only organisation in India with exclusive authority to print banknotes. Once filtered and spread throughout the market, counterfeit currency notes pose a concern for RBI every year.

A major issue that every nation is dealing with is the illegal creation of counterfeit money notes by duplicating the real manufacturing process. As a result of an unintentional and artificial increase in the money supply, counterfeit cash can lo r the value of real money and lead to inflation. A workaround involves manually authenticating cash notes, ho ver this is a time-consuming, incorrect, and challenging operation. In this research, suggest an algorithm and image processing method for detecting phoney money notes.

The suggested technology is intended to verify 500- and 2000-rupee Indian currency notes. The system verifies the legitimacy of numerous aspects on a currency note using three major algorithms. The first approach incorporates complex image processing techniques like ORB and SSIM and includes numerous processes such as picture acquisition, pre-processing, greyscale conversion, feature extraction, image segmentation, and comparisons of the input and output. While the third algorithm verifies the currency notes' number panel, the second algorithm verifies the bleed lines on the notes. Finally, each currency note's processed output is shown. This device offers a hassle-free method for swiftly and reliably authenticating banknotes.

II. Literature Survey

In this work, a technique for automatically determining if an Indian rupee note is phoney or authentic is developed. In the financial system and other industries, the automatic system is also very helpful. There are more counterfeit 100, 500, and 1000 rupee notes in India. The counterfeit problem is getting worse as technology advances such as scanning, colour printing, and duplication. In this model, picture pre-processing is applied to the image after image acquisition. Prior to conversion, a picture is cropped, adjusted, and smoothed before being segmented, extracted of features, and reduced before being eventually compared.

In this study, feature extraction with HSV colour space and other image processing applications are used to build an automatic recognition of fraudulent Indian paper money notes using MATLAB. Image Acquisition, Gray-Scale Conversion, Edge Detection, Image Segmentation, Characteristic Extraction, Comparison, and Output make up the suggested design. A note is placed in front of the camera as part of the project setup to determine whether it is real or phoney. The computer's MATLAB programme analyses the screenshots of the notes that re taken.

A hybrid fake cash detection model was put out and put into practise using MATLAB in this paper. The model was created to identify counterfeit Bangladeshi currency. To achieve better outcomes, three image processing algorithms—Optical Character Recognition (OCR), Hough Transformation, and Face Recognition (MSD)— re used for the suggested model. The outcomes of each model utilised re then contrasted with those of the suggested model. Data collection, pre-processing of the collected data, edge detection, feature extraction, identification, and output findings re the algorithm's six fundamental processes.

III. System Design

System design thought as the application of theory of the systems for the development of the project. System design defines the architecture, data flow, use case, class, sequence and activity diagrams of the project development.

A. *System Architecture*

The below architecture diagram in figure 2 illustrates how the system is built and is the basic construction of the software7method. Creations of such structures and documentation of these structures is the main responsible of software architecture.

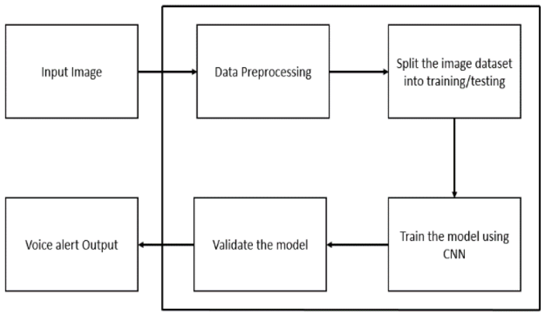

Fig. 1 Architecture Diagram of Proposed System

Our significance in this system proposal focuses on the identification of bogus currency that is pervasive in the Indian market. In our approach, counterfeit currency is found by removing the security thread component from the currency note. The most widely used deep neural network technique, transfer learning with Alex net, is used to detect counterfeit money. Convolutions, max pooling, dropout, ReLU activations, and fully connected layers make up Alex net. The layers are shown in figure 1 below. The final three levels of transfer learning are fine-tuned to meet the needs of our proposed job. For precise latent feature extraction from the image, the 'fc8' layer is t aked with a ight learning factor and bias learning factor. The ight gives the impact of the input on the network and bias is used to adjust the output with ighted sum of inputs to the neuron. The accuracy of learning feature grows with the ight and bias learning factor.

Below are our Project Design Modules:

Data Preprocessing

Here are seven significant steps in data pre-processing in Machine Learning:

1. Acquire the dataset
2. Import all the crucial libraries.
3. Import the dataset.
4. Identifying and handling the missing values.
5. Encoding the categorical data.
6. Splitting the dataset
7. Feature scaling.

Below are data pre-processing steps to be taken for Image Dataset:

1. Read image.
2. Resize image.
3. Remove noise (Denoise)
4. Segmentation.
5. Morphology (smoothing edges)

Splitting Dataset into Training & testing Dataset

The train-test split procedure is used to estimate the performance of machine learning algorithms when used to make predictions on data not used to train the model.

It is a fast and easy procedure to perform, the results of which allow to compare the performance of machine learning algorithms for the predictive modelling problem. Although simple to use and interpret, there are times when the procedure should not be used, such as when the model have a small dataset and situations where additional configuration is required, such as when it is used for classification and the dataset is not balanced.

The train-test split is a technique for evaluating the performance of a machine learning algorithm. It can be used for classification or regression problems and can be used for any supervised learning algorithm.

The procedure involves taking a dataset and dividing it into two subsets. The first subset is used to fit the model and is referred to as the training dataset. The second subset is not used to train the model; instead, the input element of the dataset is provided to the model, then predictions are made and compared to the expected values. This second dataset is referred to as the test dataset.

- Train Dataset: Used to fit the machine learning model.
- Test Dataset: Used to evaluate the fit machine learning model.

The objective is to estimate the performance of the machine learning model on new data: data not used to train the model.

This is how expect to use the model in practice. Namely, to fit it on available data with known inputs and outputs, then make predictions on new examples in the future where do not have the expected output or target values.

The train-test procedure is appropriate when there is a sufficiently large dataset available.

The idea of "sufficiently large" is specific to each predictive modelling problem. It means that there is enough data to split the dataset into train and test datasets and each of the train and test datasets are suitable representations of the problem domain. This requires that the original dataset is also a suitable representation of the problem domain.

A suitable representation of the problem domain means that there are enough records to cover all common cases and most uncommon cases in the domain. This might mean combinations of input variables observed in practice. It might require thousands, hundreds of thousands, or millions of examples.

Conversely, the train-test procedure is not appropriate when the dataset available is small. The reason is that when the dataset is split into train and test sets, there will not be enough data in the training dataset for the model to learn an effective mapping of inputs to outputs. There will also not be enough data in the test set to effectively evaluate the model performance. The estimated performance could be overly optimistic (good) or overly pessimistic (bad).

If the project have insufficient data, then a suitable alternate model evaluation procedure would be the k-fold cross-validation procedure. In addition to dataset size, another reason to use the train-test split evaluation procedure is

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computational efficiency.

Some models are very costly to train, and in that case, repeated evaluation used in other procedures is intractable. An example might be deep neural network models. In this case, the train-test procedure is commonly used.

Alternately, a project may have an efficient model and a vast dataset, although may require an estimate of model performance quickly. Again, the train-test split procedure is approached in this situation.

Samples from the original training dataset are split into the two subsets using random selection. This is to ensure that the train and test datasets are representative of the original dataset.

IV. RESULTS

Fig. 8 Result predicted as Fake currency for uploaded Image

Fig. 9 Result predicted as Real currency for uploading Image

V. CONCLUSION

In this paper transfer, Alex net served as our learning tool for choosing a model for detecting counterfeit money. Since the monetary distinctive attributes are gradually learned, the detection accuracy is at its highest. Here, the entire money picture has been taken into account, but in the future, 'll work to incorporate all of the security characteristics of cash by using appropriate structural design and training data. The acquired image may also contain noise, which must be taken into account as part of the pre-processing step in the currency detection process. By taking into account the surface patterns of the cash as features for enhancing the detection accuracy, the recognition and fake currency detection can also be expanded.

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