Identification of Fake Indian Currency using Convolutional Neural Network

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Abstract

The development of shading printing technology has increased the frequency of large-scale note counterfeiting. Because of their reliability and ease of use, banknotes are still in circulation even if electronic currency transactions are growing in popularity and the use of paper money has been declining recently. A few years ago, printing could only be done at a printing business, but today, anyone can use a simple laser printer to print money paper with the highest level of accuracy. This has led to a general increase in the problem of counterfeit currencies instead of genuine ones. India has exposed issues such as the defacement of counterfeit currency and black cash, which is also a significant problem. A deep learning-based framework is suggested as a solution to this issue.

Keywords: - Fake Indian dataset, deep learning,

1. INTRODUCTION

Globally, counterfeit money is a serious problem that affects many nations' economies. Therefore, the government disapproves of counterfeit money. Only banks are authorized to create currency in India by the Reserve Bank of India. Since many Indians work on a daily basis, workers, farmers, and those without formal education are all affected by counterfeit money. They can't tell the counterfeit money apart. As image processing techniques advanced, researchers suggested a variety of solutions to address these issues. algorithms for image processing, including currency categorization, counterfeit detection, denomination identification, and recognition. These are utilized in automated transactions, vending machines, and counting devices. However, identifying and categorizing counterfeit goods is

2. RELATED WORK

Numerous research studies address the detection of counterfeit currency using the feature extraction method. According to J. Lee et al. [1], banknote acknowledgment is an interaction stage that describes the information banknote's category, bearing, and side. The situation of a district of revenue inside a banknote, which is used to carry out the following cycle (chronic number acknowledgment, fake banknote identification, and wellness grouping), changes as indicated by the banknote's course and side, according to the justification ordering bearing and side notwithstanding section. D. Galeana Pérez and associates [2] In addition to being a very time-consuming and confusing task, manually verifying notes in exchanges has a risk of tearing while handling the notes. Consequently, programmable

Problem Statement

Globally, counterfeit money is a serious problem that affects many nations' economies. Therefore, the government disapproves of counterfeit money. The Reserve Bank of India is the only bank authorized to create currency in India. Since a large number of people in India labor every day, workers, farmers, and the ignorant are all affected by counterfeit money. They can't tell the counterfeit money apart. With the advancement of image processing techniques, researchers presented a number of strategies to address these issues. algorithms for image processing, including currency categorization, counterfeit detection, denomination identification, and recognition. These are utilized in automated transactions, vending machines, and counting devices. However, identifying and classifying counterfeit goods is a difficult task in many

3. IMPLEMENTATION

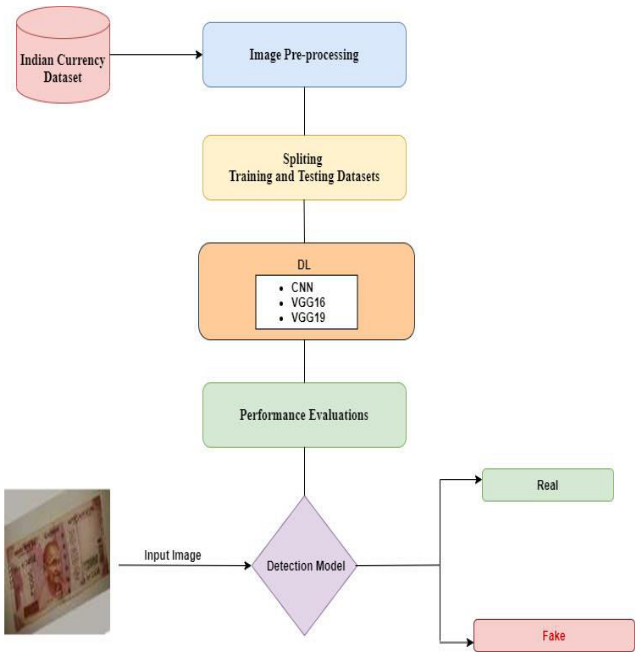

Fig: - 1 System Architecture

1) Data Pre-processing

To make sure the fake currency picture dataset is appropriate for deep learning model training, this module manages its preparation. The actions consist of:

• Reading the dataset: Pictures are taken from the directory that has data that has been tagged (such as real versus fake).

• Image resizing: To ensure uniformity, all images are downsized to a standard size (such as 128x128 or 224x224).

• Converting to array format: To enable deep learning models to use images, they are transformed into NumPy arrays.

• Label encoding: Label encoders convert text-based class labels, such as "real" and "fake," into a numeric format.

• Data splitting: To facilitate model training and evaluation, the dataset is separated into training and testing subsets.

2)Model Training

Using the pre-processed data, this module is in charge of training and assessing deep learning models. Important jobs consist of:

• Model training: The training data is used to train a CNN or other deep learning architecture. Metrics, including accuracy, loss, are used to evaluate the model's performance.

• Model saving: For future use in prediction, the trained model is saved in.h5 or a comparable format.

• Label encoder saving: For decoding predictions, the label encoder that was utilized for preprocessing is also saved.

3)DL Evaluations

In order to better comprehend the usefulness of the trained model, this module uses graphical charts to show its performance. It consists of:

• Plotting accuracy and loss curves: Matplotlib is used to plot training and validation accuracy/loss in order to identify patterns and identify overfitting or underfitting.

• Confusion matrix: To illustrate how well the model classifies each class, a visual confusion matrix can be shown.

4)Detection

Real-time prediction on fresh or unknown photos is done with this module. It consists of:

• Picture selection: A user chooses a picture to be analyzed.

• Image preprocessing: Similar to training, the chosen image is scaled and transformed into an array.

• Model prediction: The image's class is predicted using the deep learning model that has been developed.

• Label decoding: Using the label encoder that was saved, the numeric prediction is transformed back into a legible label (such as "real" or "fake").

• Presenting the result: The user is presented with the outcome, potentially accompanied by the confidence score.

Algorithms Used:

CNN, VGG16, VGG19

Dataset

We gathered this dataset from the Kaggle website, and this has two classes they are 1)real and 2)fake

Real

Fig: - 2 Dataset

Fig: - 3 Dataset Fake

Fig: - 4 Dataset Fake

Fig: - 5 Dataset Fake

4. EXPERIMENTAL RESULTS

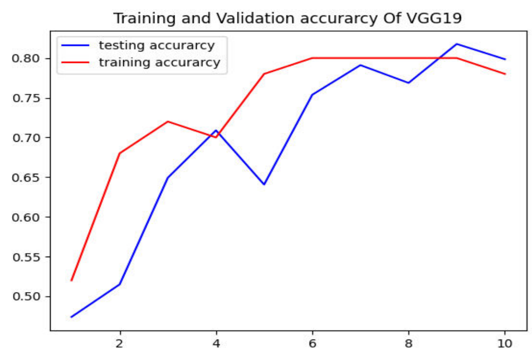

Fig: - 5 Graph-1

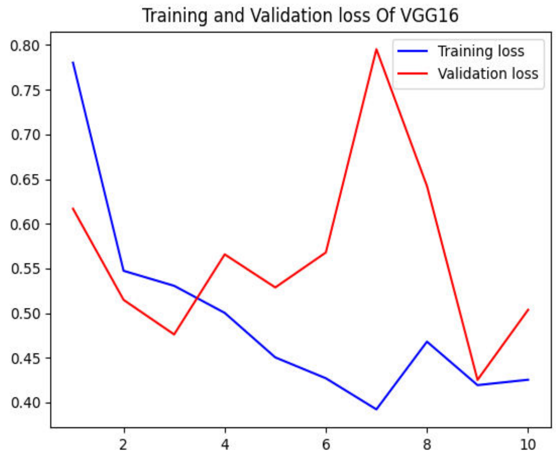

Fig: - 6 Graph -2

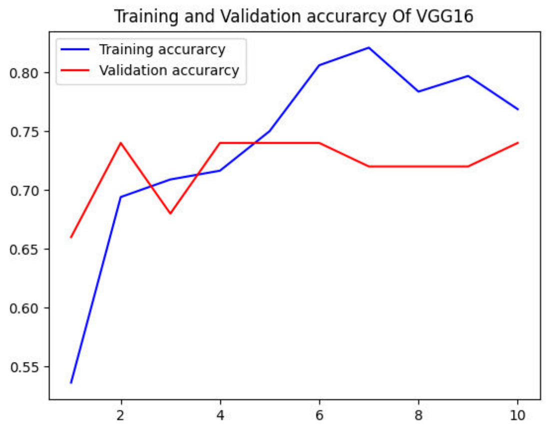

Fig: - 7 Graph -3

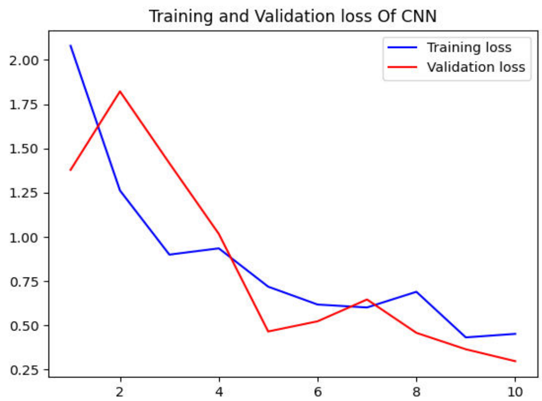

Fig: - 8 Graph -4

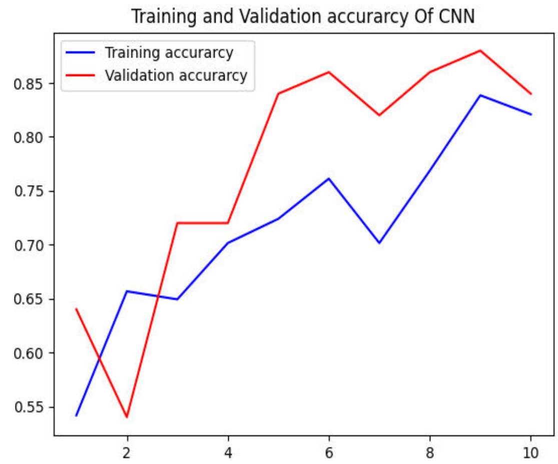

Fig: - 8 Graph -5

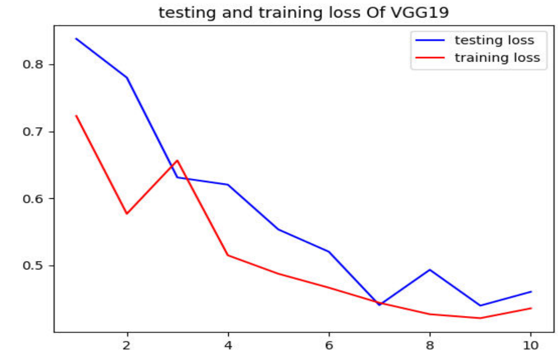

Fig: - 9 Graph -5

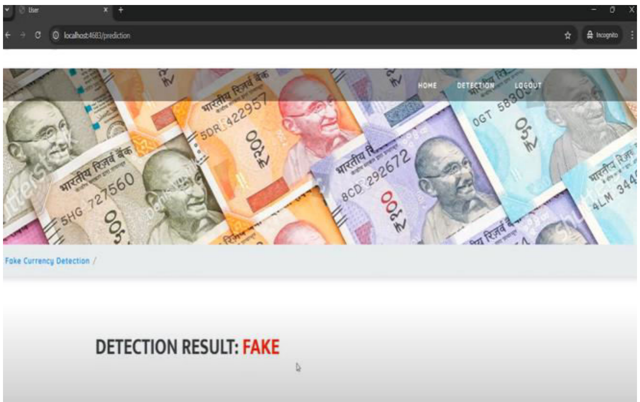

Fig: - 9 Detection

5. CONCLUSION

Day by day, the rate of fake notes in the market is 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 network for detecting 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 the created dataset. The results showed that the four predefined networks are good at one parameter and compromise on the other parameters. To overcome this problem in the future, dataset verification will be done using a novel CNN architecture to obtain better results by considering all parameters.

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