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Indian Currency Recognition System Using Transfer Learning And Extreme Learning Machine

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Abstract

While a typical human being has little trouble perceiving the differences between different banknotes, a person who is blind or has visual impairments would have a much more difficult time performing the same task. Those who are blind and mentally handicapped have a critical need for a system that can detect and identify currency in real time. Money is essential for conducting business, thus its prevalence in daily life is not surprising. An efficient and effective approach for detecting and recognising Indian currency relying on a CNN model is offered for use on mobile devices. Extreme Learning Machines were used in place of fully connected layers of pretrained trained MobileNeV2 to get more resilient result. According to the findings of the tests, the mobile net model-based approach that was recommended shows detection accuracy of 97.80%. This independent system performs its operations in real time.

Keywords: Convolutional Neural Network, MobileNet, Extreme Learning Machine

I. INTRODUCTION

Today, banknote identification is among the most explored and industrial nations in image analysis. Automatic Teller Machine (ATMs), automatic ticket devices, food and drink distributors, and personality kiosks located in banks all require a dependable money recognition system, and the blind community could also benefit from such framework. A reliable banknote identification system may be able to establish both source country and the denominations of a piece of printed currency by analysing a small set of the note's most conspicuous attributes. One of the key characteristics of a currency identification system is how well it can identify individual bills. Such a system must be able to distinguish between brand new banknotes and those that have been shredded or folded, as well as being unaffected by environmental influences such variations in brightness gradient, scaling, or perspective variation.

One specific challenge a blind person might face is knowing the worth of the coin or bill he or she is carrying, highlighting the urgent need to aid visually impaired persons. The size difference between bills helps those with vision impairments tell them apart, but it's not enough to reliably identify a bill's denomination. It's true that they can't tell one denomination of currency from another because of how similar they all look due to the small size differences between successive denominations. A small number of unique identification features are included on banknotes for the sole purpose of facilitating blind people's ability to correctly identify their denomination. The denomination printed on the top right corner of each bill is touch sensitive, however it fades after being in circulation for a while. As a result, it becomes more challenging for the visually challenged to identify the value of a certain banknote. The banking sector places a significant importance on the recognition of different currencies.

II. RELATED WORK

Different researches provide an overview of methods for determining the denomination of currency. In some cases, this is accomplished through the use of image processing and various Deep Learning algorithm models for feature extraction from the image. The use of similarity indexes for the detection of currencies has been proposed. In order to make a comparison between the input remark and also the template picture of the relevant feature, the system calculates a similarity measure between the two sets of attributes. The Jaccard Similarity Index [1] is a useful tool for determining the level of correspondence between two sets of data. The worth of money has been categorised thanks to the work of Mriganka et al. [2]. Specifically, they made use of the Aspect Ratio feature, the Color feature, and the Shape feature (also known as the Identifying mark feature). The first thing they do is bleach the note. The aspect ratio of the currency is then determined by measuring its dimensions. Identifying a marked component is the next step. The "Fourier Descriptor" is then used to determine the identity's profile. mark, the key characteristic, is essential. Following feature extraction, the forms are classified by an Artificial Neural Network, and their corresponding values in various Indian rupees are recognised. The principal component analysis [3] is then used to deal with the imbalanced dataset. The currency's principal components are extracted, and a weight vector is calculated. The Mahalanobis distance is then used to determine the degree of similarity between the weight vectors. The image with the smallest distance measure to a given class is chosen for prediction.

Several image processing techniques has been there [4][5][6] for currency classification. For those who are blind or visually challenged who have trouble distinguishing between different denominations of currency, [7] offers a solution by outputting the information as audio using ORB algorithm. When the database is training across neural network models, ensemble learning has become increasingly popular as a means of addressing computing and prediction challenges in recent years. The speed and precision of these items varies widely. In [8], the Single Shot MultiBox Detector (SSD) architecture was used to automatically extract of cash for the purpose of identifying bills of 3 distinct denominations. Since all of the images in the training and testing sets shared the same background, the augmented dataset contained no new information. A study conducted by CNN focused on the folded banknotes shown in [9], and each of the bills was of the same denomination as the others. [9] developed a method for the automatic recognition of banknotes using computer vision. This method was designed for the benefit of those who have visual impairments and used SURF features in its recognition process. This study makes use of United States banknotes, each of which features a distinct image of the person depicted on the note. This makes it much simpler to differentiate between banknotes from different countries that have the same front note characteristics as those in India. Deep convolutional neural networks trained on the DenseNet-121 architecture classify Turkish lira banknotes [10]. [11] examines Myanmar cash (kyats) in three denominations using image processing. Using Zernike moments for feature extraction and k-nearest neighbour for classification. [12] employs a neural network for visually impaired people. Their findings suggest that greater research on cognitive frameworks and brain processes could lead to better performance in these difficulties. All these methods are not suitable when the notes are old and wrinkle. Also, time consuming in training. In order to overcome this disadvantage, we proposed new method by combining pretrained model and Extreme Learning Machine (ELM).

III. PROPOSED METHOD

In this research, we proposed Extreme Learning Machines (ELMs) integrated with pretrained mobilenetv2 as feature extractor. We design a two-stage technique that combines transfer learning with effective ELMs to get over the difficulty of manual feature extraction and the length of training time. The first step is to train a MobilNet V2 that will be utilised as a feature extractor after it has been pretrained. ELMs are used at the second stage for accurate categorization. In contrast to other types of neural networks, ELMs have a unique structure. Proposed method is shown in Fig. 1

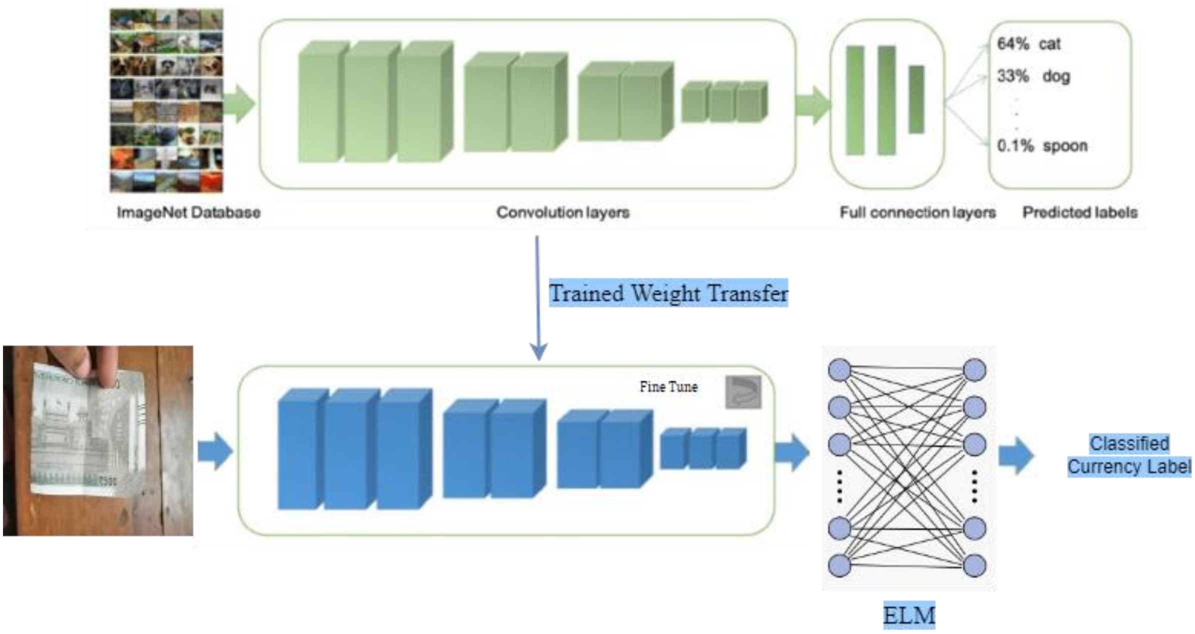

Fig 1: Proposed Method

Pretrained MobilenetV2

The problem of insufficient data can be mitigated by transfer learning. As a result, artificial intelligence (AI) projects that lack sufficient data or computer power have gradually adopted transfer learning as their preferred technology. In the domain of machine learning, neural networks are being relied on more and more for transfer learning. Transfer learning is a strategy for addressing the issues of insufficient labelled sample data and high training costs in image recognition. The term "pre-training model" refers to a model that has already been trained on massive datasets. These network layers can reprocess feature vectors and be used to train networks on smaller datasets with the same set of network parameters. Consequently, training expenses are decreased and resource utilisation is enhanced.

MobileNetV2, like its predecessor, MobileNetV1, is a compact and effective convolutional neural network. Based on MobileNetV1, MobileNetV2 suggests a reversed residue block. First, the high-dimensional features are down-sampled using a 1x1 convolution kernel; then, filtering is performed using a 3x3 convolution kernel; finally, a 1x1 permutation element is used to enhance the aspects, and rectified linears units (ReLU) are incorporated into these fully convolutional; and finally, the output attributes are introduced (the insight of the next layer) in an element manner. To reduce the dimensionality of features, the inverted residual block method uses a 1x1 convolution kernel to first raise the dimensionality of low-dimensional characteristics (other than ReLU). Instead of using ReLU, mobileNetV2 uses a linear bottleneck to keep features unaltered. The upgrades are meant to reduce the likelihood of data loss and increase the model's sensitivity to input. Using the ImageNet datasets, MobileNetV2 is pretrained and its settings are tweaked.

Extreme Leaning Machine

The Single Layer Feedforward Network is trained with an algorithm called ELM. During the training of most neural networks, the weights of the parameters are modified via a process called backpropagation; however, this is unnecessary for training ELMs. An ELM learn by making two independent but sequential adjustments to its weights. Least-squares fitting and random-feature mappings are the two phases involved. The input and hidden layer weights are initially determined by a random number generator. After the initial stage, backpropagation is unnecessary because a linear regression optimization is performed in the second stage. ELM is different from other learning algorithms because it maps the features that are given as input into a random space and then learns in that stage.

Weights between the input and the hidden nodes $(w_i, c_i)_{i=1}^{n}$ are initialised at random in ELMs. Afterwards, regularised linear least square is used to fine-tune the parameters of the layer that lies between the hidden and the output. $\varphi(x_j)$ to represent the response vector from the hidden layer to the input x_j, and let C represent the output parameter that connects the hidden layer and the output layer. ELM aims to reduce the following sum of the squared losses as much as possible.

$$\frac{D}{2}\sum_{j=1}^{n}\left\|x_j\right\|_2^2 + \frac{1}{2}\|C\|_F^2$$

Where D is the trade-off coefficient.

IV. EXPERIMENTAL ANALYSIS

In this paper, used the open-source Python Keras library and tensor flow to accomplish its goals. The Indian currency dataset was created by photographing images with mobile phones and cameras. Images were taken in various lighting conditions. Our datasets contain 700 images. Each class contains 100 images. The classes are 10, 20, 50, 100, 200, 500 and 2000. The training and test images are divided in an 80:20 ratio. The sample images are shown in Fig 2.

Fig 2: Sample Dataset Images

In order to provide a useful feature extractor for the ELM, we initially train a complete MobileNetV2 on a large dataset prior activating the ELM on the targeted dataset. In this case, we use a dataset with images from 16 different classes to train MobileNetV2. It reduced MobileNetV2's final fully-connected layer from 1,000 neurons to 16. Pretrained on ImageNet, the MobileNetV2 model is used to establish the final network layer. During training, the batch size is set to 25, the starting learning rate is 0.001, the momentum is set to 0.9, and the weight decay is set to 0.0005. The overfitting issue is mitigated by our use of a dropout's ratio of 0.5. To train and evaluate the ELMs, we use photos of seven types of Indian currency. The ELM sees the activations generated by the convolution layers after the CNN stub has finished processing the images. The last fully connected layer has been replaced by ELM. Loss and accuracy for both the training set and the test set are displayed in Figures 3 and 4.

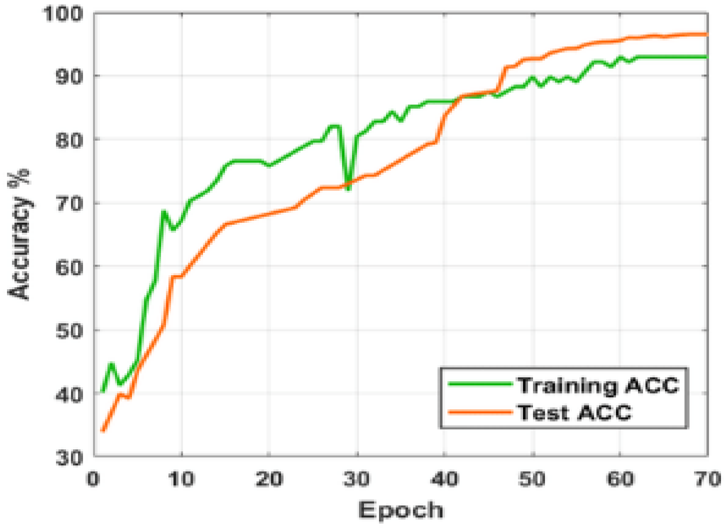

Fig.3: Proposed Method Accuracy

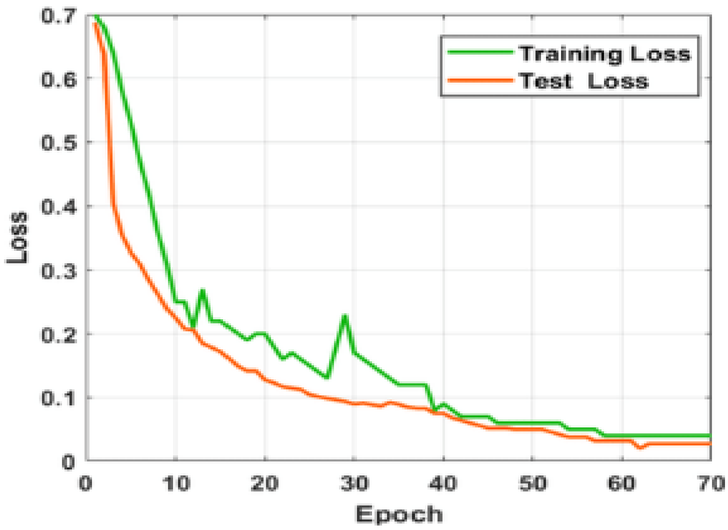

Fig. 4: Proposed Method Loss

Method	Accuracy
Baykal et al [10]	95.23%
Oyedotun et al [12]	94.12%
ORB Algorithm [13]	93.45%
Proposed Method	97.80%

Table 1: Comparison with Existing Methods

Table 1 shows the findings of a comparing between how well our proposed classifiers work and how well the best classifiers work right now. As can be seen, the ELM classification algorithm with manuscript supervised training already does a better job than the best technology we have right now. The proposed method is now almost 500 times faster than the current best solution, notably when it comes to GPU-accelerated training. The combined MobileNetV2/ELM technique requires around 1 millisecond for each image, making it possible to perform testing and training in real time. Because the feature extraction takes up more than 90 percent of the total duration, a new CNN architecture could be able to speed up this process even further. The ELM classifier with ImageNet pretraining is able to reach an accuracy that is comparable to that of the current state-of-the-art, yet only using a fraction of the amount of processing power required by the current state-of-the-art.

V. CONCLUSION

In this study, we propose a mobilenet transfer learning-based system that can detect and identify different types of currency in real time. The model is trained independently on a set of images depicting various bill denominations. The Banknotes Dataset is made under a wide range of conditions, such as high background clutter, rotation, occlusion, strong lighting, changes in size, and so on. Before training the ELM on the goal dataset, we first train a full MobileNetV2 on a large dataset in order to provide an useful feature extractor for the ELM. This is done before retraining the ELM on the target dataset. The ELM is the component that succeeds the fully connected layer as the subsequent step in the process. With an accuracy of 97.80%, the experimental findings show that our proposed strategy beats other approaches that are considered to be state-of-the-art.

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