BANGLADESHI CURRENCY NOTES (BDT) RECOGNITION USING LOGISTIC REGRESSION

Hassan, MD Mehedi, Tanmoy, Bibhas B.[1]

[1]University of Texas Rio Grande Valley

[1] bibhasbhattacharjee.tanmoy01@utrgv.edu

Abstract: Money is an important element for all the people in the world, including blind people. Blind people cannot recognize notes like any human can do, and often they are cheated by wrong people on various money issues. Therefore, they have to get assistance from technology. To solve this problem, deep learning techniques, such as Convolutional Neural Network (CNN), have been approached, which surpasses human visual accuracy noticeably. But there is another drawback, this approach requires intensive training, which is not possible for all scenarios. On the other hand, logistic regression, although being limited compared to CNN, is less intensive and can be used for similar applications as well. It has been discovered that by applying adequate tests and training, this method can achieve an accuracy rate almost equivalent to state-of-the-art. This study attempts to apply a combination of logistic regression and image classification into recognizing a specific kind of currency, the Bangladeshi Taka (BDT) and classifying them based on its different notes, aiming to reach an accuracy level equivalent to CNN.

Keywords: *Logistic Regression, Image Classification, Currency Recognition*

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1. Introduction

In ancient days, only visual examination could be used to recognize and authenticate money, particularly currency notes. Our eyesight, on the other hand, is restricted, and it is frequently impossible for humans to distinguish genuine cash without the aid of technology. Although UV-based detection technology is currently in use, it is getting increasingly difficult to identify counterfeit cash from genuine banknotes as counterfeiting technology becomes more sophisticated. With the advancement of improved image processing techniques, unique identification methods based on examining special security information of well-designed money are now being created. The tendency is toward data-driven approaches. This creates a demand for additional data, which is difficult to get by. As a result, data augmentation methods such as color analysis, picture improvement, and other similar approaches are used in currency detection systems.

In this digital age, technology has demonstrated its domination as people have pushed the boundaries of thinking by fusing artificial and human brains. Artificial Intelligence is a new area that has emerged as a result of this process. AI is defined as the creation of systems that can accomplish tasks that humans can do, such as distinguishing between two things, recognizing various voices, and so on. Machine learning, deep learning, ANN (artificial neural network), and CNN (convolutional neural network) are some of the AI disciplines that aid in the development of more advanced technologies [1]. Machine Learning is incomplete without supervised learning. When the variable to be predicted is categorical, classification techniques are applied. Logistic regression is a classification approach derived from statistics by machine learning. A statistical strategy for assessing a dataset in which one or more independent variables predict a result is known as logistic regression. The goal of logistic regression is to determine the model that best describes the connection between the dependent and independent variables[2].

In a range of image recognition challenges, convolutional neural networks (CNNs) have exhibited outstanding performance achievement. Single-label (one class label per picture) and multi-label (many class labels per image) categorization are two typical issues. While both tasks have the same learning aim of supervised training to induce a multi-class classifier CNN model, their standard objective learning functions are rather different. We frequently use the softmax regression (SR) learning technique in single-label classification learning[3]. This is based on the assumptions of per-sample single-label and class exclusion. Instead, we use the logistic regression (LR) learning approach for multi-label classification, in which a data sample may be associated with many class labels. LR evaluates per-sample prediction of all individual class labels separately without the "single-label" and "class-exclusion" priors.

Although recent developments and applications points towards the high accuracy of CNN, especially while dealing with challenges like image classification, such as classifying currencies. However, this study focuses to attempt to solve the same image classification challenge using Logistic Regression (LR), since literature have shown evidence that with adequate training and testing, LR can also achieve almost near, if not equal, accuracy as CNN. The reason behind choosing this route is that LR requires noticeably less resource and time to be trained and ready, and it does not require deep learning, which opens up the possibilities to be implemented on devices that do not possess the scope of deep algorithms to be installed, such as vending machines. As initial approach, the study will deal with only one kind of currency, the Bangladeshi Taka (BDT), and the dataset would be analyzed with multi-label classification using LR, with the objective to reach the accuracy near to CNN algorithms.

2. Literature Review

2.1. Logistic Regression

Logistic regression is one of the most basic machine learning algorithms[4]. It is a commonly used statistical modeling approach where the probability of an outcome is connected to a sequence of potential predictor variables by an equation[5]. The link between a binary outcome (dependent) variable such as the presence or absence of illness and predictor (explanatory or independent) factors such as patient demographics or imaging findings can be investigated using logistic regression[6].

Logistic Regression is an approach to learning functions of the form $f:X\rightarrow Y$, or $P(Y|X)$ in the case where Y is discrete-valued, and $X=<X1\cdots Xn>$ is any vector containing discrete or continuous variables. In this section we will primarily consider the case where Y is a Boolean variable, to simplify notation. More generally, Y can take on any of the discrete values $y=\{y1\cdots yk\}$ which is used in experiments[7].

Only the factors that are deemed "relevant" in predicting an outcome are often included in logistic regression models. The statistical significance of the coefficients for the variables is determined using P values, which are used to quantify the relevance of variables. When testing for statistical significance of variables, the P.05 significance threshold is typically utilized; however, such criteria might change based on the quantity of data provided. When the number of observations is high enough, predictors having minor influence on the outcome can become significant. A stricter criterion (e.g., P.001) can be employed to prevent inflating the relevance of these predictors[6].

Although it is most commonly used to predict binary target variables, logistic regression may be further categorized into three forms, as listed below[2]:

- **Binomial**: The target variable can only be one of two kinds. Predicting if a message is spam or not, for example.
- **Multinomial**: When the target variable has three or more categories, none of which are statistically significant. Predicting sickness, for example.
- **Ordinal**: The target variables have categories that are ordered. Web Series ratings, for example, go from 1 to 5.

The advantages of LR can be considered the following[8][4][9][10]:

- It is simple to build and, in some situations, delivers excellent training efficiency. Because of these factors, training a model with this technique does not necessitate a lot of computing resources.
- Logistic regression is more straightforward to apply, analyze, and train.
- It doesn't make any assumptions about class distributions in feature space.
- It's easier to expand to several classes (multinomial regression) and a probabilistic view of class predictions.
- It not only indicates the suitability of a predictor (coefficient size), but also the direction of relationship (positive or negative).
- It classifies unknown records fairly quickly.
- It works well when the dataset is linearly separable and has good accuracy for many basic data sets.
- After training the logistic regression model, the resultant weights are found to be highly interpretable. If x i increases by 1 and all other x's remain constant, the weight w i can be interpreted as the amount log chances will increase. Any training example from I = 0 to n is referred to as i.

2.2. Previous Implications of Logistic Regression in Classification Problems

The large amount of data stored and flowing online, according to Prabhat and Khullar (2007), cannot be mined successfully to extract important information, and decisions cannot be made based on extracted information. Sentiment analysis is a way for evaluating people's thoughts, views, feelings, attitude, cognition, and belief about a topic. The authors used a Naive Bayes classifier and logistic regression to classify sentiment in Big Data. The authors utilized both supervised and unsupervised learning methods in their research. Algorithm performance has been assessed using several factors such as accuracy, precision, and throughput. When compared to the Naive Bayes classifier, the analysis using logistic regression delivers 10.1 percent greater accuracy and 4.34 percent more precise findings with approximately one-fifth the implementation time for the same quantity of data set[11].

For Chinese text classification, Yen et al. (2011) used a logistic regression model. The authors have introduced a new technique that employs an N-gram-based language model instead of tokenizing the words, which is a typical strategy in text categorization. For Chinese text classification without a Chinese word tokenizer, this approach considers word relations. We also suggest a unique smoothing strategy based on logistic regression to increase accuracy and prevent out-of-vocabulary. To smooth the probability of n-gram, they employed logistic regression. They suggested a new feature selection strategy that works well with N-gram models. Second, they demonstrated that it could improve the F-measure in the vast majority of cases[12].

Liu et al. (2014) stated up front that while multi-label categorization has grown in popularity in recent years, there is still a need to deal with omnipresent data. As a result, the authors have provided a unique framework for multi-label learning that can concurrently fulfill the goals of classification learning and variable selection. As a result, logistic regression was used to train the models for multi-label data classification. They also used a quadratic approximation strategy to handle the convex optimization issue of logistic regression with the elastic net penalty for improved performance. The model outperformed the other six models in terms of performance and accuracy, and it was also competitive[13].

2.3. Previous Studies on Currency Recognition

Debnath et al. (2010) employed an ensemble neural network to recognize currencies. Individual Neural Networks (NNs) in an ENN (Edited Nearest Neighbor) are trained using negative correlation learning. There are several sorts of notes, such as ancient notes, that are difficult for the machine to distinguish. As a result, a system built using ENN can simply and properly detect them. They employed notes with varied dominations for testing, including 2, 5, 10, 20, 50, 100, and 500 Taka. The picture of the note is first converted to gray scale, and then compressed. The compressed image is then fed into the system as a recognition input. The ENN-based device can quickly distinguish between cash with noise and old currency notes. There are less risks of misclassification with autonomous training.

Two problem-solving strategies (Artificial Neural Networks and Gene Algorithm) were studied by Qing and Xun (2010). They employed Gene Algorithm because of the sluggish convergence and uncertain starting weights of Back Propagation Neural Networks. The Gene Algorithm is used to obtain the proper connection weights and network connection results. The GA-BP (Gene Algorithm: Back Propagation) is utilized for image processing since it has a quick training period and a high recognition speed[14].

Guo et al. (2010) presented the Local Binary Pattern (LBP) method for recognizing paper currency. It is important to extract high-quality characteristics in order to recognize money notes. They introduced the LBP algorithm, which is based on the LBP approach, for character extraction. The LBP approach offers the advantages of being simple and quick. This approach effectively detects currencies with a high ratio[15].

To detect Bangladeshi banknotes, Jahangir and Raja (2007) employed a neural network recognition approach. They employed low-cost hardware to construct this approach, which may be applied in a variety of settings. The picture of a banknote is used as an input by the system. Less costly sensors are used to scan the notes. The Back Propagation technique is used to train the notes for recognition. Because the axis symmetric mask is employed in the preprocessing stage, accurate recognition is ensured even if the note is reversed. They used eight TAKA notes for the experiment notes, which were correctly identified[16].

3. Methodology

3.1. Workflow

There is a plethora of machine learning methods that are employed in image classification. However, they do not all have the same accuracy or precision, i.e., one may have poor accuracy while another may have better accuracy. Three distinct machine learning techniques that have been built on a data set are used to classify images. The logistic regression classifier, random forest classifier, and K-nearest neighbors classifier were employed as classification algorithms. They've helped to evaluate machine learning algorithms by providing a far more simple and clear answer. Each of these three algorithms operates in a completely different way from the others, as one relies on a specific formula for classification and prediction, while the other relies on the construction of nodes and trees (random forest)[1], [12].

Figure 1 illustrates an architectural overview. It begins by importing the necessary libraries, which may then be included in code as proceeded. The data set on which the classification is to be done is then loaded. The dataset used to analyze was the Bangla Money Dataset by N. Sojib[17]. The data set contains different images of all the 9 notes of Bangladeshi Taka, varying on orientation and lighting condition. Before performing the testing and training, image processing algorithms were executed on to the images in the dataset. Later on, the LR algorithm trials ran altering the tuning parameters, and finally computing and comparing the accuracy score.

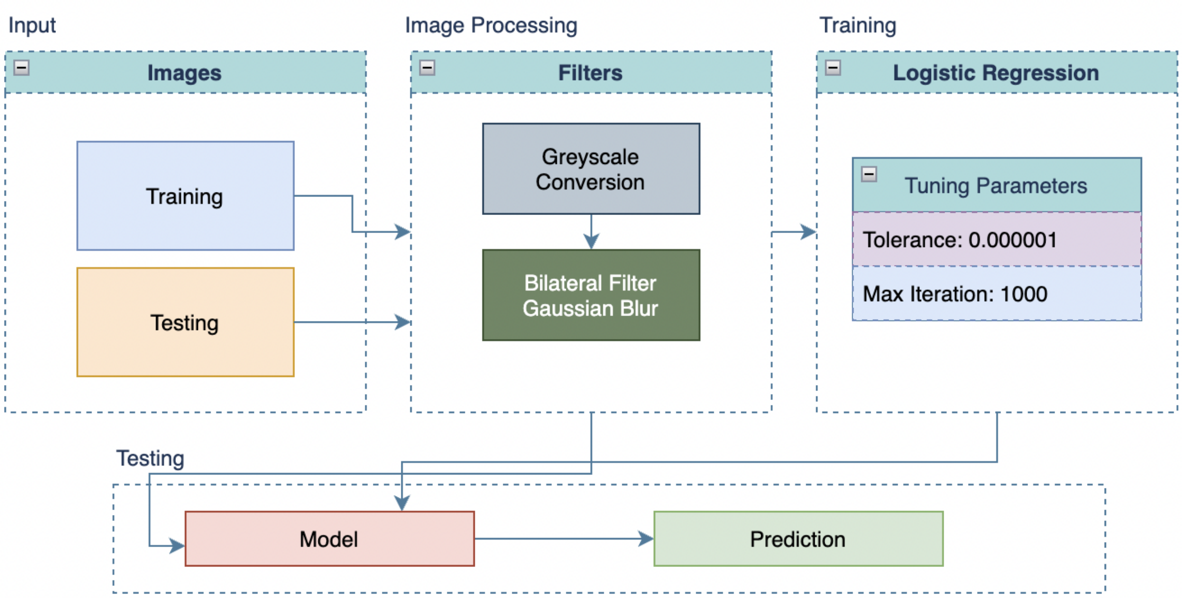

Figure 1: Process Flowchart of the study

3.2. Dataset

The dataset contains 1657 images for training and 333 images for testing. The images are divided into different classes and cropped into a specific proportion.

3.2.1. Classes

The dataset is divided into 9 classes, each class represents each bank notes of the Bangladeshi Taka, also known as Taka. The list of the notes follows below:

i. 1 Taka
ii. 2 Taka
iii. 5 Taka
iv. 10 Taka
v. 20 Taka
vi. 50 Taka
vii. 100 Taka
viii. 500 Taka
ix. 1000 Taka

Figure 2: The 9 types of banknotes in Bangladeshi Taka

3.2.2. Image Proportions

All the images are cropped into the same proportion before being analyzed with the LR model. The figure below shows the actual scaled view of the cropping.

Figure 3: Image Proportion of the notes

3.3. Libraries

The following libraries were imported for the specified purpose before beginning the analysis. These libraries were simultaneously included in the script as the analysis proceeded further.

Table 1: Libraries

Library	Purpose
cv2	To work on vision and images
numpy	For mathematical operations
os	For using directories
sys	Dealing with filenames
time	To show the progress duration
pandas	For analyzing the dataset
matplotlib	For plotting
sklearn • *RandomForestClassifier* • *make_classification* • *KNeighborClassifier* • *accuracy_score* • *LogisticRegression* • *svm*	For trials and analysis

3.4. Image Processing

In the field of computer vision, image processing is crucial since features plays a vital role in processing information[18]. An image gets corrupted by noise during the acquisition and transmission. Unless the noise is eliminated, it will influence the accuracy of other high level image processing techniques such as segmentation, feature extraction, object recognition and detection etc.[19].

Most studies, or experiments uses the following the workflow for preprocessing and post processing the images in the dataset before the initiation of the main analysis[18], [20], [21]:

Figure 4: A typical process flowchart for Image Processing

The model in this study follows similar process flow before initiating the algorithm. The image processing workflow and purposes are explained in the following sections.

3.4.1. Step 1: Image Acquisition

The image of the currency that must be reviewed or certified as a genuine currency is taken as an input for the system[20], [22]. The input image can be retrieved using approaches like scanning the image or clicking a photo with the phone and then sending it to the system. However, in this study, this part was already taken care of in the dataset, since all the images in the dataset are images of genuine Bangladeshi taka, hence the genuinity is justified.

3.4.2. Step 2: Greyscale Conversion

Converting a color image to a grayscale image necessitates a greater understanding of the color image. In an image, a pixel color is made up of three colors: red, green, and blue (RGB). A Grayscale image, on the other hand, may be seen as a single layered image[22]. This conversion helps the analysis to reach higher accuracy in lesser runtime.

3.4.3. *Step 3: Noise Reduction*

Although typical CNN algorithms are supposed to be capable enough to move on to image classification just after greyscale conversion, since LR being comparatively simpler than CNN, the noise reduction algorithms were also applied before the initiation of analysis. Following the studies of Yu and Pan (2019)[18] and Majeeth and Babu (2019)[19], two widely used noise reduction filters: Bilateral Filter and Gaussian Blur were chosen to be applied for the processing of the notes.

- **Bilateral Filter**: Bilateral filtering is a technique to smooth pictures while preserving sedges. Its concept is simple: each pixel is replaced with a weighted average of its neighbors. This characteristic is significant because it makes it easier to develop intuition about its behavior, to adapt\sit to application-specific requirements, and to implement it. It depends solely on two parameters that define the size and contrast of the characteristics to maintain. It can be used in a non-iterative fashion. This makes the parameters straightforward to adjust since their influence is not cumulative over numerous repetitions[21], [23].
- **Gaussian Blur**: Named after mathematician Carl Friedrich Gauss, Gaussian blur is the application of a mathematical function to an image in order to blur it. A sort of low-pass filter, Gaussian blur smoothes unequal pixel values in an image by filtering away the extreme outliers. Photographers and designers choose Gaussian functions for numerous objectives. If snap is shot in poor light, and the resulting image contains a lot of noise, Gaussian blur can quiet that noise[19], [24].

These filters were applied in this model, separately. The results were compared afterwards.

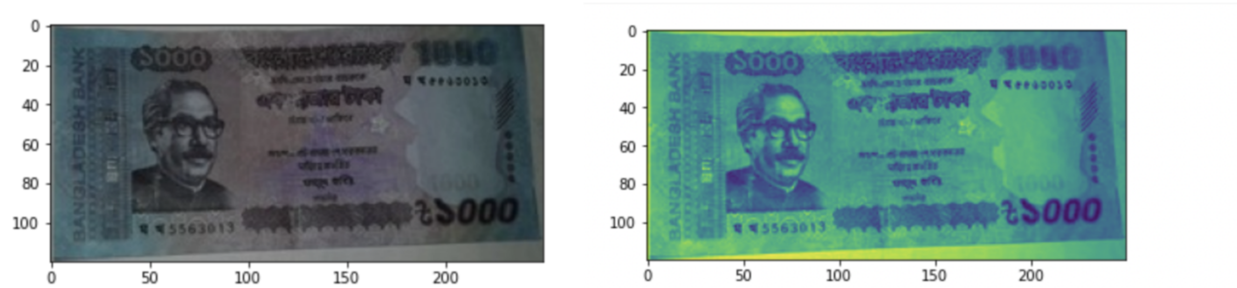

Figure 5: Before and after Image Processing

3.5. Class Implementation and Renaming Files

Before executing the conversion process, the images in the dataset folders were stored temporarily based on the 9 classes, each representing the different notes. The filenames were also adjusted accordingly to make the conversion faster.

3.6. Feature Extraction

The main purpose of applying greyscale conversion was to turn the images into single layer images, so that the pixels in the images can be converted into 2D matrices, and each grid will act as an exclusive feature for that specific image. These features will be used for training and testing the accuracy of the model while execution, where the X axis will serve as all the pixels, and Y axis for prediction and matching, hence the accuracy.

4. Results

4.1. Analysis with KNN

Before executing LR, the converted images were trained and tested with KNN as an initial attempt. Although the model executed successfully, the accuracy was below average, resulting only 45%.

4.2. Analysis with LR

At the first trial, the LR algorithm was ran with only greyscale conversion. However, this trial also did not compute a decent accuracy, even after adjusting the tolerance level and maximum iteration level.

On the second trial, Bilateral filter was applied on the image conversion, and the accuracy showed massive improvement, resulting into an 89% accuracy. This improvement pointed towards the fact that noise reduction might be a deciding factor for higher accuracy.

On the third trial, Gaussian filter was applied, and the accuracy increased even more, resulting into 93%.

5. Discussion and Limitations

The analysis with LR and the result output boldly demonstrates that the accuracy of this model is almost equivalent, and in some instances even better compared to different non-LR currency recognition models found on literature. A comparison chart follows below:

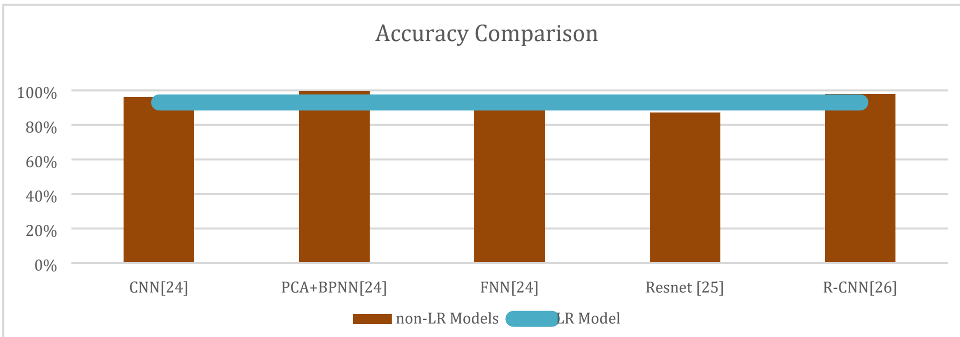

Figure 6: Accuracy Comparison with Literature

It is evident that even though the algorithm used in this model is one of the most basic algorithms in the field of data science, adequate training can make its accuracy equivalent to and/or even better than similar models developed with comparatively complex and deep architecture. Also, in this specific case, it can be concluded that, the image processing played the most important role here, since the alteration in the LR parameters did not affect the accuracy.

However, one major limitation of this study is that, as of being a model designed specifically to recognize and classify images, this model will not be able to handle real world scenarios, instances that will involve object detection and localization. Along with that, as a parallel to the disadvantage of logistic regression algorithm itself, the accuracy might decrease if the dataset is extremely huge, containing millions of images.

6. Conclusion and Future Scopes

In a nutshell, the logistic regression, in this case, to classify currency can be used to develop a model with a decent accuracy. The main deciding factor for the accuracy is undoubtedly the image processing algorithms applied before the trials, which points to the fact that if even more precise processing algorithms are applied, the accuracy may increase even higher, since the alteration of tolerance level and max iterations does not play a role here.

This model can bring about a big change in the field of classification models, especially for organizations and students outside computer science and engineering background, but in need of a model to classify and process a huge amount of data in hand, since developing a model with LR does not require that much of a knowledge of this field. Furthermore, basic, and simple machines like vending machines which does not have the resource or capability to execute complex models in their systems can be benefited easily using LR models, since LR is the least resource hungry algorithm available currently.

Although this model handles a specific type of currency, it is not limited to this boundary. For instance, adding a class for ‘not Bangladeshi Taka’, will enable this model to be open to images of any currencies in the world, and the result will be classification of the Bangladeshi Taka, and the rest would be classified as “other currency”. This expansion can be carried out even further, by adding classes for different currencies as different classes individually, making the model even robust and versatile.

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