Machine Learning Approaches for Banknote Recognition: A Comparative Study of KNN and Random Forest

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***Abstract*—Millions of individuals worldwide suffer from reduced or absent vision.It might be challenging for those with visual impairments to discern between different cash denominations and currencies. This work takes a dataset of different currencies, trains the model to recognise the denomination, currency, and orientation, and then provides the user with the information.The dataset consists of 24,826 photos of banknotes in various adaptive settings, including 112 denominations and 17 different currencies. We create a machine learning model for worldwide money recognition using supervised contrastive learning. With the help of this model, banknote images can be embedded compliantly in a range of scenarios.We compare the performance of two machine learning algorithms—K-Nearest Neighbors (KNN) and Random Forest (RF)—in recognizing the banknotes.Our analysis provides insights into the feasibility of each method for practical assistive applications by comparing their relative efficiency in terms of accuracy and computing performance.**

***Index Terms*—banknote recognition, machine learning, assistive technology, visually impaired**

I. INTRODUCTION

A. Visual Impairment and the Currency Recognition Problem

Recent studies indicate that over 200 million individuals experience moderate to severe vision loss, with 43 million classified as blind. A significant majority—89%—reside in low- to middle-income countries, and 55% of this population are women. By 2050, due to population growth and the rise of specific health conditions, the number of blind individuals is expected to reach 61 million, with those experiencing moderate to severe vision loss increasing to 235 million. For these individuals, recognizing banknotes—a routine task for most people—presents a significant challenge.

B. Modern Machine Models Learning

Several machine learning models have been developed for different currencies, including the Indian Rupee, US Dollar, Canadian Dollar, Euro, Bangladeshi Taka, Thai Baht, Egyptian Pound, and Pakistani Rupee. The models use large amounts of annotated banknote images across various denominations. Still, they often fail in real-world issues such as blurry images, occlusions, poor focus, varied backgrounds, and orientations. Moreover, because of the lack of a large public dataset, such models are limited to very few countries and currencies.

C. Research Goal

The paper will reduce complexity in training machine learning models to identify any banknote in different environments. We will use BankNote-Net, the largest public accessible dataset for currency recognition, containing 24,826 images across 112 denominations and 17 currencies. The images were taken in different conditions like orientation, lighting, background, and occlusions to represent real-life scenarios that are encountered by a visually impaired individual.

D. Proposed Methodology

While the traditional method of currency identification largely depends on the state-of-the-art deep learning techniques, like Convolutional Neural Networks, our proposed method depends on the 256-dimensional feature vectors for each image of banknotes. We are dealing with two machine learning algorithms widely used in practice: K-Nearest Neighbors (KNN) and Random Forest (RF). Feature vectors allow predictions on currency denomination, type, and even orientation. The comparison in this work goes into the trade-off between efficiency and precision.

E. Paper Outline

The structure of the paper is as follows: A review of relevant work in this field is presented in Section II, currency properties are described in Section III, the methodology is explained in Section IV, the experimental findings are shown in Section V, and the study is concluded with recommendations for future research in Section VI.

II. LITERATURE REVIEW

Banknote recognition systems have been highly developed, with datasets like BankNote-Net [1] being of crucial resources. The dataset contains more than 24,000 images corresponding to 112 denominations of 17 currencies and is aimed to mimic the conditions of real-world difficulties, such as blur,occlusions, and varied orientations. Based on such sources, initial research has applied decision tree-based approaches and machine learning techniques to the problem of banknote verification, which proved very effective in identifying the legitimacy of authentic and forged notes [2].Recognition accuracies have greatly improved with the new techniques in neural networks, including Probabilistic Neural Networks (PNNs), which classify currency with strong performance in controlled environments [3][4]. It further depicts continuous learning using DSP units for Thai banknotes as the neural networks adapt well to changes in the data sets [4][5]. SVMs have also been applied in counterfeit detection wherein multikernel approaches further strengthen adaptability in different datasets [6][7]. These have proven useful, not only in the detection of fake currency but also in practical applications like note-to-coin exchange and other. The latest comparative studies that came out on machine learning models revealed that RF and SVM do much better regarding the detection and classification of counterfeit issues [8]. Publicly available repositories, such as BankNote.ws, have also contributed by consolidating global currency features, aiding research in designing robust and scalable recognition systems [9]. Works also pointed out the necessity to develop solutions for the target group according to the general tendencies of blindness and visual impairment in the world [10]. The most actual systems with modular design are, for example, component-based recognition, prepared specially for people with visual impairments, and improved access [11]. Region-specific researches are also very important. Models of neural network for Pakistani banknotes take into account their unique geometrical and texture features [16]. while Faster R-CNN methods have been used for Bangladeshi note to make it detect in real-time [17]. Texture and color- based features have been extensively used for Mexican banknote recognition [18]. Experiments on Indian currency have employed radial basis functions along with SVMs to classifications of the denominations are correct [19]. Deep learning models have formed the center of interest, especially CNNs, in work as has been applied for fake currency detection along with feature-based classification [20].

Although the present studies have proven to be highly successful, there are still challenges with regard to scaling solutions for real-world conditions. Further research should concentrate on enlarging datasets, improving feature extraction methods, and including state-of-the-art models like CNNs and RNNs to ensure robustness and adaptability in practical applications.

III. CURRENCY FEATURES

Currency notes have different designs and templates that are often put into measures in machine learning classification. These elements do not only relate to certain currencies but also to specific notes facilitating perfect identification. In this research paper, the authors concentrate on image editing for the images of banknotes, saved in the formats of 256 dimensional vectors in importance vectors that include the major attributes of the each and every bank note. Such features include:

A. Denomination Symbols

Values of a bill in numeric or graphic formats. Such texts are highly visible in most currencies and the size, font and style may differ among others.

B. Color and Patterns

A set of notes belonging to the same denomination or country moves with varieties of color and patterns. The color patterning are represented in the vectorized data set and therefore this feature coined has been very helpful.

C. Textual Elements

In every bill, there may be so many words in different languages, or numbers, or any writing that relates to an authority that issues those notes. Those constantly read or seen aspects are useful in identifying different currencies or segments of them

D. Geometric Structure

Geometric characteristics such as form, measurement, and arrangement of elements called banknotes are known to be different across various denominations and currencies. Placement features including the position of symbols, sound vibrations, written language, and pictures enhance the placement of depictions.

E. Security Features

Watermarks, microprinting, and holograms although not within our approach are frequently important in practice. They add extra difficulties which advanced models are able to utilize for correct identification

F. Orientation

Banknotes have many angles of peculiarities, especially when in the hands of a blind person. Further, the orientation of a note is another aspect that is recognizably different from other aspects, and such a feature is more challenging because models are required to correct for rotation and alignment discrepancies

In this manner, this model utilizes these features that are also encoded as 256 dimensional vectors to perform the recognition of the denomination, currency as well as the orientation of the banknotes in different assistive scenarios without the aid of image processing whaling.

IV. Methodology

A. Dataset Description

The dataset used for the experiments is collected as part of the BankNote-Net project. A total of 24,826 pictures from 17 different currencies were gathered. Figure 1 shows many samples of the gathered photographs as well as the distribution of the images by class and between currencies. The pictures cover 224 classes and 112 denominations; each value corresponds to two classes, which represent the banknote's front and back sides. As can be seen, there are 110 photos on average each class. Each version of a banknote that is in circulation is classified as belonging to a certain class.

B. Data Preprocessing

It was observed that there were NaN values in the Denomination column, which were substituted with pd.NA. This modification helped the column effectively handle missing data. Finally, the Denomination column is converted to float type in order to ensure uniform treatment of missing values.Then, the SimpleImputer class was used with a strategy of mean to fill in the missing values in the feature vectors so the model performance would not be prejudiced by these missing values. Now, the imputed feature set, X_imputed, was used to train the models.

This initial examination was conducted to collect insights about the organization of the data. Because each row corresponds to a specific image, the distinctive pairing of the Currency and Denomination columns creates a one-of-a-kind representation for every type of banknote. An example is the front view of a 100 Australian Dollar note shown in the first row. Refer to Figure(2).

The chosen currencies for embedding visualization include AUD, USD, EUR, BRL, and TRY. In the initial step, the high-dimensional embeddings were reduced to two dimensions using t-Distributed Stochastic Neighbor Embedding with a perplexity of 20 and 1000 iterations to visually show clustering patterns in various currencies.Refer to Figure(3).

This data was finally organized into training sets. The feature vectors were separated from the labels and then organized into three target variables: currency, denomination, and orientation. The numerical value of denomination was found by using regular expressions, and the orientation defining whether a note is facing front or back was found by identifying the last number.

The categorical labels of Currency, Denomination, and Orientation were changed into numerical ones using the class LabelEncoder for label encoding. This was one way to ensure that the target variables would make sense in the models when training. The data is split into two different parts: a training set and a test set. Here, an appropriate split is 80-20, respectively, using a random state of 42 in order to address concerns over reproducibility. The machine learning models were trained using the training dataset, and the testing dataset generated data for performance assessment

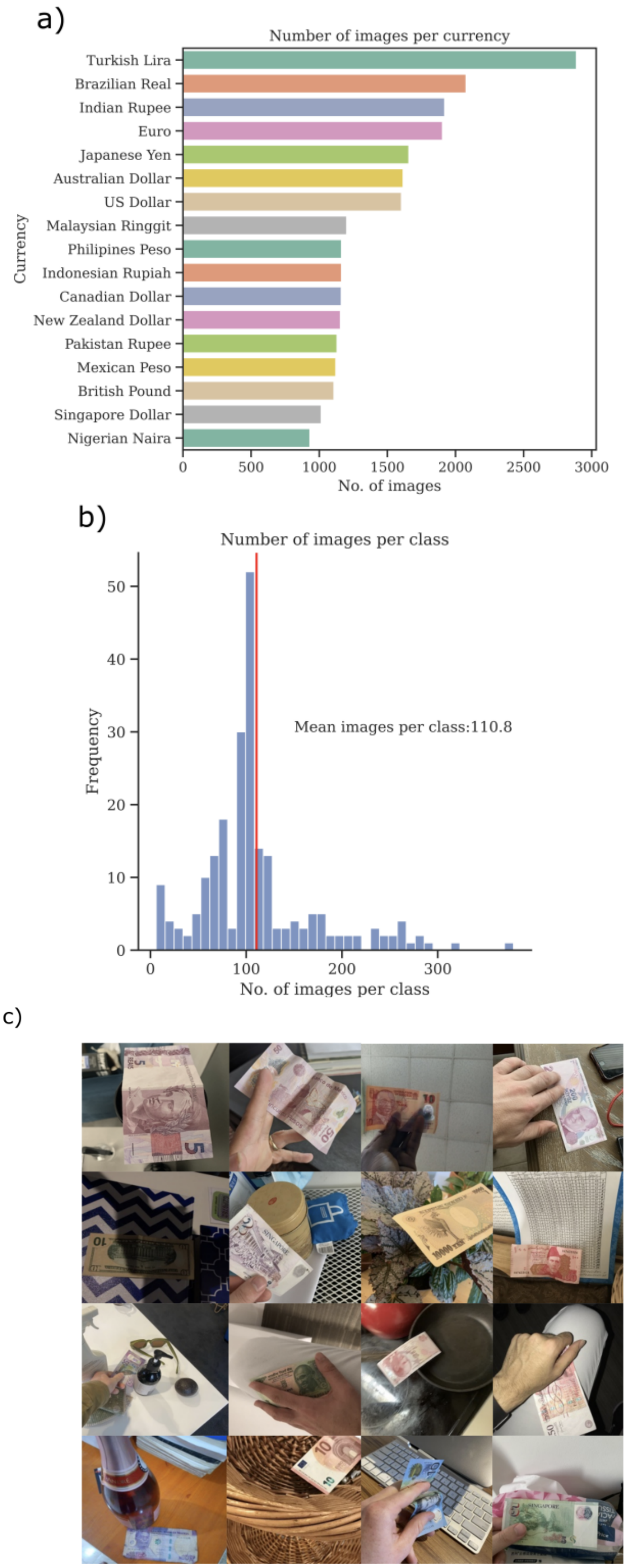

Fig. 1. Overview of BankNote-Net: a) Total number of images per currency. b) Distribution of number of images per class (combination of denomination and front/back side, e.g. "5 USD - Front Side" is a class). c) Example of images in the dataset, collected in diverse accessibility scenarios.

	Currency	Denomination
0	AUD	100_1

Fig. 2.

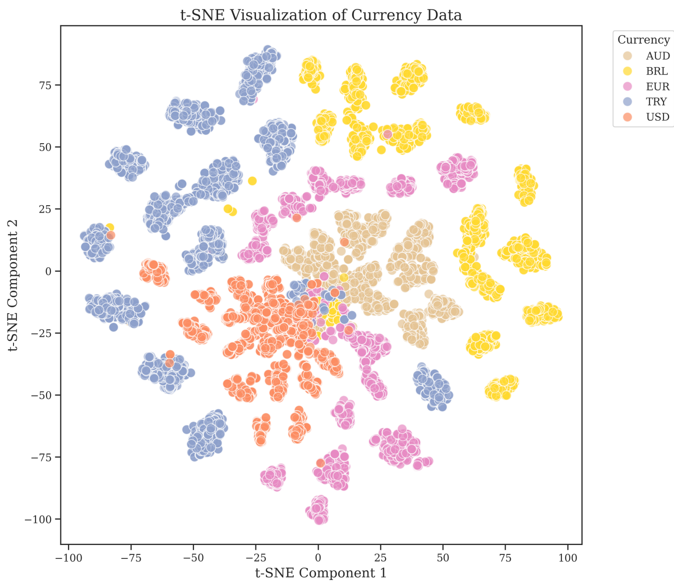

Fig. 3. The t-SNE visualization highlights distinct clusters of currency embeddings, demonstrating the model's ability to differentiate between various banknotes effectively.

C. *Machine Learning Techniques*

Machine learning techniques used in this paper are as follows :
A description of an SML method that uses learning curves and ROC to gauge accuracy for an 80:20 train-test ratio.

- KNN: Although it may also be used for regression and prediction applications, this SML model is mostly used in the industry for classification challenges. The KNN algorithm is a slow algorithm, meaning that it learns very slowly since its training is very slow, because it uses the complete dataset for classification. Furthermore, it is sometimes referred to as the parametric learning algorithm as it disregards any information from the underlying data. KNN basically uses the idea of feature similarity to find the new data point values. That is, the value assigned to a new data point is determined by how well its value matches the points in the training set. See Fig. 5(a) for the ROC curve for currency and learning curves for the train test ratio of 80:20. KNN accuracy for currency is observed to be almost 100% ; see Fig. 4(a).

- RF: Various decision trees are combined to construct this classifier. Subsets of the original data set are randomly selected to build the sub classifier. The RF classifier is then produced by combining these subclassifiers. The predictions made by each sub-classifier on a class are then submitted to a vote. The model predicts the class with the most votes [5].Fig. 5(b) shows the ROC curve for currency and learning curves for the 80:20 train test ratio; Fig. 4(b) shows the 98% accuracy of RF.

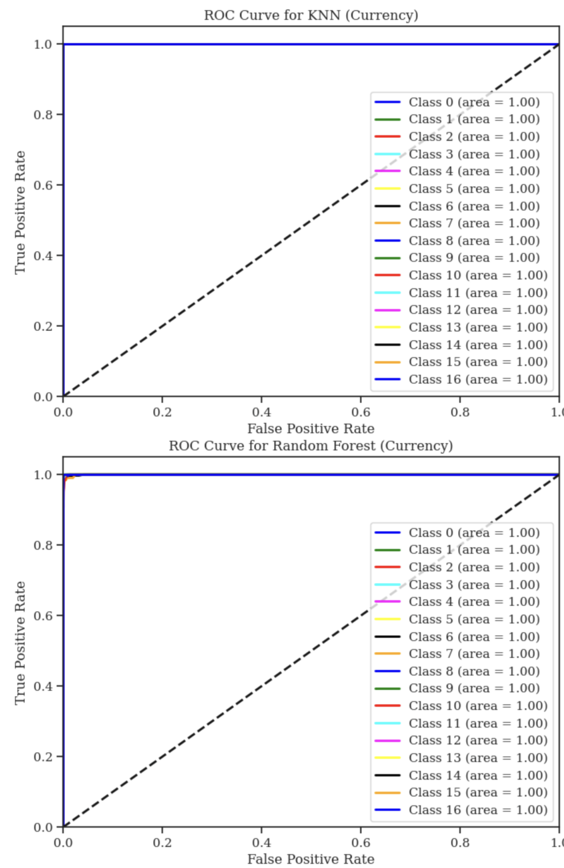

Fig. 4. ROC curve a) KNN and b) Random Forest for train test ratio 80:20.

V. Results and Discussion

In this section, we provide a comparative analysis of the Random Forest and K-Nearest Neighbors (KNN) models for the classification tasks of currency, denomination, and orientation. Various evaluation metrics including precision, recall, f1-scores, and support are addressed herein with regard to every classification category. The reports of the two models have been presented and analyzed below.

A. *Currency Classification*

- Random Forest: The performance of the Random Forest model is very encouraging for the currency classification task with the accuracy rate of 98%. As for most of the currencies, the precision, recall, and f1 scores are over 90% with no considerable limitations except for the downturn in excels such as INR and GBP as compared to other polite currencies in terms of their precision and recall values.

- KNN: While executing the currency classification task, the KNN model registers impeccable currencies classification performances across all currencies as evidenced by precision, recall and f1 scores of 1.00. This means that KNN is ideal for this dataset assuring accurate classification in all categories of the dataset without any errors.

TABLE I
COMPARISON OF PRECISION, RECALL, F1-SCORE, AND SUPPORT FOR CURRENCY CLASSIFICATION

Currency	Precision (RF)	Recall (RF)	F1-Score (RF)	Precision (KNN)	Recall (KNN)	F1-Score (KNN)	Support
AUD	0.99	1.00	1.00	1.00	1.00	1.00	322
BRL	1.00	0.99	0.99	1.00	1.00	1.00	441
CAD	0.99	0.98	0.99	1.00	1.00	1.00	245
EUR	0.98	0.97	0.98	1.00	1.00	1.00	386
GBP	0.99	0.91	0.95	1.00	1.00	1.00	211
INR	0.89	0.99	0.94	1.00	1.00	1.00	374
TRY	0.99	1.00	1.00	1.00	1.00	1.00	598
USD	1.00	1.00	1.00	1.00	1.00	1.00	304

Analysis: Clocking high scores on all metrics for all currencies, KNN emerges the best out of the two models in this case and partially overcomes Random Forest. In some currencies (GBP and INR), invoking the underperformance of Random Forest remains constant at recall and precision scores which consequently give rise to low f1-scores.

B. Denomination Classification

- Random Forest: The Random Forest model is able to classify denominations with an accuracy of 95%. Certain denominations, for instance, the 5000 and 100000 denominations are classified with maximum precision and recall, while others such as 500 and 2000 show slight deficiencies due to low recall.
- KNN: Equally, The KNN model's precision, recall, f1 scores for each of the denominations is perfect across the board, as was also the case with the currency classification task. Its accuracy rate is 100%, which is better than that of Random Forest in this task.

TABLE II
COMPARISON OF PRECISION, RECALL, F1-SCORE, AND SUPPORT FOR DENOMINATION CLASSIFICATION

Denomination	F1-Score (RF)	Precision (RF)	Recall (RF)	Precision (KNN)	Recall (KNN)	F1-Score (KNN)	Support
1	0.97	0.96	0.97	1.00	0.99	1.00	122
10	0.91	0.97	0.94	1.00	1.00	1.00	723
50	0.94	0.94	0.94	1.00	1.00	1.00	741
200	0.99	0.93	0.96	1.00	1.00	1.00	334
500	0.99	0.87	0.93	1.00	1.00	1.00	142
100000	1.00	1.00	1.00	1.00	1.00	1.00	34

Analysis: KNN does not misclassify any of the denominations for all currencies and does support Random Forest although it records good but mediocre results for some denomination classes 500 and 2000 in this last task. This again reaffirms the strong profile of KNN for this dataset.

C. Orientation Classification

- Random Forest: With respect to the orientation classification, the Random forest model attains an overall accuracy of 95% providing equal precision, recall, and f1-scores for both of the orientations (1 and 2). Thus, the performance of this approach is reliable for orientation detection of banknotes.
- KNN: The KNN model again exhibits almost equal levels of success in this classification with the exception of one, in which 99% accuracy is achieved but with a tiny variation in the recall for orientation 2 (0.99). Precision and f1's are again at perfect levels.

TABLE III
COMPARISON OF PRECISION, RECALL, F1-SCORE, AND SUPPORT FOR ORIENTATION CLASSIFICATION

Orientation	Precision (RF)	Recall (RF)	F1-Score (RF)	Precision (KNN)	Recall (KNN)	F1-Score (KNN)	Support
1	0.95	0.95	0.95	0.99	1.00	1.00	2528
2	0.95	0.95	0.95	1.00	0.99	1.00	2438

Analysis: Both models perform exceptionally well for orientation classification, with KNN slightly outperforming Random Forest in terms of precision and recall for orientation 1.

VI. CONCLUSION AND FUTURE SCOPE

In the present study, we put to test the performance of Random Forest and K-Nearest Neighbors classifiers on feature vectors of 256 dimensions that describe banknotes. Our findings indicate that KNN always outperforms Random Forest in all metrics for the following tasks: recognizing currency, denomination, and orientation.

To check for robustness against overfitting, we also report training and test accuracies. For KNN, these were high both for training and testing in all three classifications:

Classification of Currencies: The Training Accuracy was high, as was the Test Accuracy, which stood at 100Denomination Classification: Training Accuracy was high, and so was the Test Accuracy, standing at 100Orientation Classification: Training Accuracy was high, and Test Accuracy was also 100These consistencies show that the KNN model performs well on the training data and extends well to unseen, new data-a fact that describes the true robustness of the model.

In practical terms, the noisy and distorted robustness of KNN with respect to retaining accuracy is an added advantage it brings to real-world applications. It would be of great use for the KNN in the case of images that are visually impaired and blurred to correctly identify banknotes by their correct denomination. Its sensitivity to local patterns enables it to handle variations and imperfections that may occur under such conditions.

In other words, the better performance and robustness against attacks make the KNN classifier much more suitable for banknote recognition tasks. Furthermore, under such challenge conditions as visually impaired and blurred images, it turned out to be effective, which underlines its value in practical applications and sets it apart from the Random Forest classifier.

In the future, we would like to extend our banknote recognition system by embedding it into a practical application. We will develop an API to perform real-time banknote recognition from images. The approach will be such that after preprocessing the images into 256-dimensional feature vectors—similar to how our dataset is presented—they can be inputted into the trained KNN model, which will further classify currency, denomination, and orientation.

This API will enable us to evaluate the performance of this model in real-world environments, considering variations of lighting conditions and other image qualities. By extending this API, we will actually be in a position to validate its robustness for practical applications and, hence, work towards refining the accuracy.

Apart from this, more research work can be initiated for the proper conversions of vector approaches. New enhanced image preprocessing methods can be integrated to enhance accuracy even in the case of poor visibility and blurring of images. More experiments can be done on the feature extraction methods, such as more feature dimensions and new data sources, so that the general robustness of the model in more adverse conditions can be challenged.

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