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Machine learning based approach for detection of fake banknotes using support vector machine

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ABSTRACT

Currency counterfeiting is a significant offense that has an impact on a nation's finances. Due to the enormous progress in printing technology, it is now quite simple to create fake currency that resembles real currency in both appearance and texture, making it nearly difficult to manually tell them apart. The suggested approach will be helpful in identifying fake currency in financial systems. Because of the rise of fake currency in the market, numerous false note detecting techniques are available globally to address this issue, however the most of them rely on expensive technology. In this paper, we'll introduce a revolutionary way for separating fake banknotes from real ones using the support vector machine (SVM) approach. To categorize bank notes as authentic or counterfeit utilizing the data retrieved from the photos of the bank notes, SVM performs better overall and is more effective, particularly when it comes to pattern categorization. Finally, the results of our experiment will demonstrate that the suggested algorithm does really yield extremely good performance.

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1. INTRODUCTION

Despite the country's recent increase in internet users, which is mostly attributable owing to the accessibility of low-cost, high-quality internet, the number of individuals using the option of online currency exchange remains negligible [1]. Therefore, the primary means of trade continue to be bank notes, which are tangible forms of money. With the development of printing technology, it is now quite simple to create counterfeit money that is identical in appearance and feel to real money [2]. Due to this, it is now very difficult to manually distinguish a fake note from a legitimate one simply by glancing at them. This has made it necessary to construct machine learning such as support victor machine (SVM) that can extract certain crucial characteristics from these bank notes to distinguish the real notes from the fake ones [3].

This algorithm can be installed in a variety of locations where there is a big inflow of cash, such as banks, automated teller machines (ATMs), vending machines, and malls. The primary social issue that our project seeks to address is reducing the market's influx of fake currency [4]. The banknote authentication dataset is the one required for our work, which was produced using images of real and counterfeit banknote-like specimens along with various wavelet transform tools to extract specific features from the images, such as variance of the wavelet transformed image, skewness of the wavelet transformed image, curtosis of the wavelet transformed image, and entropy of the image [5].

The security measures on the fake currency make it challenging to identify them [6]. Therefore, it is essential to use advanced identification techniques to distinguish between real and counterfeit banknotes by seeing past the prevarication built into the notes. Many various methods have been suggested and developed to combat the counterfeiting of banknotes [7]. Pattern identification of pictures is difficult work in digital image processing since a large number of features are retrieved but not all of them are truly discriminative in many practical situations including visual recognition, microarray analysis, and text classification [8]. We thus attempted to make finding the most effective algorithm that may be used to precisely distinguish fake bank notes from genuine notes the major objective of our research. Finally, the objective of our project is to use supervised learning algorithms like support vector machines on the provided dataset to calculate and demonstrate the accuracy of the algorithm in classifying the bank notes as genuine or fake in order to prove the most effective classification technique that can be incorporated into our model to address the issue [9], [10].

The identification of fake and counterfeit banknotes has been the subject of extensive research in the literature [11]. This section summarizes the effort made to address the issue of banknote detection. Khairy *et al*. [1] suggested using a radial basis function (RBF) neural network to recognize cash in the form of banknotes. The Saudi money was the target, and after feature extraction and classification, the findings of the suggested model's accuracy were reasonable. A mix-margin approach, which is the foundation of an enhanced feed forward neural network, calls for fewer samples for a more flexible network and more accuracy [12]. When applied to banknote data, the margin-based feed-forward neural network outperformed the artificial neural network (ANN) and AdaBoost algorithms in terms of accuracy [13]. The results of the experiments using Swiss franc bank note datasets and datasets for banknote authentication shown that the ensemble algorithmic models are capable of increasing the accuracy of individual algorithms' detection. Also the study verify that it is highly effective and suited for spotting fake currency [14], [15].

2. THE PROPOSED MODEL

The objective of this paper is to determine from a variety of measurements collected from a photo if a certain banknote is real. We implemented support victor machine algorithm using python to build the machine learning model to predict whether new banknotes are genuine or not [16]. The dataset we utilized in our experiment was the data set used for banknote authentication from the University of California (UCI) machine learning repository. Using an advanced print inspection camera, this dataset was produced by photographing real and fake banknote-like samples [17]. Using a variety of wavelet transform tools, the characteristics (such as variance of the wavelet transformed picture, skewness of the wavelet transformed image, curtosis of the wavelet transformed image, and entropy of the image) were retrieved from these photographs [18]. The dataset has five properties in total, the first four of which are the retrieved features, namely the wavelet curtosis, skewness, and variance of the transformed picture [19]. The final property is the target class, which has two class labels: 0 (represents authentic notes) and 1 (represents the transformed image and the entropy of the picture) (represents forged notes). Total cases in the dataset are 1,372, of which cases1 through 762 belong to class 0 and cases 763–1,372 to class 1. The dataset description shown in Table 1.

Table 1. Dataset details

Indicator Name	Description
Wavelet transformed image variability	A pixel's variance from nearby pixels is measured by variance.
Wavelet transformed image skewness	Skewness meausres the degree of the image's asymmetry.
Wavelet transformed image curtosis	Kurtosis measures how heavily or lightly the data deviates from a normal distribution.
Entropy of image	An image’s entropy, also known as its average information, serves as a gauge for how random the image is.
Class	Genuine notes are represented by class 0, whereas fake notes are represented by class 1.

The proposed model is continued in the procedure, the dataset will be divided into a training and a testing dataset, in training dataset section we use it to train our SVM classifier and in our testing datset, after predicting the class of each case in the testing dataset using the predict method, we calculate the Euclidean distance of each instance from all of the training dataset's occurrences. After prediction, we arrange the Euclidean distances in ascending order and choose the class label of the first three instances. Finally, in final stage which it is accuracy we will match the predicted label with the actual label for all the instances in the testing dataset and print the accuracy of the model, it is checking the currency is real or not.

3. METHOD

We provide an introduction to SVM in this section. SVM is designed to effectively handle two-class classification problems [20]. The fundamental principle of SVM is to build a suitable separating hyperplane as the decision surface in order to maximize the difference in distance between two patterns [21]. We will first go through how to create an ideal hyperplane for patterns that can be separated linearly before moving on to the non-separable situation [22]. The fundamental architecture will then be expanded to include nonlinear SVM. Let S = {(x_i, y_i)}, $R^d \times R$ be a set of training, where $x_i \in R^d$ the ith examples input pattern is R^d and $y_i \in \{1,-1\}$ is the associated desired result. The patterns in the subsets $y_{i=1}$ and $y_{i=-1}$ are thought to be linearly separable, according to our presumption. In this situation, a set is referred to as linearly separable if we can create a hyperplane-shaped decision surface by finding any (w,r), where w is a vector of adjustable weights and b is a bias.

$$w.x + b = 0 \tag{1}$$

Such that,

$$yi(w.xi + b = 0) > 0, i = 1,2, \dots \dots,. \tag{2}$$

We can rescale (w, b) to produce a canonical hyperplane in a linearly separable situation so that

$$y_i(w.x_i+b=0) \geq 1 \text{ , } i=1,2 ,\dots\dots,. \tag{3}$$

The distance between the hyperplane and the nearest data point for a particular weight vector w and bias b is known as the margin of separation and is represented by the symbol. The separating hyperplane with the greatest margin is referred to as the ideal separating hyperplane among all feasible ones. The weight vector and bias for the ideal separating hyperplane are denoted by (w_o, b_o). Finding the best separating hyperplane such that the pair (w_o, b_o) fulfills the constraint is the primary objective of SVM.

$$y_i(w_o.x_i+ b_o =0) \geq 1 \tag{4}$$

Support vectors are the specific data points (x, y) for which (4) is satisfied with equality. The data points that are hardest to categorize and are closest to the decision hyperplane of the support vectors. The geometric design of the ideal separating hyperplane for a two-dimensional input space is shown in Figure 1. We have decided on four features that will be examined for authenticity. With these features as input, the SVM is trained for classification. Once the security features have been extracted and the machine learning model has been trained, each feature set vector is treated as a single feature. We provide a setting to simulate the operations carried out in a genuine banknote acceptor in order to evaluate the efficiency of our recommended solution.

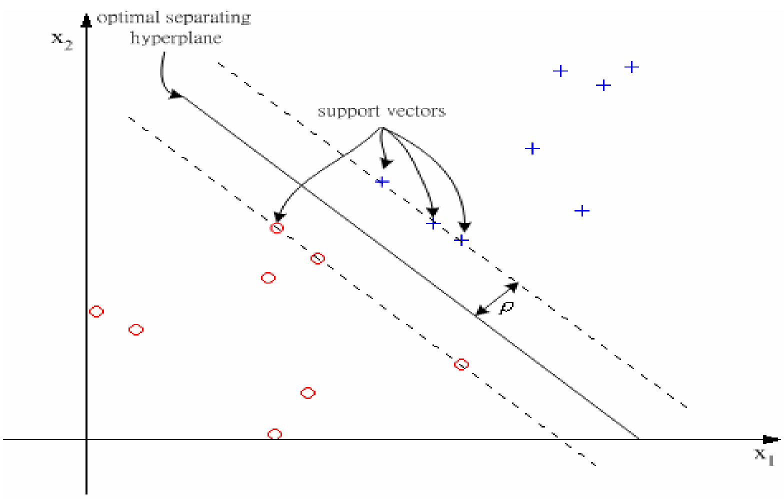

Figure 1. Illustration of an optimal hyperplane for linearly separable patterns

The simulation will exclude the numerous paper money recognition step because the suggested solution solely concentrates on the function of verifying banknotes. Some samples are very new, while others are somewhat worn out, to further enhance the realism of the simulation. We only extract three important properties from each sample, as was previously described, the simulation is shown in Figure 2.

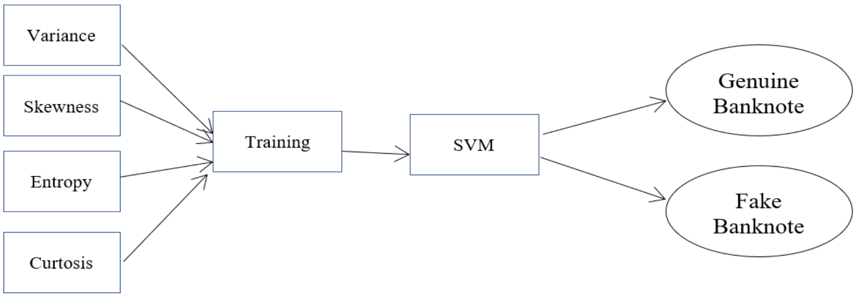

Figure 2. The suggested scheme's simulation process

4. RESULTS AND DISCUSSION

In this section, we'll go into more depth about the tests and their findings. The test's accuracy is measured by how well it can distinguish between real and fake note test instances [23]. In our research, we have settled on four feauters that will be tested for fakeness. The SVM is trained for classification using these feauters as input. Each feature set vector is handled as a separate feature once the security features have been extracted in order to train the machine learning model. Our goal is to maximize the classifiers' precision and interpretability [24]. Finding the ideal hyperplane that linearly divides the data points in two components by maximizing the margin is the goal of the support vector machine classifier [25]. Also, SVM is employed to best locate the separating hyperplane soensure the test's provided categorization error is kept to a minimum sample. An SVM may find the best hyperplane by increasing the distance from the hyperplane and linearly classifying (separating) the majority of the training data points [26], [27]. The margin is defined as twice this distance. Some of our results are presented in Table 2.

Table 2. The comma-separated values (CSV) dataset

Variance	Skewness	Curtosis	Entropy	Class
3.9433	2.5017	1.5215	0.903	0
3.931	1.8541	-0.023425	1.2314	0
3.9719	1.0367	0.75973	1.0013	0
0.55298	-3.4619	1.7048	1.1008	1
0.26877	4.987	-5.1508	-6.3913	1
-1.1306	1.8458	-1.3575	-1.3806	1
1.9572	-5.1153	8.6127	-1.4297	0
0.5706	-0.0248	1.2421	-0.5621	0
-1.1859	-1.2519	2.2635	0.77239	1
3.2585	-4.4614	3.8024	-0.15087	0
5.0297	-4.9704	3.5025	-0.23751	0
0.39012	-0.14279	-0.031994	0.35084	1
-0.2361	9.3221	2.1307	-4.3793	0
-2.0042	-9.3676	9.3333	-0.10303	1
2.5605	9.2683	-3.5913	-1.356	0
1.8373	6.1292	0.84027	0.55257	0
4.9923	7.8653	-2.3515	-0.71984	0
3.3004	7.0811	-1.3258	0.22283	0
-1.2537	10.8803	1.931	-4.3237	0
1.7819	6.9176	-1.2744	-1.5759	0
3.7798	-3.3109	2.6491	0.066365	0
-0.87834	3.257	-3.6778	-3.2944	1

Our dataset contains 1,372 banknotes, in which cases 1 through 762 belong to class 0 and cases 763-1,372 belong to class 1. We have utilized 99% of the data and the SVM approach to evaluate the classifier to be trained. The following settings have been used to implement the support vector machine algorithm: the number of iterations is 1,000 and the learning rate is 0.001. The classifier's output can either be 1 for a counterfeit banknote or 0 for a genuine one. As we have thought about using four characteristics to train the classifier, they are variance, skewness, curtosis and entropy. The SVM is trained for classification using these characteristics as inputs. The accuracy produced by the suggested technique is around 99.55%, we also applied another supervised learning algorithm perceptron on our dataset and the accuracy were around 98.36%, the system evaluates the performance of two models and results have been shown in Table 3.

Table 3. Accuracy of all the model

Model	Correct	Incorrect	Accuracy
SVM	545	3	99.55%
Perceptron	539	9	98.36%

We evaluated the performance of the proposed support vector classifier with different machine learnings classifying technique in order to optimize the accuracy of the classifiers. Finding the ideal hyperplane that linearly divides the data points into two components by maximizing the margin is the goal of the support vector machine classifier [28]. Additionally, SVM is utilized to locate the separation hyperplane ideally in order to reduce classification error for the provided test samples. Our SVM model found the best hyperplane by increasing the distance from the hyperplane and linearly classifying (separating) the majority of the training data points. The margin is defined as twice this distance [29]. So it is a practical approach to finding a solution that works for all banking machines and all note varieties. This paper explains the fundamental ideas of bank note detection. The fundamental issue of checking whether currency is real or counterfeit, together with classifying each currency, was then the emphasis.

5. CONCLUSION

This paper presented banknote authontecation which uses two supervised learning algorithms to determine if a banknote is real or counterfeit after analyzing various techniques used to detect forged banknote, to determine which model is better for classifying the notes, several tests employing both models have been run on the banknote dataset. The outcome demonstrates that the support vector machine has a 99.55% success rate. This model is an effective solution to solve the issue for all ATMs that take all sorts of notes. some of our results where class 1 refers to counterfeit banknote, class 0 to real one with accuracy rate 99.55% for all the dataset, presents the comaprsion of models which have been used to test our dataset for the accuracy. The findings show that the SVM almost perfectly verified the data, with a perfect accuracy rate of 99.55%. This indicates that the data was linearly separable, and the outcomes came out as we had anticipated. Moreover, there are support vector machines like nu-SVM, smooth support vector machine (SSVM), and reduced support vector machines (RSVM), will be used in our future work to verify paper currency and to address the issue of numerous types of paper currency identification. Additionally, we are interested in the problem of feature selection for various support vector machines.

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