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Real-Time Recognition and Detection of Iraqi Currency Using DNN

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Abstract

Our daily lives are not possible without money. However, the most crucial issue at this time is how to distinguish between real and fake currencies. The accuracy of cash recognition will be dramatically increased if a computer is used, and the workload of the workforce will be much decreased. It generally uses deep neural networks to learn a dataset. This paper endeavor can make use of a wide variety of models. Accuracy of currency recognition can be increased using these models. Convolutional Neural Networks (CNN) are often quite suitable for our needs regarding money detection. The denomination and front/back sides of a piece of currency can still be determined even when it is tilted or shifted. In order to more precisely identify the denomination of the paper cash, both on the front and back, we primarily employ the CNN model in this research to extract the properties of paper currency. The primary benefits of employing CNN are the up to 98% average accuracy of currency recognition.

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Introduction

There are many different methods of recognition that are utilized in the modern world, and some of the most common are image recognition, behavior recognition, face recognition, and license plate identification. Money is the basic medium of transaction, and each nation has its particular characteristics that set it apart from others. As a result, figuring out how to employ identification technology to evaluate whether or not a given form of currency is legitimate has emerged as a topic of intense interest and a task of critical importance right now. Following the events of 2003, the monetary system in Iraq underwent a complete redesign, and brand-new banknotes that adhered to unheard-of levels of security were introduced into circulation. This was done in a manner that was previously unheard of. Large value bills were the focus of many forgery attacks, which has a severe impact on society as a whole. Despite the considerable security measures that were put into place to fight against counterfeiting, large value notes were the target of these attacks. Although the letter's brightness and texture may become less obvious with time, other properties, such as the identification mark, security thread, latent image, and watermarks, should remain constant and untouched by deterioration. These include the latent image and watermarks. The UV illumination authentication function that is present in Iraqi banknotes serves as the primary subject of this investigation. A built-in ultraviolet fluorescent fiber that, when illuminated by ultraviolet light, transforms into extraordinarily one-of-a-kind patterns and colors (Young, 1989).

The realization of event-based currency recognition functions as the primary point of contention throughout this work. The method that is explained in this paper and the step-by-step process of recognizing currency entails determining the denomination of the currency as well as both the front and back sides of the coin. In this article, these concepts are presented in the following order: first, the collection and processing of data; second, the augmentation of data; third, the extraction of currency features; fourth, the identification of currency; and fifth, the subsequent analysis of currency recognition. Authentic Peruvian banknotes can be determined with the help of a portable X-ray fluorescence (pXRF) spectrometer by analyzing their spectra and contrasting them with those of counterfeit bills. There was a total of 77 data sets and 11 points of study for each of the Peruvian Nuevo Sol banknotes that were analyzed, of which there were 4 genuine and 3 counterfeits (Eason, Noble, & Sneddon, 1955).

The majority of study in this field is concentrated on identifying counterfeit currency by employing image processing and the physical characteristics of the notes (Maxwell, 1873). Jacobs (1963) presents an approach to the detection of banknotes that integrates back propagation neural network (BPNN) with principal component analysis. This approach is proposed for use in the detection of banknotes (PCA). A thorough survey covering all areas of currency detection and verification, including the identification of a banknote's serial number, may be found in (Yorozu, et al., 1987). This publication is cited as the source. Both a scale-invariant feature transform (SIFT) algorithm and a mobile camera are applied in the process of identifying currency (Young, 1989). The average level of accurate recognition achieved by the color SIFT is a value of 0.79. While the overall accurate identification rate for Gray SIFT is 0.53, on average. The proposed method for similarity mapping, which was used in the study by Saifullah (2015) to recognize photos of banknotes recorded by light sensors, has a significantly lower error rate of 0.002 and a rejection rate of 0.004, making it a significant improvement over the methods that are currently in use. The authors of the work that was published in 2015 by Sarfraz attempted to use simple algorithms in an effort to successfully boost the rate at which the Chinese yuan (RBM) could be recognized. (Reel et al., 2011) describes a method that employs an image processing strategy for the recognition operation in a Matlab program. This method achieves a success rate of one hundred percent when used to the authentication of the Bangladeshi currency known as the 100 teka (Bharkad, 2013). The average recognition rate for the set of 110 photos was calculated to be 91.51% based on a radial basis for classification, which recognizes cash by utilizing fundamental features and correlation. The collection included a total of 110 photographs. In the study that is referenced in (Jain, and Vijay, 2013), a heuristic analysis of the serial number for nine characters is performed. This study takes into account four distinct characteristics of a character in order to obtain the precise features of the characters of the note that are necessary for recognition.

A discussion of the many mechanisms of recognition may be found in (Mirza, & Nanda, 2012). (Pathrabe, & Karmore, 2011) employs a neural networks method for identification after first classifying the gathered image with particular filters. The development of a software that is capable of universal currency recognition is the primary objective of that study. The proposed algorithm was applied to five different currencies, and the results were quite encouraging. In (Abbas, 2019), the approach of Matlab recognition with the most common security characteristics is discussed. An embedded system for identifying counterfeit dollars was introduced by Debnath et al. (2010). This system relied on certain monetary features, a neural network for detection, and an LED to make its determinations. The algorithm used in Hassanpour and Farahabadi's (2009) research makes use of information regarding shape and color, and the program's database makes use of two distinct monetary systems. The findings indicated that the scanned photographs produce outcomes that are superior to those acquired by images obtained with a digital camera. (Liu, 2008) makes use of an ensemble neural network (ENN), which leverages negative correlation learning (NCL) to acquire competence with a variety of input pattern subsets or sections. In order to identify objects, a technique based on neural networks is used, and then specific filters are applied to the obtained image (Mahmood, 2021). Real-time recognition has made it possible for people with vision problems to benefit from using the camera on their cell phone. The technique that is being developed to detect Indian paper currency takes into account a total of six distinct varieties of cash paper. In order to extract the features of the new Indian rupee note, the YOLO V3 architecture was utilized. This allows for quicker recognition of currency notes (Padilla, Netto, & Da Silva, 2020).

Deep learning Model

A data analysis method known as perceptron, which is part of the supervised learning process, is utilized by a specific type of artificial neural network known as a convolutional neural network (CNN). CNNs have applications not only in image processing but also in the processing of natural language and other cognitive tasks. The input layer, the output layer, and many of the hidden layers of an artificial convolutional neural network are very similar to the input layer, the output layer, and the hidden layers of other types of artificial neural networks. In order to transfer results to subsequent layers, convolutional layers make use of a mathematical model. This replicates some of the functions that are performed by the visual cortex in human brains. As a fundamental example of deep learning, CNNs advance the development of artificial intelligence by creating systems that imitate a variety of forms of biological human brain activity (see figure 1 for an example of this). The process of training involves minimizing the difference between the outputs and the ground truth labels by using an optimization technique such as (backpropagation and gradient descent), amongst others. This is done through the process of training, which is the process of optimizing parameters such as kernels.

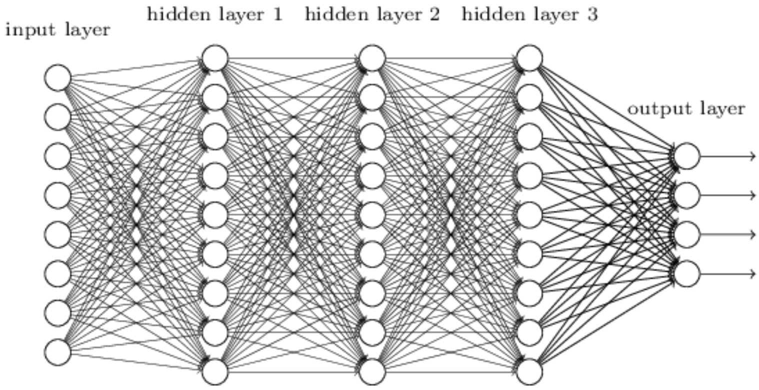

Figure1: Deep learning architecture *maintaining the Integrity of the Specifications*

Methodology

A fundamental principle underlying the acknowledgment of currency. It is vital to begin with the question of how to quickly capture high-quality and clear images of currency in order to construct the dataset and guarantee the clarity of the photographs of cash. In order to give credence to the idea of money recognition, it is essential to make certain that the information regarding the location of the currency is as specific as is practically possible. The Convolutional Neural Network, often known as CNN, was chosen to remove noise from the data collection since it contains a large number of pictures of noisy currency. We may be able to better fulfill the requirements of money recognition with the assistance of CNN's convolutional layer. The specific paper procedure is the core concept that was used in the creation of this flowchart, which can be seen in Figure 2. The gathering of datasets is the initial and most crucial phase in the process of money recognition. We took a single still image from the movie in order to retrieve the data image of the currency. The image that fits the experimental requirements is selected as a dataset prior to training the data, and then the data argumentation is carried out utilizing the marked photos in order to grow the size of the dataset.

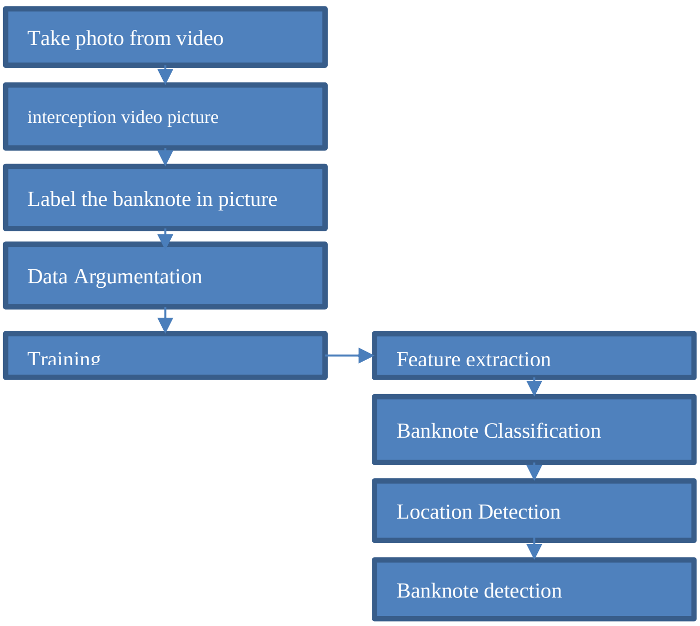

Figure 2: The steps of currency recognition

It ultimately decided to use real money as a data source to improve research outcomes. It has decided on the monetary denominations of 250IQD, 500IQD, 1,000IQD, 5,000IQD, 10,000IQD, 25,000IQD, and 50,000IQD for currency recognition. Each denomination's money will have a front and a back. Each side of these seven denominations were first captured on video. In order for the currency to be fully visible in the video, it must be flat during the video-shooting process as shown in figure 3 which shows training datasets that has been taken. The dataset's content was improved by moving the currency simultaneously in all directions, including forward, backward, left, right, and bevel. In order to more clearly catch the intricacies of the cash, it must also make sure that there is enough brightness around it when recording video.

Figure 3: The training dataset

It has added data argumentation on the original data and generated new data in order to improve the training of the data; this method has raised the volume of data in general. After data argumentation, Figure 4 shows the amplified impact of one of the dataset's raw data points.

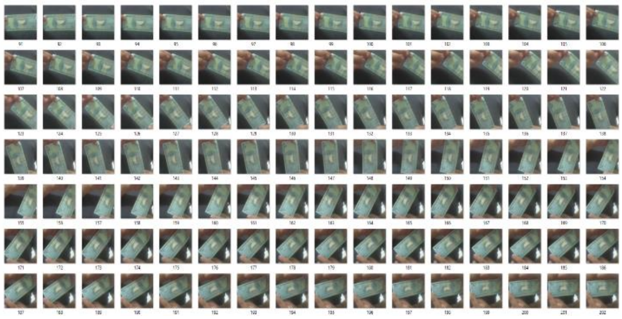

Figure 4: Data argumentation

Results

After the data gathering was finished, we obtained 50 samples for each image. The original data consists of 500 photos altogether. Then, our final dataset will consist of 25000 photos in total. We need to manually label the data after gathering the aforementioned information. At the same time, it apply the quadrilateral mark depicted in Figure 5 to show fully use the benefits of self-collecting and labeled data to label the position of the cash. Authors and Affiliations. The position of this currency can be defined more precisely with the quadrilateral mark than with the corresponding rectangular frame. The tilt of the cash in the image can also be seen, in addition to its position in the image.

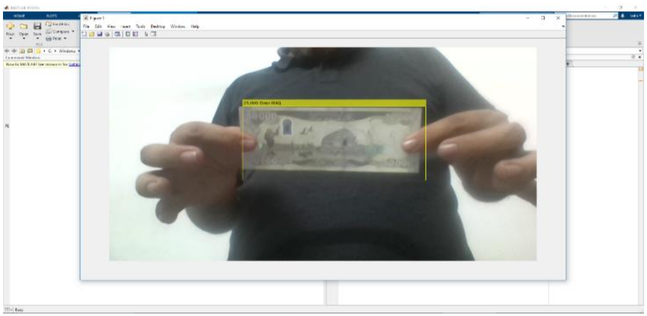

Figure 5: Manual marking a currency

To mark the video frame, it created the Matlab software that is depicted in Figure 5. Simply begin marking in the upper left corner and go clockwise to mark the locations of the four vertices. It can drag the four vertices to adjust them after marking them. We decided to employ hand marking to obtain an exact mark of the currency position. Figure 5, which depicts the seven denominations with the front and rear sides, provides this illustration. An Intel Core i7 CPU 2.0GHz laptop running Microsoft Windows 10 is used to conduct the experiment. In Matlab R2020a, all data tagging and data augmentation were performed. Table 1 shows the accuracy each type of banknotes.

Table 1. Accuracy for each type

No	banknote	test images	Precision Average AP(%)
1	250 Dinar	500	99%
2	500 Dinar	500	98%
3	1,000 Dinar	500	98%
4	5,000 Dinar	500	99%
5	10,000 Dinar	500	99%
6	25,000 Dinar	500	98%
7	50,000 Dinar	500	98%

The position of this currency can be defined more precisely with the quadrilateral mark than with the corresponding rectangular frame. The tilt of the cash in the image can also be seen, in addition to its position in the image. To mark the video frame, it created the Matlab software that is depicted in Figure 6. Simply begin marking in the upper left corner and go clockwise to mark the locations of the four vertices. It can drag the four vertices to adjust them after marking them. We decided to employ hand marking to obtain an exact mark of the currency position. Figure 6, which depicts the seven denominations with the front and rear sides, provides this illustration. An Intel Core i7 CPU 2.0GHz laptop running Microsoft Windows 10 is used to conduct the experiment. In Matlab R2020a, all data tagging and data augmentation were performed.

Figure 6: The sample of manual marking data

Conclusion

The primary purpose of this paper is to do research on monetary recognition. A foundation in empirical technique can be found in these models. In addition to that, the results are to one's liking. After recognizing the importance of currency, I will now summarize the key contributions made by this study. It came to the conclusion that a 7-layer CNN model should be developed. The fact that the trained model is capable of achieving an accuracy rate of 98% suggests that the dataset has been subjected to comprehensive training. It is possible to deduce from the loss function that the model did not become overfit while it was being trained. The final findings, which include correctly identifying the currency range in the classification label, the currency denomination, and both the front and back of the currency, are satisfactory. Additionally, one may say that a very high degree of precision is present in the process of money recognition. After conducting research on the topic, they found that recognition is brisk and accurate when the currency is displayed in a clear state across the entirety of the screen and the angles are parallel. The accuracy of currency recognition will suffer slightly whenever the cash moves at an obvious angle or appears on a screen at a distance from the camera; however, given that the dataset has been adequately trained, tests involving currency recognition can still be carried out successfully.

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