BuckTracker: System For Multi Banknotes Tracking

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***Abstract*—BuckTracker is a software that allows users to track their money transactions on a daily basis. Users scan cash banknotes using BuckTracker, which localizes each serial number, detects the currency denomination, and records the location of the scan. BuckTracker presents a novel solution for tracking money transactions, effectively enhancing transparency, accountability, and security in a wide range of financial operations. Users can track their transactions and retrieve the money in case of theft crimes. While the user is counting the money, the BuckTracker system scans each banknote, extracts its serial number, and detects the currency denomination. In this paper, two different object character recognition (OCR) techniques were experimented with in order to maximize the accuracy. The methodology used in this research improved previous work by enhancing the accuracy. The proposed system achieved an average accuracy of 92.3% on different data-sets, compared to a similar work that achieved 91.7% accuracy.**

***Index Terms*—Serial number Recognition, Optical character recognition, Convolutions neural network, Hash table.**

I. Introduction

Real money transactions continue to be crucial in the worldwide market, despite a decline in the usage of currency due to the recent rise in the use of electronic money transfers [9]. In recent years, many studies have focused on detecting and securing cash payments [5], [7], [8], [13], [20]. According to the Bank of England [2], over 4.7 billion England notes worth approximately £82 billion were in circulation annually among people in 2017. Schneider et al. [16] have stated that each banknote has a unique serial number assigned to distinguish it from the rest. The United States dollar banknote starts with 1 or 2 letters followed by 8 digits followed by 1 letter. The Euro combination is 2 letters followed by 10 digits. The English pound combination starts with 2 letters followed by 8 digits [1]. One way of tracking cash is to scan each banknote's serial number and assign it to a user. Passaro et al. [9] used fitness classification to scan banknotes, while Mohamed et al. [12] used OCR to scan banknotes. However, little attention has been paid to the time consumed in scanning each banknote, making these solutions unfeasible. This paper presents a solution for tracking and recognizing multiple types of banknotes along with their denominations using OCR. The ability to track banknotes can be particularly valuable in cases of robbery or theft, as it provides a means to trace and identify stolen money.

Fig. 1: (A) Challenging banknote image (B) Ideal banknote image

However, there are some challenges associated with scanning a banknote's serial number, including altering lighting conditions, eliminating video noise, reading the serial number on the banknote, and removing unwanted frames. Complex backgrounds may also lead to segmentation errors. The diversity of banknote scenes creates additional challenges such as variations in text color, font, size, and language, as shown in Figure 1A.

The proposed solution, BuckTracker, utilizes the OCR framework to perform serial number recognition. Specifically, Tesseract, an open-source OCR engine built on a convolutional neural network model, was used. While there are several types of OCR engines available, such as ABBYY OCR engine and Microsoft Oxford, Tesseract was chosen for its high accuracy and robustness [17]. In this paper, we present a system that localizes banknote serial numbers and performs hashing to store all transactions. The paper is organized as follows: Section 2 discusses related work and previous approaches, while Section 3 presents an overview of our methodology and system. The experiment and results are described in Sections 4 and 5, respectively. Finally, Section 6 provides the conclusion of our study.

II. Related Work

A significant amount of research has been conducted in this area previously [7], [8], [13]–[15], [20], [21]. In the following paragraphs, we review some of the previous approaches related to our work. Pachon et al. [7] discussed two approaches for detecting fake banknotes. The first approach used transfer learning, while the second approach used a classical deep learning CNN based on the AlexNet architecture. The AlexNet-based approach achieved an average test accuracy of 99.3%, with faster estimation time compared to the transfer learning techniques in an embedded system.

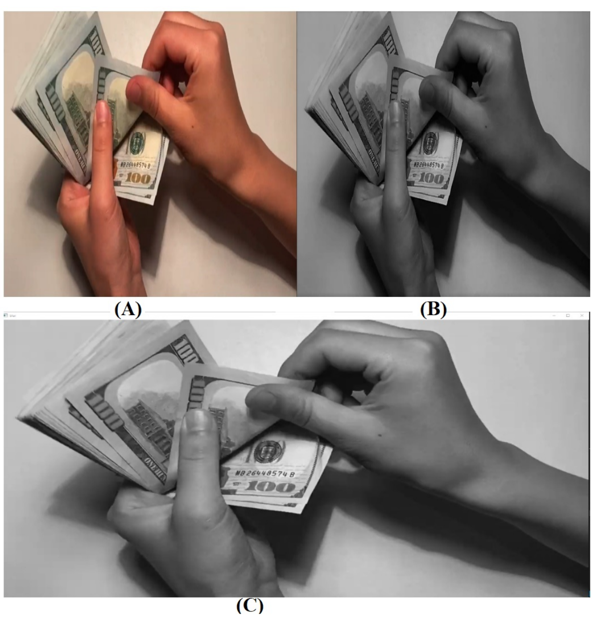

Fig. 2: Pre-processing stages:(A) Normal picture. (B) Applying the grayscale filter to the image. (C)Applying median blur to the image.

Pachon et al. [7] proposed an approach to recognizing banknotes that involved using YOLO net for Mexican notes [14], transfer learning with histograms for Euro banknotes, and custom CNN architectures for US dollar bills [7] and Jordanian dinars [13]. Chinese banknote serial numbers were recognized using morphology transformation and filtering [15]. In a separate study, Thyagharajan et al. [8] reviewed various systems for detecting nearly duplicate images. They reviewed a key point-based feature extraction algorithm that achieved an accuracy of 82.3%. However, the high cost of image matching due to the high number of key-points selected posed a major challenge. Another approach involved an image clustering-based system that utilized a map-reduce image constructor to create image clusters, but it encountered a higher possibility that images belonged to multiple clusters, which confused the model and led to some false positives. This reviewed solution achieved an accuracy of 84%.

Minghao Li et al. [10] presented TrOCR which is an end-to-end Transformer-based OCR model for text recognition with pre-trained CV and NLP models. The proposed method achieved a test accuracy of 96.57% on large dataset. The author has stated that Recognizing scene text images is more challenging than printed text images due to the bluring, occlusion and bad resolution effects.

Yan Ma developed a network for banknote serial number detection using a CRNN neural network with a DenseNet backbone in Keras ImageDataGenerator [20]. However, the CRNN model encountered a runtime problem, as it took a long time to extract the output. To enhance the results, an attention layer module was added. The achieved test accuracy was 96%. Lin et al. [21] developed the SNRNet algorithm, a hybrid RNN-CNN model with a CTC layer that does not require a pre-processing stage. They achieved an average accuracy of 99.93%.

OCR technology is a useful algorithm that can save time, money, and other resources. Agbemenu et al. [3] proposed a system for car license plate recognition, but their model faced two issues. The first issue was character segmentation, and the second issue was that their solution was not universal, as it only worked with Ghanaian car plates. The model achieved an accuracy of 60% for tested car images. OCR algorithms extract data from scanned documents or images by first extracting single letters, then combining them to form words and ultimately constructing the output text data.

Wang et al. [19] presented a system for bi-lingual OCR translation, but their model encountered a problem in the character recognition phase, in which some combined characters, such as 'w' $\rightarrow$ 'vv', 'm' $\rightarrow$ 'rn', and 'd' $\rightarrow$ 'cl', confused the model. The model achieved an average accuracy of 83.4%. Cecotti et al. [6] developed a hybrid OCR and ICR technique for recognizing ancient documents. They found that the combination of OCRs increased recognition by about 3%, while ICR improved the recognition of rejected characters by more than 5%. The overall accuracy of the combined model was 85.14%. The authors chose to use a voting technique to fuse the combined model, which was not as effective as other ensemble options, resulting in discouraging results.

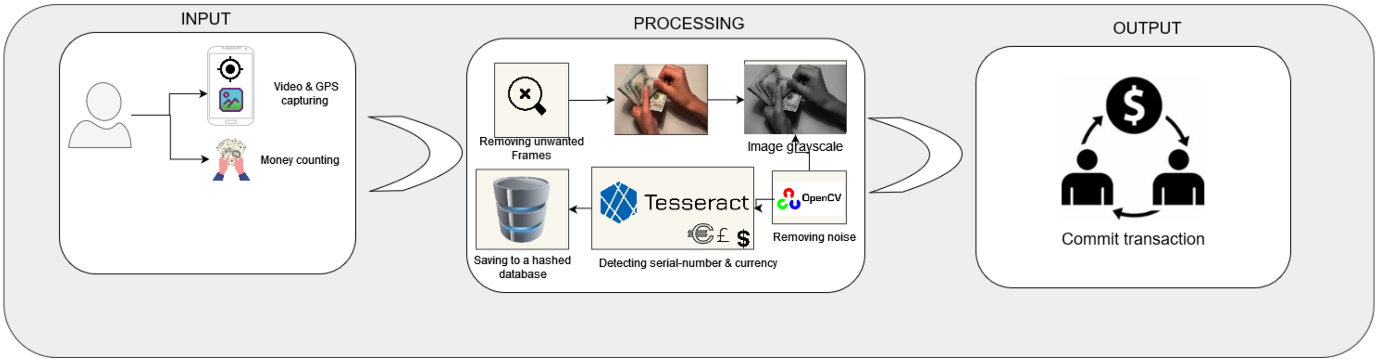

Fig. 3: System Architecture

III. Methodology

The proposed system operates in several phases. First, the user places a camera directly facing their hand while counting the money. At the same time, the system records the GPS location, scans the image, and retrieves the serial number. Once this information is obtained, the system saves the transaction in a hashed table for future reference. The system architecture is illustrated in Figure 3, and the following sections provide a detailed description of each phase.

A. Pre-processing

To detect the serial number of a banknote, the user is instructed to count the banknotes and place the mobile camera directly above them, as shown in Figure 2. The proposed system receives frames and GPS data from the user and sends them to a server for processing. However, it can be challenging to properly identify the serial number's location when processing the frames, as the system processes many frames at once. To tackle this challenge, the system records RGB frames of the currency, as depicted in Figure 2. A gray filter is then applied to the frames using OpenCV to reduce some of the noise. The noise is further eliminated by applying median blur, as shown in Equation 1 and Figure 2 [18]. It is worth noting that pre-processing can be a challenging task, and the accuracy of the model can be impacted by any rotations or misalignments of the banknotes in front of the camera. Therefore, it is assumed that the banknote frames are in a steady position to the camera to ensure the overall accuracy of the model.

$$f(x, y) = median(g(s, t)) \tag{1}$$

B. Localization

According to [11], the system implements a frame skipping technique where only one frame is processed out of every six frames to reduce the computational cost, as processing all the frames simultaneously consumes a significant amount of power. This approach helps in identifying the serial number accurately.

C. Recognition

Various approaches have been employed in the character recognition phase, with CNN being a favored method for character detection from images [4], [7], [14], [20]. In the proposed system, the serial number is recognized by Tesseract, an open-source OCR engine that is based on a convolution neural network model. Tesseract is also compatible with numerous programming languages. The recognized serial number format is then utilized to differentiate between the different types of banknotes.

D. Hashing Data

The final part of the proposed system involves saving the scanned banknotes, GPS coordinates, and user ID in a hash table. Each value is assigned a unique index value in the table. The hash table is used for security purposes in the proposed system. When a transaction occurs, the system saves the scanned serial number, timestamp, old and new user ID, GPS location, and a unique transaction ID. These values are passed through a hash function, and the resulting indexes are saved in the table.

IV. Experiments and Results

In this study, two distinct techniques were employed to identify the serial number of banknotes, while also determining their respective types (i.e., dollar, euro, sterling), through the utilization of Tesseract version 5 and OpenCV for the purposes of localization, detection, and annotation of position on the bills. Furthermore, the banknote denomination was detected based on the serial number combination.

A. Data-set

The dataset used in this research consists of three classes of banknotes: USD, GBP, and Euro, comprising a total of (160) 100-dollar bills, (120) 1-dollar bills, (120) 5-dollar bills, (40) 50-dollar bills, (40) 20-dollar bills, (80) 20-GBP bills, (80) 5-GBP bills, (40) 50-GBP bills, (40) 10-GBP bills, (80) 20-euro bills, (120) 100-euro bills, (40) 10-euro bills, and (40) 5-euro bills as shown in (Fig 4). A portion of the dataset was collected from YouTube, while the remaining data was gathered using physical banknotes. To ensure consistency across the experiment, volunteers were recorded counting money in the same manner as shown in Fig 5.

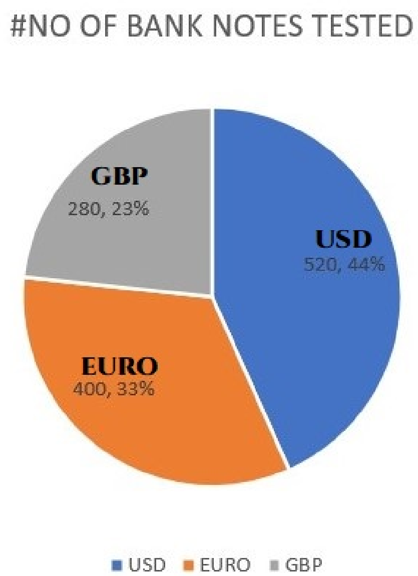

Fig. 4: Dataset distribution of banknotes by class

B. Setup

During the experiment, a hardware device with an 8 MP camera, 2.50 GHz 10 core CPU, NVIDIA GTX 1650, and 32GB RAM was used. Tesseract parameters was configured to work with "—psm 12 —oem 3".

C. Experiment 1

The primary aim of this experiment is to identify the serial number of various banknotes. In the processing phase, Tesseract is utilized to extract the region of interest from the image and generate an array comprising its output character, width, height, and position (x, y) (refer to Fig 5).

Initially, the Tesseract output is segmented based on the characters and filtered by their size (width, height) and the gap between them (refer to Fig 5). Each character in the serial number is uniformly spaced and has identical size. The proposed approach can discard undesirable outputs from Tesseract by applying size and distance filtering.

Next, the filtered output is split into the corresponding serial number combinations. The serial number of a 100 bill is composed of two letters, eight numbers, and one letter (refer to Fig 5). The obtained information, including the serial number, banknote type, and GPS location, is then stored for the new owner.

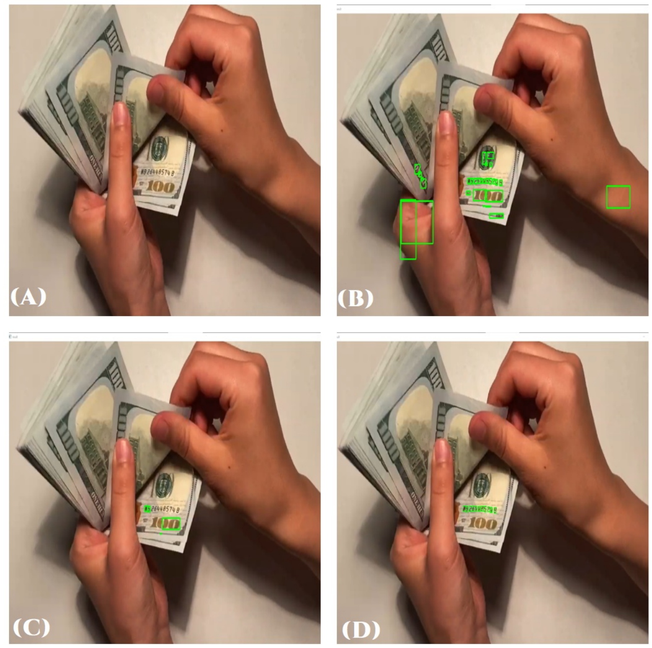

Fig. 5: Different stages of frame processing. (A) User counting money. (B) The returned output from the Tesseract without segmentation. (C) Applying the first layer of segmentation to the output. (D) Applying the second layer of segmentation to the output to recognize the serial number.

	USD	GBP	EURO
Detection Accuracy	96%	92%	89%

TABLE I: Banknotes category recognition accuracy

D. Experiment 2

This experiment involves the use of Tesseract OCR (optical character recognition) technology to process frames and extract complete text from images of banknotes. The extracted text is then subjected to further processing to remove any noise and spaces. After this, regular expressions (REGEX) are utilized to extract specific information from the processed text data, such as the serial number and bill category. The Tesseract ROI (region of interest) function is also employed to determine the precise location of the serial number on the bill that was previously detected, as illustrated in Figure 5. The data extracted through this process is stored in a manner similar to that used in Experiment 1.

By combining both approaches - image-to-string for accurate recognition of serial numbers and ROI for positional localization - it is possible to achieve slightly improved performance while also reducing the overall execution time required for the experiment.

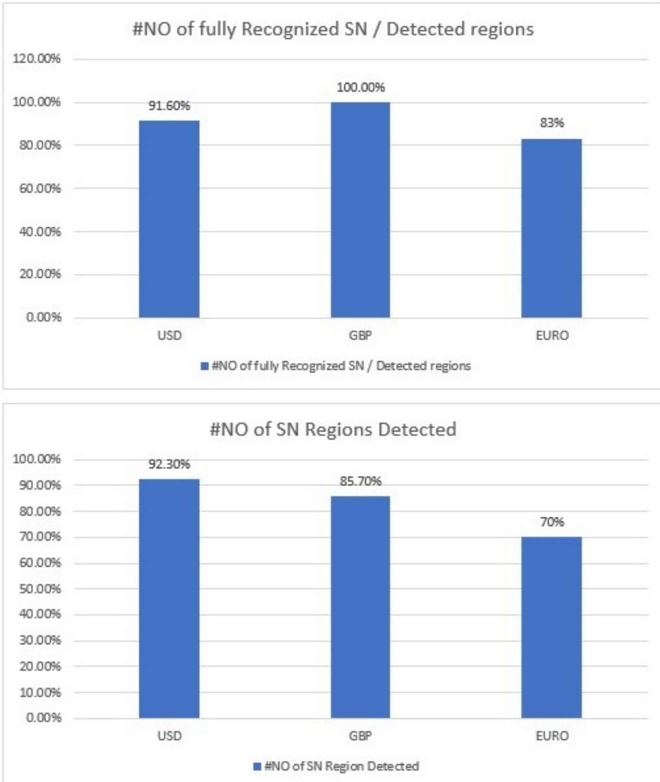

Fig. 6: Bar charts for both serial number Region detection and character recognition.

Reference	Currencies	Time	Average Accuracy
Expirement 1	3	12.29 s	92.3%
Expirement 2	3	15.85 s	92%
[12]	1	52 s	91.7%

TABLE II: Comparing results with previous work

V. Results and Discussions

The two approaches mentioned in the previous paragraph were subjected to experimentation and testing using a collection of banknotes, as depicted in Figure 4. a total number of 1200 banknotes were utilized to conduct this experiment. The results of this experiment are presented in the form of a chart, which can be seen in Figure 6. This chart simplifies the representation of the data collected during the experiment and allows for easy analysis and interpretation of the results.

The results are presented as a bar chart with two columns. The first column represents the number of serial number region detection, indicating that the system was able to recognize most characters of the serial number and their position on the frame. The second column represents the accuracy of the detected serial numbers in the regions from column 1.

The average accuracy of the detection experiments was 92% as shown in Table II. The average time for counting and processing each frame was 12.29 seconds, with a maximum time of 15.85 seconds.

Out of the 1200 banknotes used in the OCR region detection phase, 1000 of them were detected correctly with an accuracy of 83.3%. The algorithm faced several challenges, including angled images, uneven illumination, and font color issues as shown in Table 6. The model scored 92% accuracy in detecting the serial number as well as detecting the type of bill from the successfully detected regions as shown in Figure 7. The model was able to detect 923 out of 1000 bills.

The system determined the type of currency from the serial number discovered as a result of the serial number detection. Each banknote has a unique set of serial numbers, as previously mentioned. The system segments the extracted serial number to identify the type of currency depending on its combination. The experiments scored 96%, 92%, and 89% for detecting US dollars, GBP, and Euros, respectively, as shown in Table I.

Fig. 7: Output frames

A. Discussion

The findings of this research and its experiments have provided insight into the technical aspects of an optical character recognition application. This system has the potential to improve the reliability of banknote transactions and limit crimes related to the financial sector. However, users should be cautious when interpreting the results. The banknote serial number recognition system encountered some false character identification errors due to certain character combinations that were difficult for the OCR to recognize properly, such as 'fr', 'rt', 'ff', 'ft', 'fi', and 'rn'. The model also struggled with Euro banknotes due to their complex background and the inconsistent pixel spacing orientation of the serial number. As a result, the tesseract either failed to recognize some of the characters or recognized them as other characters. Additionally, another limitation to consider is the impact of lighting conditions on the visibility of the banknote. Variations in lighting, such as uneven illumination or glare, can affect the legibility of the banknote's serial number. In situations where the lighting is insufficient or too harsh, the optical character recognition system may encounter difficulties in accurately detecting and interpreting the characters.

B. Future Work

As OCR technology advances, it will be able to detect text on images from different angles. However, Tesseract may still encounter difficulties in identifying serial numbers that contain symbols, such as identifying '*' as '+'. Further pre-processing is also needed to remove unwanted frames where the serial number is not fully visible to achieve maximum optimization. Additionally, it was assumed during the experiments that the image was correctly registered, i.e., it did not need to be rotated or cropped. In the near future, a well-structured API will need to be developed to ensure both the availability and reliability of the service.

VI. CONCLUSIONS

In conclusion, given the persisting issue of cash security in many countries, an easy and feasible solution is needed to address the problem. The experiment aims to quickly identify a banknote's serial number region and determine its location and category using optical character recognition (OCR) to track banknotes. The proposed BuckTracker system offers a secure money tracking and transaction process. Users of the system should ensure that the phone is stabilized in a vertical position while counting money, with a clear view of the serial number for the camera. Through standardized testing, the results showed higher accuracy with banknotes that had less noise. However, the euro banknotes posed a challenge to the system as multiple unwanted image patterns misled the OCR algorithm. The system achieved an overall average accuracy of 92.3%.

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