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Currency Recognition Using EAST for Text Detection and Tesseract OCR for Text Recognition

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***Abstract*—This research study presents a novel approach for detecting currency utilizing cutting-edge technologies such as the Efficient and Accurate Scene Text (EAST) model and Tesseract Optical Character Recognition (OCR). The EAST model is employed to identify text within scenes, whereas Tesseract OCR is utilized to effectively recognize and classify monetary units in real-time video stream input. The empirical results demonstrate the efficacy of the suggested methodology in discerning and classifying distinct monetary units, a pivotal necessity in diverse financial scenarios. The amalgamation of the EAST model with OCR can augment money identification technology, strengthening the dependability of financial services such as ATM operation and currency conversion and ultimately elevating consumer happiness during financial transactions.**

***Keywords*—Currency recognition, Currency identification, EAST model, Tesseract OCR, Text detection**

I. INTRODUCTION

In contemporary society, there is a proliferation of image recognition technologies that fulfill a wide range of purposes, encompassing the identification of various objects and faces and the recognition of license plates and human behavior [1]. Nevertheless, a distinctive obstacle arises within the domain of currency identification, as the distinguishing characteristics of different nations' currencies differentiate them[2]. The unintended consequence of currency appreciation is the potential increase in the circulation of counterfeit money, which poses a significant risk to a nation's interests. Consequently, a significant and imperative issue in contemporary times revolves around recognizing technology to preserve the genuineness of cash [3].

However, there is an additional aspect to consider regarding the importance of money recognition technology. Individuals who experience visual impairments frequently encounter challenges in discerning various cash denominations, primarily due to the similarities in paper texture and size[4]. As a result, there is an increasing demand for technological interventions to mitigate this situation, guaranteeing that visually impaired individuals can engage in financial transactions with assurance and security.

The recognition of currency holds significant importance within financial technology (FinTech), extending beyond a mere technological innovation[5]. Implementing precise and effective currency identification systems is crucial in automating many financial services. Recognizing currency using traditional approaches has faced significant difficulties in dealing with diverse currency designs, unpredictable lighting condition changes, and isolated real-world situations[6].

The field of automated systems and techniques for currency recognition has witnessed a significant evolution throughout the years [7]. Artificial intelligence (AI) has significantly penetrated diverse sectors, encompassing civil engineering, medical disciplines, and image processing. Neural networks have become an effective currency recognition method [8]. This encompasses various tasks, including detecting currency note portraits, identifying counterfeit notes, recognizing currency note serial numbers, and extracting and identifying features on currency notes [9]. Cash identification has developed substantially due to the progress made in scanner-based and camera-based technology. Scanner-based systems are designed to collect images of paper currency, whereas camera-based systems are utilized to record specific paper components. Scanner-based systems are frequently utilized; however, camera-based systems are increasingly being adopted by those with vision impairments[10].

Deep learning techniques are being investigated as a prospective approach to tackling the complex challenges of money recognition[11], [12]. This study examines how to train Egyptian paper currency through a camera-based technique. The methods employed in this study involve the utilization of the Efficient and Accurate Scene Text (EAST) model for text identification[13], together with the Tesseract Optical Character Recognition (OCR) technique for text recognition[14]. [15]Significantly, the system demonstrates proficiency in processing money notes that have been partially captured, even when subjected to different lighting conditions.

The future sections of this paper are organized in the following manner: Section 2 offers a comprehensive analysis of the extant scholarly literature about the recognition of paper currency. Section 3 provides a comprehensive study and explanation of the proposed system. Section 4 presents the empirical findings, while Section 5 provides a concluding analysis of the investigation on currency recognition, shedding light on its significant implications in financial technology and beyond[16].

II. Related Work

The topic of currency recognition has been significantly influenced by numerous researchers, who have contributed by offering their distinct perspectives and views. This part thoroughly examines prior research on methodologies utilized for currency recognition. This analysis aims to elucidate this field's significant discoveries and accomplishments.

In 2019, Zhang, Yan, and Kankanhalli produced a notable work that utilized a fusion of deep learning methodologies to address the complex task of money recognition[17]-[20]. The researchers directed their attention toward the New Zealand Dollar (NZD) currency and opted to examine three specific monetary denominations, 5-NZD, 10-NZD, and 20-NZD, as the focal points of their study. To construct their coin identification model, the researchers diligently recorded video footage of each side of the denominations separately. The undertaking produced a collection of fifty image samples for each denomination, resulting in a comprehensive dataset of 300 image samples. Each image in the dataset possesses a resolution of 1280x720 pixels[21].

The researchers employed a thorough data augmentation methodology to enhance the variety of a dataset and generate additional samples, thereby strengthening the training efficacy of deep learning models. The plan encompassed a five-step method, which entailed the resizing of images, the application of random clipping or expansion techniques, the implementation of random rotation, the resizing to achieve consistency, and the incorporation of random color adjustments. The purpose of this technique was to address the limitations imposed by the restricted dataset.

Their study's scope encompasses activities beyond collecting and augmenting datasets. Zhang et al. [22]. Conducted a comprehensive analysis of the experimental methodologies and results of two separate systems, highlighting their similarities and differences. The researchers' investigation focused on the application of Principal Component Analysis (PCA) in combination with Back-Propagation Neural Networks (BPNN) alongside the Feedforward Neural Network (FNN) classifier. The research conducted by Zhang, Yan, and Kankanhalli demonstrated notable precision in currency detection, with a recognition time of 0.4249 seconds. The researchers conducted a comparative analysis of various classifiers, namely F-NN, PRFNN, C-NN,[23] and Ada-Boost. Their findings revealed that the Feedforward Neural Network (F-NN) exhibited the highest level of Accuracy. The accuracy rate of the Convolutional Neural Network (CNN) model reached 96.6 percent; nevertheless, it is essential to note that achieving this level of Accuracy necessitated substantial training of the dataset. The research emphasizes the intricate correlation among the dataset's quantity, the model's quality, and the detection speed. This underscores the researchers' commitment to surmounting currency recognition obstacles and inventive strategies to augment datasets with limited accessibility. The research conducted by the authors makes a substantial contribution to the field of money recognition approaches, offering vital insights[17].

Table 1 Comparative Results

Name	Model	Accuracy (%)
Method I	CNN	96.6
Method II	PCA + BPNN	99.6
Method III	FNN	92.4

In a study by Jadhav et al., deep learning techniques were employed to discern between authentic and counterfeit currency notes. Cameras were employed to capture visual representations of counterfeit currency notes from India and Saudi Arabia[24]. Subsequently, characteristics were extracted from these images utilizing dissimilarity and discontinuity techniques[25]. The obtained characteristics were used to discern counterfeit cash. A note's genuine or counterfeit character was determined by using comparative degrees of the two notes. Deep learning algorithms with a MATLAB program facilitated the automated identification of counterfeit rupees and other currencies. The developed method exhibited a higher cost-effectiveness and efficiency than the existing methodology. Prior studies in the field of currency recognition have investigated many approaches, encompassing conventional machine learning and deep learning methodologies. Deep learning methodologies have exhibited considerable promise, notably ineffectively addressing intricate and diverse currency designs. Our methodology is based on the foundation laid by earlier studies, utilizing the EAST model for text identification and Tesseract OCR for text recognition.

Velasco[26] has presented a nonparametric methodology in which a nonparametric model is derived from the average of aligned banknote samples. Next, the coefficients of determination are computed to assess the relationship between an unidentified banknote and each model. In conclusion, a discriminant analysis allocates a model to the unidentified banknote. The proposed methodology was effectively used to accurately identify three distinct types of Saudi banknotes, yielding an error rate of 10%.[27]

The authors presented a cash recognition system based on the bionic eyeglass[28]. The extraction of pertinent shapes from the picture flow of the Hungarian banknote, as observed by the mobile Camera, is achieved through adaptive thresholding and morphological shape filters. A two-tiered classification approach was employed to categorize various types of patches, namely portrait, denomination, and tactile marks. The ensemble decider was utilized to aggregate the votes from the classification process.

Furthermore, many money identification applications can be found on Google Play, although many programs lack explicit documentation regarding their specific scientific contributions. The IDEAL Currency Identifier is an Android smartphone application designed to assist those with visual impairments in identifying United States currency denominations. The LookTel Money Reader application for iOS is designed to help individuals identify and quantify their currency. Text-to-speech (TTS) technology has the potential to assist individuals with complete visual impairment by providing auditory notifications regarding the quantity of recognized notes. Additionally, this technology has the potential to assist individuals with visual impairments by displaying the identified denomination of currency in a prominent font size positioned at the center of the screen[29].

Detecting text is essential for future extracting and comprehending textual information. This phase is of significant importance to the whole method. Previous studies on text detection have shown encouraging results on many benchmarks in the field [27]-[30]. The fundamental aspect of text detection involves the development of distinct features that may effectively differentiate text from surrounding backdrops. In the conventional approach, features are typically crafted manually to capture the scene text's characteristics. However, effective features are acquired immediately from the training data in deep learning approaches.

Nevertheless, whether traditional or based on deep neural networks, the current approaches predominantly comprise multiple phases and components. This composition is likely less than ideal and might consume much time. Hence, the precision and effectiveness of these procedures remain somewhat inadequate. The image undergoes a sequence of algorithms that comprise the preprocessing processes.

De-skewing is a procedure that involves the identification of the bounding box of scanned text, followed by the rotation of the image to align the document in a standard upright orientation[34].

De-noising refers to the reduction of noise originating from the image capture device. Various forms of noise may be present and necessitate removal[35].

Character Enhancement: De-noising can result in a reduction of clarity and loss of edge definition in characters. To enhance the edges of characters, it is necessary to apply an image-sharpening technique[36].

Histogram equalization is a technique used to address the issue of uneven exposure in some regions of an image, which might occur due to variations in scanning devices. This inquiry seeks to elucidate the underlying cause for the disparity in brightness observed between several sections of the paper. The Histogram Equalization method aims to provide a more uniform distribution of pixel intensities throughout the image, thereby equalizing the representation of the brightest and darkest parts.[37]

The optimal performance of optical character recognition (OCR) is observed in cases where individual characters are accurately identified [38].[39]

III. CHALLENGES IN CURRENCY RECOGNITION

The work of currency recognition is characterized by its complexity and presents numerous inherent obstacles that necessitate the efforts of researchers and engineers to develop a solution that is both efficient and dependable[40]. The consideration of these challenges is crucial in the development of a currency recognition system.

The design variability of currency notes can be observed in the diverse range of designs found across different countries and denominations[40]. Every country has the potential to own a currency design exclusive to its own identity, characterized by various distinguishing attributes such as color schemes, intricate patterns, symbolic representations, and advanced security measures. Certain currencies even integrate numerous languages and scripts. The presence of diverse design components in currency requires developing a recognition system capable of discerning between different currencies and accommodating their varied design elements[41].

Lighting circumstances: Currency notes have the potential to be scanned or photographed under a wide range of lighting circumstances, encompassing both intense natural daylight and subdued indoor lighting. The presence of diverse lighting conditions can substantially influence the visual characteristics of currency notes, leading to reflections, shadows, and alterations in color and contrast[42]. To achieve accurate recognition under all situations, a currency recognition system must possess robustness that enables it to effectively handle variations in lighting conditions.

Occlusion refers to the phenomenon where currency notes exhibit partial visibility when subjected to scanning or photography. Other items may obscure the objects and be folded or crumpled. The presence of occlusion is a significant challenge for the recognition system in accurately identifying and localizing the cash inside an image. Managing obscured currency notes is a crucial component of a comprehensive system for recognizing cash[43].

The noise in photos can potentially generate errors during the recognition process. The generation of this auditory disturbance might arise from many origins, encompassing scanning apparatuses, cameras of substandard quality, or the process of compressing images. The recognition system's design should prioritize identifying essential characteristics of the currency note while effectively eliminating any extraneous noise, ensuring high Accuracy and reliability in the recognition process[44].

It is imperative to tackle these issues about money recognition to develop a system that can effectively operate in real-world situations. Researchers and engineers must devise algorithms and models that can adjust to the inherent variety found in currency designs, effectively handle a wide range of lighting situations, accommodate instances where currency notes are partially obscured, and effectively minimize the adverse effects of picture noise. Through this approach, researchers and developers can construct currency identification systems that exhibit high levels of Accuracy, resilience, and applicability across several domains, encompassing but not limited to banking and retail sectors.[45]

IV. PROPOSED APPROACH

The present method employs deep learning concepts to categorize various denominations of currency notes. The procedure commences with the real-time capture of frames from a camera, which functions as visual depictions of currency notes necessitating identification and categorization. The system's capability to process currency notes upon receipt enables its applicability in diverse contexts, including currency exchange services and automated teller machines (ATMs).

The dataset has been successfully loaded and comprises a collection of photos of Egyptian currency notes. The classification procedure entails categorizing these photographs into distinct classes, each representing a specific monetary denomination. The VGG16 architecture is frequently utilized for training purposes, and the model has undergone training using a dataset comprising Egyptian cash notes.

Preprocessing procedures are employed to attain uniformity and optimize the model's efficacy. The input images are resized to a standardized dimension to address variations in image dimensions and then normalized. Convolutional, max-pooling, and thick layers are employed in neural networks to extract features from images. Convolutional layers are crucial in extracting features, while max-pooling layers reduce the spatial dimensions of the obtained features. Dense layers, sometimes called fully connected, do the ultimate classification task by leveraging retrieved characteristics.

The algorithm under consideration incorporates the EAST Model, a widely used method for Text Detection, and Tesseract Optical Character identification (OCR), a renowned technique for text identification. Additionally, the program includes the capability of recognizing monetary values. The EAST model is a neural network architecture specifically designed to detect text in photographs. On the other hand, the OCR software is generally acknowledged for its proficiency in accurately recognizing and extracting text from images. Both components have received training with the SynthText dataset.

Real-time testing evaluates the system's real-time performance using input from the camera feed. The system's ability to accurately identify different cash denominations and extract relevant textual information is assessed in real-world operating contexts. In conclusion, this algorithmic framework presents a sophisticated approach for the real-time recognition of currencies and identifying textual components.

The proposed system's workflow can be succinctly outlined as follows:

1. Dataset Collection: To commence the process, the required datasets are gathered. This includes the SynthText dataset for text and images featuring EGP Banknotes captured from various angles and under diverse conditions.

2. Camera-based image capture is employed for real-time recognition of money notes, emphasizing the importance of live input for accurate and quick processing.

3. Image Preprocessing: The initial step in the processing pipeline involves utilizing OpenCV to read the input image. Subsequently, a preprocessing stage is conducted to ensure compatibility with the MobileNetV2 model's input specifications. This consists of scaling the image to a standardized dimension and normalizing the pixel values.

4. Text Detection with EAST: The EAST model is employed to identify precise regions within input photos of currency notes where text denoting the denomination is situated.

5. Text Recognition through Tesseract OCR: Once text regions are successfully detected, the next phase involves applying the Tesseract Optical Character Recognition (OCR) tool to recognize the text within these regions. This step extracts valuable information, such as the denomination, from the identified text regions.

6. Currency Denomination Classification: The recognized text is mapped to the corresponding currency denominations. This mapping allows the system to determine the currency note's denomination accurately.

Define abbreviations and acronyms the first time they are used in the text, even after they have been defined in the abstract. Abbreviations such as IEEE, SI, MKS, CGS, sc, dc, and rms do not have to be specified. Do not use abbreviations in the title or heads unless they are unavoidable.

A crucial concept known as a "blob" is introduced to facilitate the deep learning model's operation. A blob is a preprocessed image that serves as the input to the deep learning model. The system loads the EAST text detector model and initializes the camera object. It then enters a loop to capture frames continuously from the Camera. The original frame is preserved to display the final output, which may include annotations like bounding boxes and recognized text.

In the process, frames are resized to a standardized size of 640x320 pixels to optimize image processing speed. Non-maximum suppression is applied to eliminate overlapping bounding boxes. Subsequently, Tesseract OCR is deployed to extract text from each bounding box. The system draws bounding boxes around the detected text regions to provide visual context and showcase the output frame. The system is designed to monitor key presses, facilitating a graceful exit from the loop. Once the process concludes, the camera object is released, and all associated windows are closed.

The EAST model, which specializes in text detection, generates two key outputs: scores and geometry. The scores measure the probability that a given region contains text, while the geometry output precisely describes the position and dimensions of the bounding boxes encircling the text regions. Each frame is transformed into a blob, preparing it for further processing by the deep learning model.

Number equations consecutively. Equation numbers within parentheses will be positioned flush right, as in (1), using a right tab stop. You may use the solidus (/), the exp function, or appropriate exponents to make your equations more compact—Italicize Roman symbols for quantities and variables, but not Greek symbols. Use a long dash rather than a hyphen for a minus sign. Punctuate equations with commas or periods when they are part of a sentence, as in:

WORD RECOGNITION OF TESSERACT

The Tesseract engine is a highly proficient Optical Character Recognition (OCR) system specializing in word recognition. It can convert printed or scanned text into formats that machines can easily read and edit. The open-source software known as Tesseract has significantly transformed how humans engage with textual content by facilitating the conversion of physical documents into digital representations. The versatility and capacity to extract textual information from photographs, irrespective of the image's source or format, render it an essential element in diverse settings. The utilization of Tesseract, with its capacity to accurately identify words and accommodate various languages and typefaces, renders it a suitable option for data extraction and input automation. Consequently, this technology significantly influences cataloging, information retrieval, and content analysis tasks.

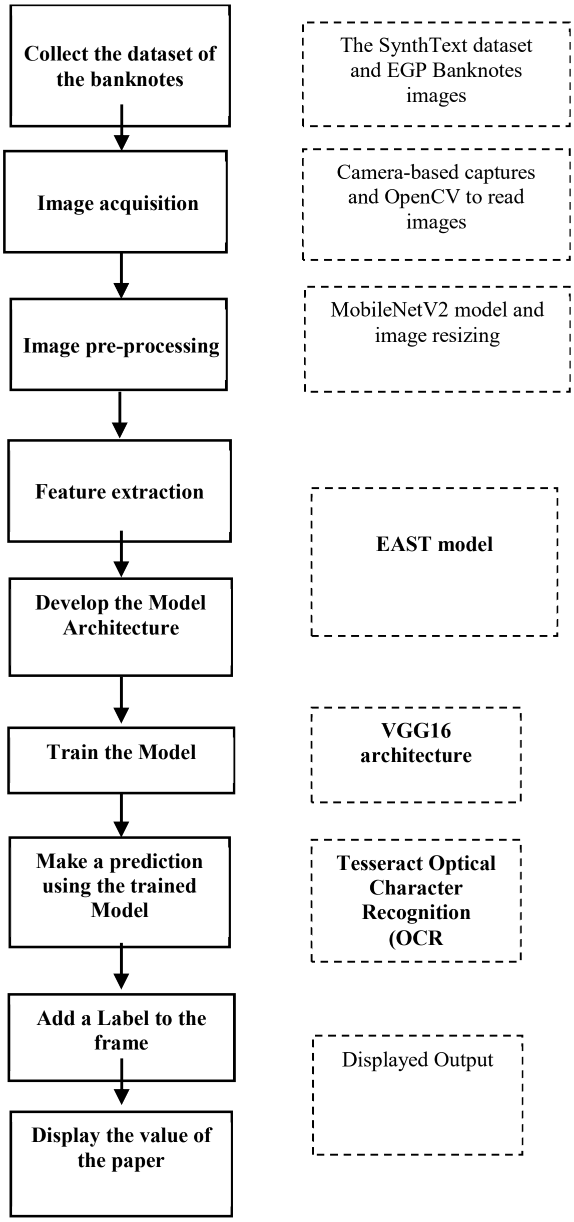

Fig. 1 Proposed algorithm framework

The capabilities of Tesseract span from the recognition of individual words to the processing of complete textual texts with a high level of precision while preserving the integrity of the original material. The tool's adaptability renders it an essential instrument for various text-related endeavors. Fig. 2 shows the basic components block diagram for Tesseract [10].

Figure 3 illustrates the dataset of the Egyptian currency banknotes used to train the proposed algorithm. Figure categorizing them into distinct classes to facilitate the training process.

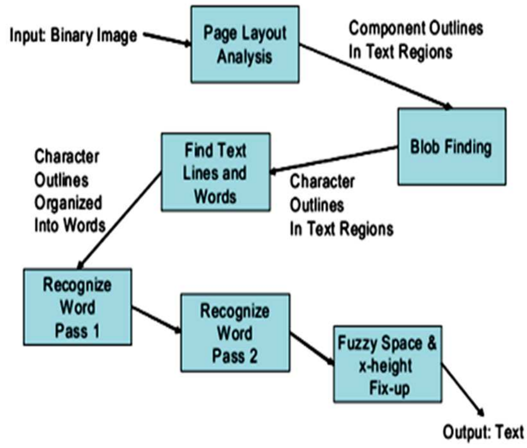

Fig. 2. Block diagram of essential components of Tesseract[14].

A pre-trained MobileNetV2 architecture is then utilized to train the model using images of Egyptian currency notes. The resulting trained model is preserved for future applications.

Fig. 3 The dataset of the Egyptian currency banknotes

V. Experiments and Results

The present study assessed the efficacy of a methodology employing authentic photos of tangible currency in a real-world context. The dataset encompassed a range of denominations and lighting settings, thereby simulating real-world scenarios—the evaluation metrics comprised Accuracy, precision, recall, and F1-score. Real-time input frames were captured using a live stream camera for detection. The frames were subjected to preprocessing techniques such as scaling, normalization, and reshaping to facilitate prediction. The frames that had undergone preprocessing were subsequently assessed using a constructed model. This model ascertained the class with the best prediction probability and assigned a corresponding label to the frame. The research conducted a thorough evaluation of the system's overall performance.

The model's architecture is constructed utilizing frameworks such as TensorFlow and Keras, facilitating the efficient processing and categorization of photographs. The process of scaling input photographs and performing image processing techniques such as Gaussian blurring is facilitated by OpenCV, a computer vision toolkit that is open-source in nature. The model's architecture uses the Keras Sequential API, including four convolutional blocks succeeded by two thick layers. Each block incorporates numerous Conv2D layers, a MaxPooling2D layer, and a Dropout layer to boost performance. The model's efficiency is improved using Gaussian blurring and image processing methodologies.

The choice of optimizer for building and training the model was the Adam optimizer[46], [47], [48], [49], [50], [51], [52], accompanied by a Sparse Categorical Cross-Entropy loss function and Accuracy as the evaluation metric. The findings are depicted in visually informative figures, representing the experimental results visually.

The model is meticulously compiled and trained using an extensive dataset, ensuring the network can discern intricate patterns among currency notes. To assess the model's Accuracy and reliability, a rigorous evaluation is conducted using an independent testing dataset, as shown in Figures 4 and 5. Following successful evaluation, in Figure 4, the recognition of 100 LE banknotes is determined with an Accuracy of 57.63%, then with an Accuracy of 62.6% and enhanced while testing the 20 EGP Banknotes as in Figure 5 to 100%.

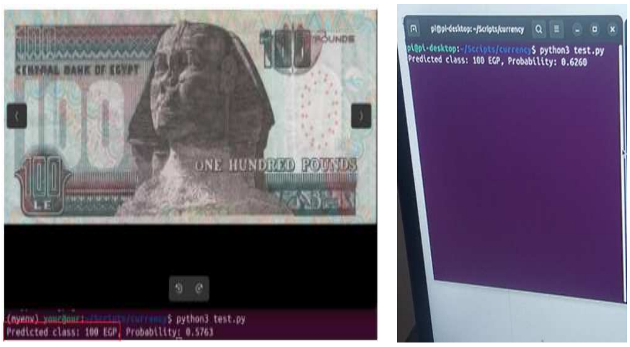

Figure 4: Testing the recognition of 100 LE banknote with online photograph

Figure 5. Predicted currency detection results, with the identified output highlighted within a red rectangle.

The experiments encountered the ESP32-CAM Development Board (with Camera): The ESP32 Camera module includes an OV2640 camera sensor capable of capturing 2-megapixel photos and 720p videos. It can be programmed using various platforms such as the Arduino IDE, MicroPython, and the Espressif IoT Development Framework (ESP-IDF). Connect the ESP32 Camera module to the Raspberry Pi using jumper wires. The connection pins on the ESP32 Camera module should be connected to the corresponding GPIO pins on the Raspberry Pi.

In real-time currency detection scenarios, the system utilizes live-stream camera input. Each frame captured by the Camera undergoes preprocessing, including resizing, normalization, and reshaping, aligning with the model's input requirements. The model predicts the currency class with the highest probability for each preprocessed frame, and the predicted class label is added to the frame, enabling real-time currency detection in practical and varied scenarios, as demonstrated in figures 6, 7, the Prediction of the 50 EGP and 200 EGP banknote classes.

Figure 5: Testing the Model recognition with an online photo of the 20 EGP banknote

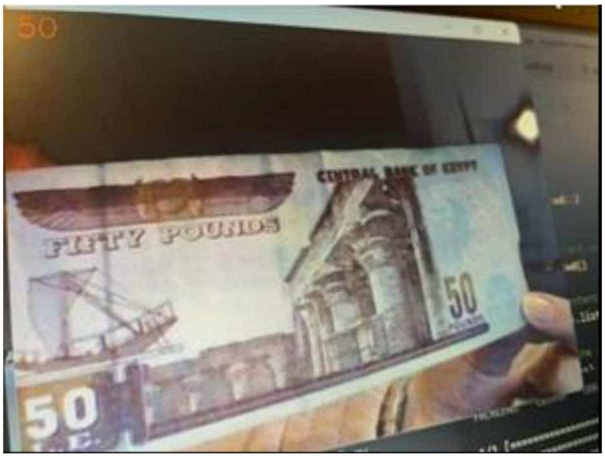

Figure 6: Predicted currency of 50 EGP banknote photo capture with the ESP-32 CAM

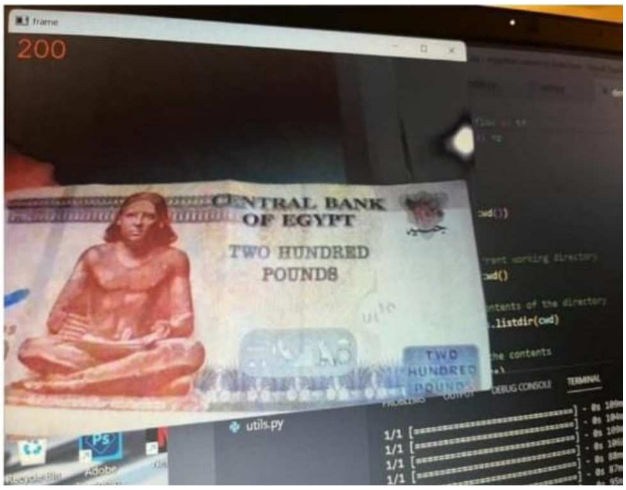

Figure 7: Predicted currency of 200 EGP banknote capture

VI. CONCLUSION

This research study introduces a novel methodology for identifying cash, incorporating the EAST model for text detection and Tesseract OCR for text recognition.

The study provides evidence of the efficacy of this approach in appropriately discerning different cash denominations. This study signifies a notable advancement in the field of financial technology, facilitating the use of automated currency recognition systems across many financial services and retail sectors. The EAST model is important in identifying text regions on currency notes, while the Tesseract OCR system exhibits remarkable precision in text recognition. The technology effectively functions in real-time and handles variations in currency designs, lighting circumstances, and image quality, thereby showcasing its capacity to revolutionize the operational efficiency and precision of the financial industry. The integration of EAST and Tesseract OCR in a symbiotic manner offers a convincing resolution to the difficulties associated with currency recognition. This integration can potentially automate crucial financial operations, creating new opportunities. The study has implications in various fields, including automated teller machines and currency exchange services, potentially improving consumer satisfaction and operational effectiveness.

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