Medical Prescription Recognition using Machine Learning

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***Abstract*—Admittedly, because of how busy doctors are nowadays, they tend to scribble unreadable prescribed medicines which leads to the problem of misinterpreting medicine names. Patients are sometimes curious to know information about their prescribed medicines before purchasing them. Recently, developers have been searching for a method to address this problem efficiently but, no technique leads to full recognition of medicine names due to the bad handwriting of doctors and its variety so that leads us to machine learning where the system will learn various types of handwritings for the same medicine to be able to recognize new handwritings. This paper proposed a system that presents a solution for both the pharmacist and the patient through a mobile application that recognizes handwritten medicine names and returns a readable digital text of the medicine and its dose. The System identifies the medicines' names and the doses for the collected data set with some, pre-processing techniques like image subtraction, noise reduction, and image resizing. After that, the pre-processed images will undergo some processing as it will be classified and feature extracted through Convolutional Neural Network and finally Optical Character Recognition technique applied on the medicines with low accuracy in the post-processing phase to identify their names by comparing the result with the dataset containing all the medicines. This will help in diminishing the instances of distortion of medication names assisting pharmacists in limiting their doubts. The proposed system tested on different real cases, and accuracy has reached 70% using (CNN) model.**

***Index Terms*—CNN, OCR, Classification, Machine learning, handwriting recognition**

I. Introduction

A Doctor's medical prescription [1][2] is a handwritten paper that a doctor writes to prescribe the medicine to the patient according to the injury or sickness that the patient has been experiencing. Misread medicine names in doctors' medical prescriptions are frequently a consequence of either unreadable handwriting or a pharmacist's incapability to identify drug names in medical prescriptions. The National Academy of Science has estimated that at least 1.5 million people each year are being killed or sickened due to reading medical prescriptions incorrectly [3][4]. Normally, a medical prescription, which is written by a doctor who uses common medical terminologies and Latin abbreviations, is usually extremely hard to be read and understood by a person who has no prior medical knowledge or background. It cannot be denied that it is very threatening when medicines are wrongly given to patients as it can lead to some major health problems because of the side effects that some medicines have over each other when taken at the same time, not only that but also the wrong medicine is taken over a long time without a need for it. Another issue is that patients purchase medicines blindly without knowing anything about the medicines prescribed for them and see if the side effects will be suitable for them will cause them any harm or discomfort. As a result, it is of the utmost importance to read the medical prescription precisely and correctly to avoid any detrimental consequences and impacts, thus, finding a solution for this problem will be presented in the proposed system. The proposed idea has of course been implemented before but neither so popularly nor so successfully and sufficiently as most of the apps or approaches used Optical Character Recognition (OCR) technique and other techniques [5][6][7][8][9] which solved the problem but not completely as OCR at some point cannot fully recognize characters written in bad handwriting or bad format. Some countries went through an easier path of using an electronic medical prescription form in which the doctor prescribes the medicine on the computer and a medical prescription is generated and ready to be printed. However, this method has not been applied yet in Egypt. Accordingly, the proposed system is going to admittedly breakthrough in Egypt due to its high demand and importance as a survey was conducted on regular users and pharmacists to clarify whether the application would be beneficial as shown in figure 1 and if it would be of great use for them or not as shown in figure 2. the results showed that 96% of the people were in favor of the application and found it very useful and beneficial whereas only 4% found it otherwise.

The main contribution of this paper is proposing a solution system for both the pharmacist and the patient through providing a mobile application that recognizes and reads doctors' handwriting in the medical prescription and returns a readable digital text of the medicine and its dose.

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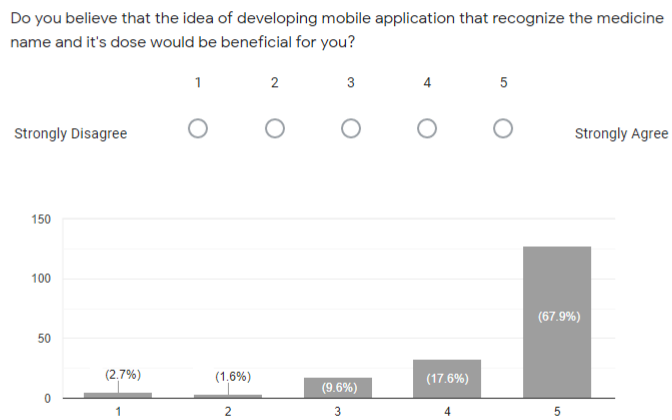


Fig. 1: proposed Model Benefits

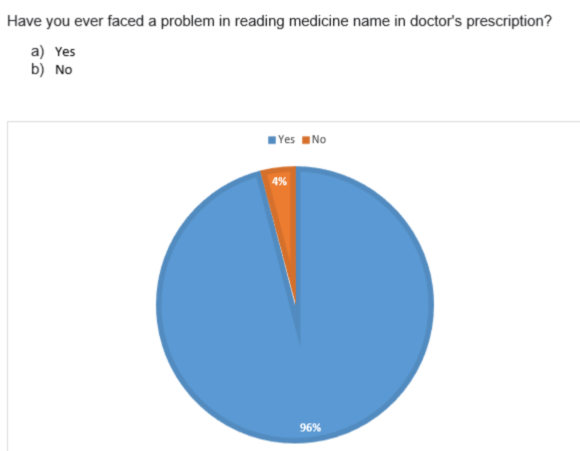


Fig. 2: Reading doctors' handwriting problem

II. Literature Survey

Handwritten recognition has been receiving a huge attention from a lot of researchers with different techniques and approaches such as Optical Character Recognition (OCR), hybrid whale Optimization Algorithm with neighborhood rough set, or Recurrent Neural Network (RNN). Doctor's handwriting has always been a challenge that even pharmacists have a problem reading it. Some of the research works that focus on that problem and the suggested solutions are discussed below.

Kamalanaban et al. 2018 [10], used medicine box and smartphone application based upon Convolutional Neural Network (CNN) to identify and perceive doctor's handwritten medicine names and return a more readable and coherent digital text. The results showed that an increasing amount of data in the training model will increase accuracy.

Ananthu et al. 2018 [11], used Personal Digital Assistant (PDA) to recognize the written text on the prescription and convert into digital readable form. The system is divided into three main part, first image preprocessing, thresholding, and thinning, second the prediction of medicine from the doctors keypad by recognizing the characters, lastly managing the central storage where the whole data set which is MINIST is stored, the LetNet5 which is applied as the foundation architecture to build further recent CNN accomplished the best performance of 99.5% of recognition accuracy.

Rosaly et al. 2013 [12], created an android application using OCR to scan handwritten medicines' names and deliver back clear digital text. The results showed that with help of the database used, medicine names written with different handwriting in separate papers, convert into text.

Tolosana et al. 2018 [13], used RNN for online signature verification for novel writer independent. While Xia et al. 2018 [14], proposed a reliable and dynamic signature verification method that is applied on mobile phones. SG-NOTE database taken by "Samsung Galaxy Note mobile", also, "MCYT-100 database by WACOM pen tablet". The experiments showed that the regional features accomplished excellent performance on both databases used.

Chernyshova et al. 2020 [15], used the field recognition step for recognizing low-quality images that concentrate on text line detection and recognition. They used different datasets such as MIDV-500 and MNIST datasets to analyze character classification. The results obtained by using online augmentation on the non-ensemble model were 0.25% counter to 0.23% and 0.14% by the ensemble one.

Achkar et al. 2019 [16], used Artificial Neural Network (ANN) to build a system that recognizes English handwritten medical prescriptions. While D.Fang and C.Zhang 2020 [17], proposed an isolated Handwritten formula symbol recognition. The interactive interface stores the data in order which is split into online mode.

P. S. Dhande and R. Kharat 2017 [18], used a segmentation method that is established on the horizontal projection and vertical projection for text-line and word break-down using the IAM database, and it showed 95% accuracy in text-segmentation and 92% accuracy for word segmentation.

Xu et al. 2019 [19], focused on Chinese character recognition methods. The Hidden Markov Model (HMM) is applied for data training and experiments showed improved execution than the "state-of-the-art methods". Also, Zhu et al. 2018 [20] constructed their framework with customized Fully CNN, multilayer residual Long Short-Term Memory networks, and transcription layer. Experiments showed that the softer character erasure will create more intersection errors, and for the noise background issue, recognition can easily differentiate characters from the background. Also, Rajalakshmi et al. 2019 [21], proposed a model based on CNN that is divided into online and offline handwritten recognition.

Eltay et al. 2020 [22], Ghanim et al. 2020 [23], Sahol et al. 2020 [24], and Hamdani et al. 2013 [25], proposed systems for acknowledging handwritten Arabic text through varieties of techniques as adaptive data augmentation algorithm, Hierarchical Agglomerative Clustering technique, hybrid machine learning, and N-gram Language Model "LM" on the handwritten text along with HMM.

Kumar et al. 2019 [26], focused on Multilingual texts using OCR to convert textual symbols on paper into a machine-processable. The multi-lingual text stages applied Linear-Support Vector Machine (LVM), k-Nearest Neighbors (K-NN), and Multilayer Prescription (MLP) classifiers and the experiments showed that maximum accuracy in character recognition of English.

Fajardo et al. 2019 [27], applied DCNN to identify the text in the prescriptions and shows readable conversion of handwriting. The experiments were done on 540 images of prescription that achieved 76%.

Dhar et al. 2020 [28], distinguished the doctor's handwriting by firstly allocating the position of texts in the doctor's prescription and separates the text. After that, they used OCR. Results showed that the proposed method's output is 2.2754% Relative Absolute Error.

Waranusast et al. 2009 [29], recommended a method based on the analysis of Spatio-temporal graphs obtained from the online patient record and the SVM classification.

Garain et al. 2020 [30], used the classification of handwritten texts and OCR. Images that are used are categorized into 4 categories: Handwritten, Mixed, Other, and Printed. Results showed that the model achieved 99.5 percent accuracy in classifying the images.

Gao et al. 2011 [31], used the Cloud-based recognition platform which applied the changed quadratic discriminant function and SVM Classifier. It showed that it can deliver dependable handwriting solutions with higher recognition performance across different mobile Operating Systems.

Most of the above systems used OCR while others used HMM for data exercise. The segmentation algorithm or RNN is applied to take the labeled data frames as input. As well as different data sets have been used whether it is collected from the CENPARMI data set, standard XiaoZhuan font database or MIDV500, and MNIST data set to evaluate character classification. On the contrary, the proposed model will be approached from a different point of view, as using only the OCR will not be that accurate in reading or recognizing the doctor's handwriting. Figure 3 will view the system overview, and the challenges the proposed model is facing.

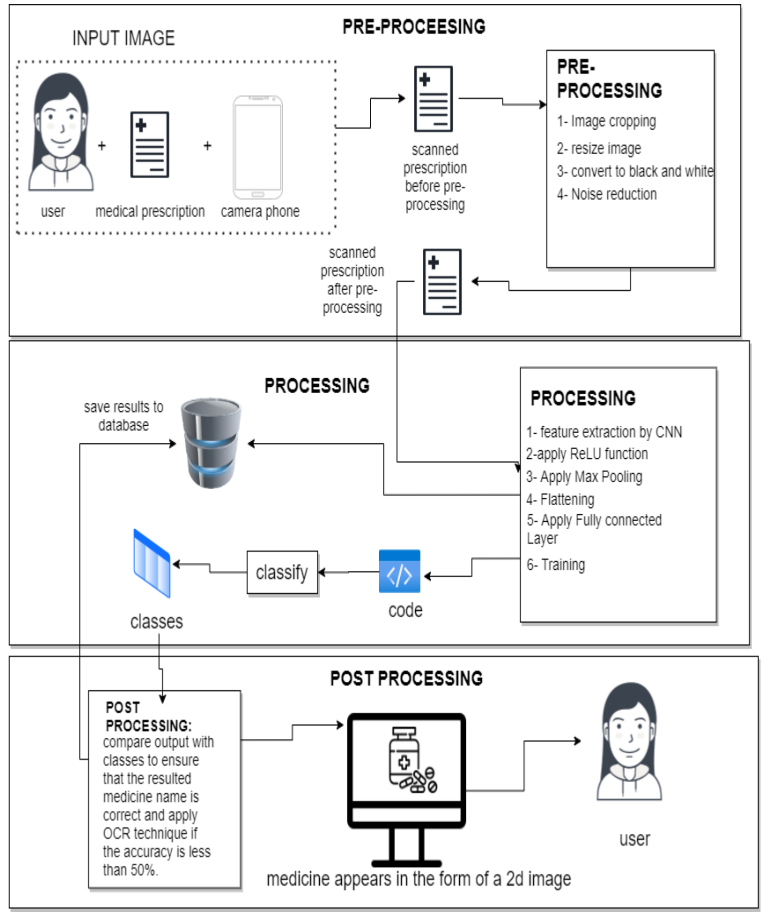


Fig. 3: Proposed Model Overview

III. Methodology

In the proposed model, the medical prescription will be first scanned by the mobile camera, then it will go through pre-processing phase like image subtraction, black white conversion, and noise reduction, and image resizing. After that, it will go through the processing phase where feature extraction and classification for training the collected data set will be applied using the Convolutional Neural Network (CNN) [24]. Finally, the post-processing phase will take place by comparing the output with 20% of the collected dataset. OCR technique applied to the medicines with low accuracy to identify their names by comparing the result with the data set contains all the medicines.

A. Pre-processing Phase

In the pre-processing phase, firstly scanned prescriptions' images enter the system as an input using the mobile camera and the extension type of the image is set to PNG. Secondly, the size of the image is normalized by cropping white spaces and converting the image into black and white. Thirdly, the morphological operation technique is applied on the image to make all the images of the same size based on a comparison of the corresponding pixel in the input image with its neighbors. Finally, the cropping operation is applied to crop the prescription into 3 parts.

The first part is from the beginning of the prescription till (R/) symbol which includes the name of the doctor as shown in figure 4 . The second part which starts right after the (R/) symbol that includes the prescribed medicines, doses, and instructions that is the most important part as the system will identify the medicine and the dose from this part as shown in figure 5. In this case, the prescribed medicines and the doses will be trained with the medicines in the system based on the doctor's major which is identified from part one. The third part which is the least important part of the system as it contains the doctor's phone numbers and the hospital or doctor's clinic addresses as shown in figure 6. The block diagram shown in figure 7 shows the main steps of the pre-processing phase.

Fig. 4: Header

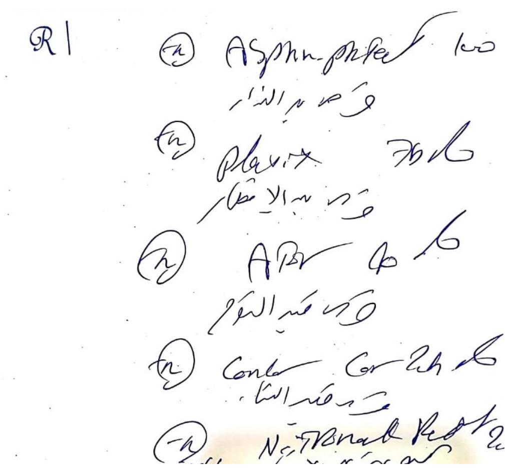


Fig. 5: Middle part

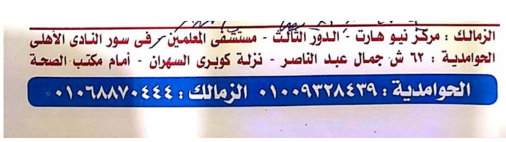


Fig. 6: Footer

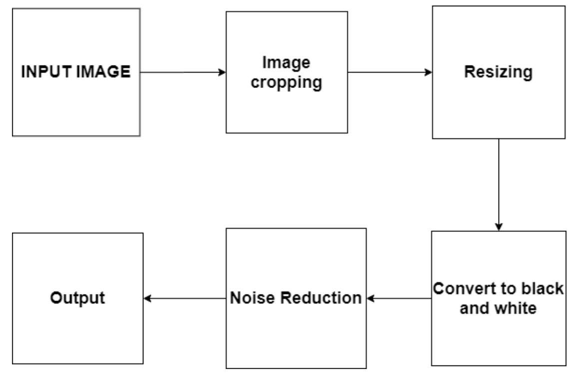


Fig. 7: Pre-Processing Diagram

B. Processing phase

After the pre-processing part is done, on the middle that includes the prescribes medicines as shown in figure 9 then will be classified, and the feature extracted by the Convolutional Neural Network (CNN) using backward and forward propagation technique, CNN performs two tasks which are feature extraction and classification to correctly classify images. It consists of multiple layers which are categorized under feature extraction and classification in which the Convolutional layer, Relu layer, and Maxpooling layer are known as feature extraction techniques that are applied on the input image, and then the fully connected layer is applied for classification and output the image as shown in the figure 8.

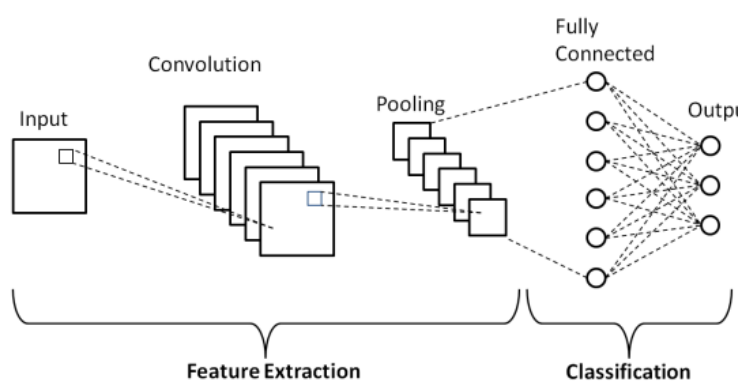


Fig. 8: CNN Layers

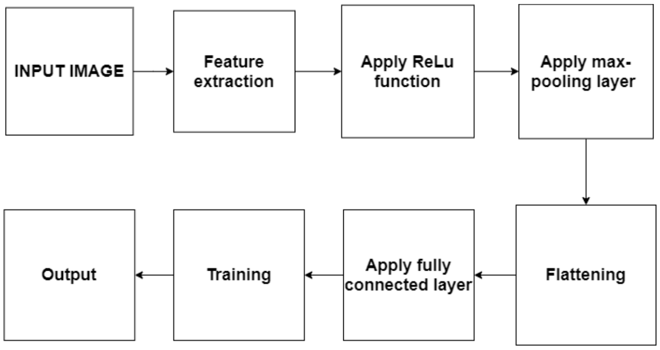


Fig. 9: Processing diagram

Firstly, we are going to start the convolution step which is known as the feature extraction step, it includes the input image, a feature detector, and a feature map, secondly the filter is taken and applied pixel block by pixel block through the multiplication matrix to the preprocessed middle image so the feature map is filled or completed. Many feature maps are created to get our first Convolutional layer. Secondly, we are going to create an edge detection filter using the Sobel operation. Thirdly, the Rectified Linear Unit (ReLU layer) is another step to the Convolution layer as an activation function is applied to the feature map to increase the nonlinearity in the network. Fourthly, to achieve spatial variance, we use the max-pooling technique to gradually reduce the input representation size as it makes it easier to detect and identify objects wherever they are located inside the image. Not only does pooling aid in reducing the amount of processing and the number of required parameters required but also, it controls the issue of overfitting. Finally , the pooled feature map is flattened into a sequential long vector to allow the information to enter the input layer in the ANN to be furtherly processed.

C. Post-processing

Improving the performance and the accuracy of the model, A more handwritten medical prescription will be collected to reach higher accuracy. Also more classification techniques like Optical Character Recognition (OCR) will be applied on the resulted medicines if accuracy is 50% or less to process character by character, comparing the OCR result with a data set contains all the medicine names to recognize which medicine in the dataset nearest to the result.

IV. Results and discussion

A. Data set description

An experiment has been conducted with various real cases from the dataset. The implementation is done using python. After doing some pre-processing for the data set as image subtraction and normalization, the output is processed using CNN as feature extractor and classifier for the medicines in the prescription.

The dataset is collected from multiple doctors and hospitals with varying specializations, our main aim is to collect numerous different prescriptions of each medicine with different hand-writings.The dataset has been divided into 70% training and 30% testing to train proposed model. The medical prescription is divided into 3 main parts, the first section until the R/ includes the name and the specialization of the doctor which will help in classifying the medicine according to the doctor's specialization, the second part which starts after the R/ which includes the handwritten prescribed medicines which will be classified and lastly the third part which is the footer includes the addresses and contact numbers of the hospital or clinic will be eliminated. There are various types of data sets as shown in the figures 10.

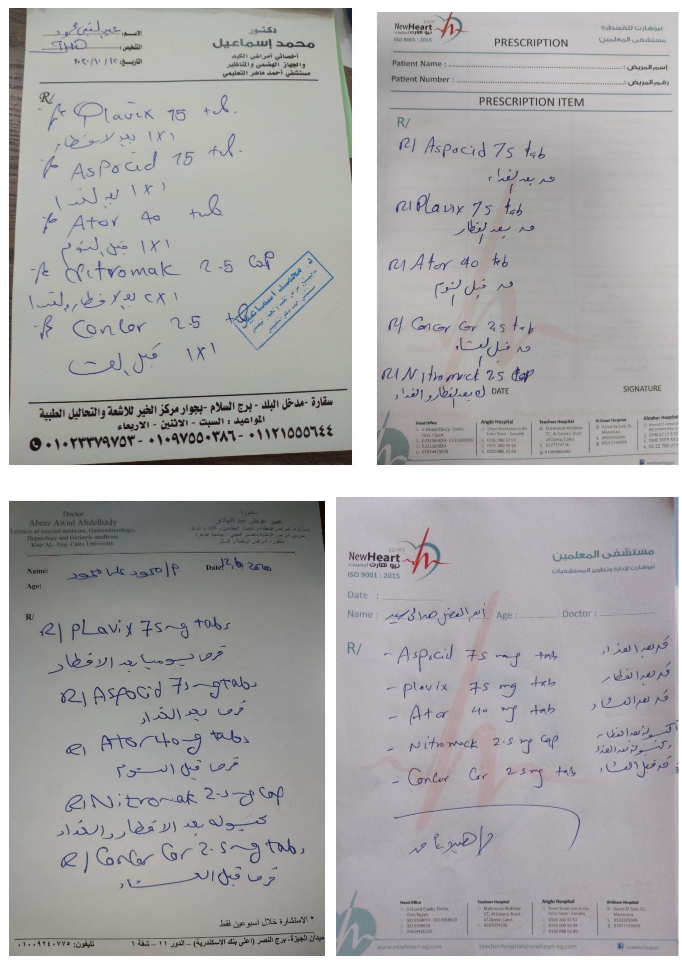


Fig. 10: Prescription templates

B. Results

In the scanned prescriptions shown in figure 11 will be converted to black and white first as shown in figure (12-

a) and then convert to grey-scale as shown in figure (12-b) after normalizing and cropping as shown in figure (12-c) will appear in a segmented form as shown in figure (12-d), and the in the processing phase CNN classified the dataset over 50 epochs and 35 batches using cross-validation, and the training accuracy resulted to be 73% and the testing accuracy resulted to be 50% as shown in figure 13.

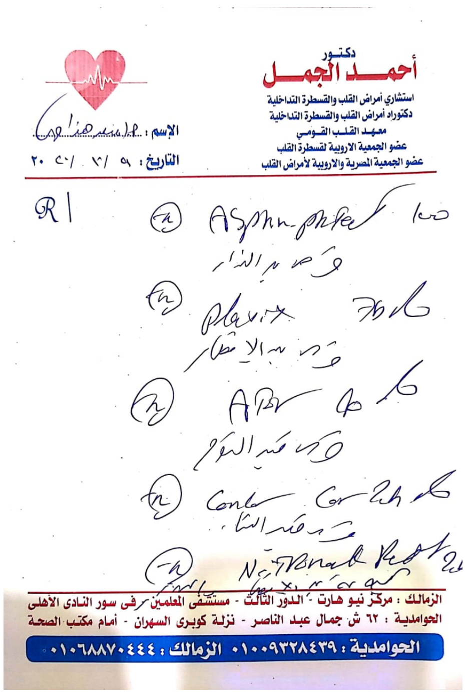
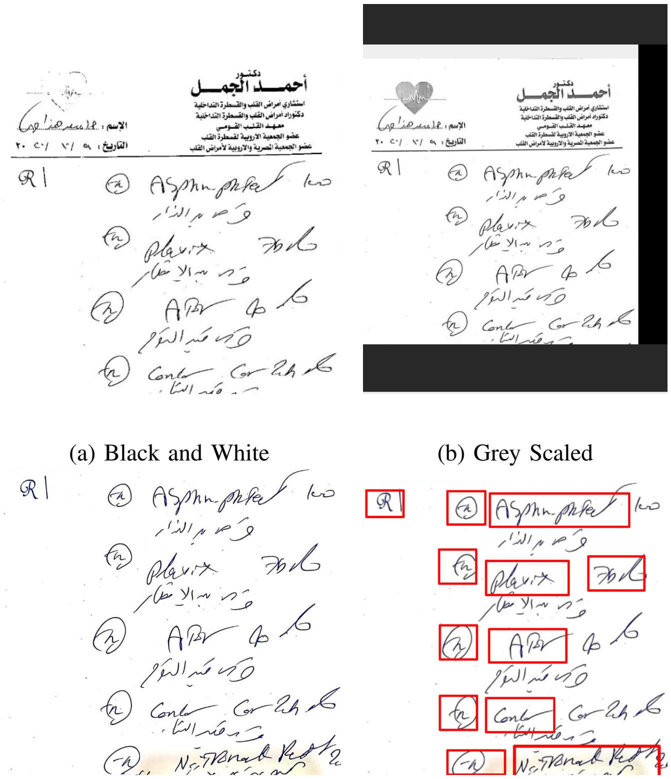


Fig. 11: Scanned Prescription



(a) Black and White (b) Grey Scaled

(c) After Cropping (d) After Segmentation

Fig. 12: Pre-processing Phase

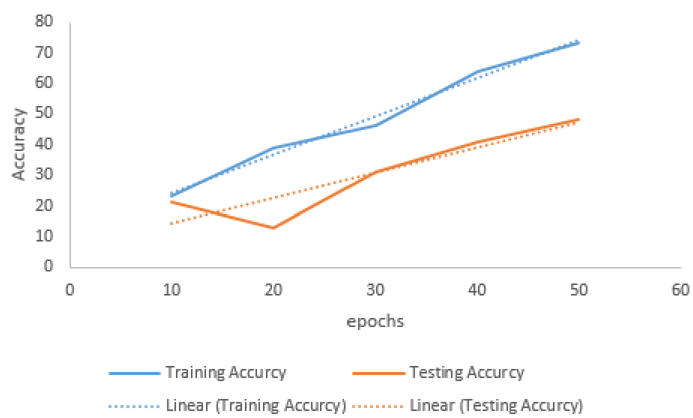


Fig. 13: Training and Testing Accuracy

V. Conclusion And Future Work

In conclusion, the paper shows how vital medical prescription recognition for its significant role in diminishing the problem of misinterpreting medicine names by users and pharmacists. This research came with a solution using machine learning. The system will be trained by various types of hand-writings for each medicine to be able to recognize new hand-writings for the medicine by using the CNN model as a classifier and feature extractor, which showed over 50 epochs and 35 batches using cross-validation, the training accuracy resulted to be 73% and the testing accuracy resulted to be 50%.

The proposed system faces some hardware limitations that stops the system from working properly and accurately. Medical prescriptions should be scanned by a camera phone with high camera resolution, photos should be taken from an appropriate and zoomed in angle, to ensure that the scanned image is clear, and its content is visible.

As for the future work, a larger dataset with more handwritten medicine names will be used and trained to reach higher accuracy. Moreover, more classification techniques alongside the OCR in the post processing phase will be used to achieve higher accuracy and precision in identifying the prescribed medicine.Comparing the OCR result with a dataset contains all the medicine names to recognize which medicine in the dataset nearest to the result.

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