

AI System for Substitutable Low Cost Medicine based on Clinical Note

P Nageswara Rao ¹, SK Mastanbi ², Subba Rayudu ³

¹ Assistant professor, ² Assistant Professor, ³ Assistant professor
Department of Computer Science Engineering
Priyadarshini Institute of Technology & Science, Tenali, Guntur

Abstract— A prescription is a handwritten document issued by a doctor to a patient who is experiencing health problems. Most individuals may not understand the prescription since it contains medical acronyms and has readability concerns with diverse kinds of doctor's handwriting. Prescriptions may be understood by those who work in the medical sciences, such as pharmacists. Bad repercussions may arise if the prescription is not accurately recognized. This work overcomes the issue of recognizing the pharmaceuticals recommended by the doctor by using the Google OCR technology and also proposes a low-cost medicine to the user if the prescription provided by the doctor is expensive. This assists folks who are unable to afford expensive drugs. Google OCR has been trained on several doctors' handwriting. The input may be uploaded as a picture from the gallery by users. It will compare the prescriptions given by the doctor with the accessible medicines after identifying the characteristics. If the prescription recommended is expensive, it shows the pharmaceutical with the same drug composition that is inexpensive. The prescription medications are shown in a text file to users.

I. INTRODUCTION

The art of handwriting allows each person to convey their ideas on paper in their own unique way. Depending on the individual, it might vary greatly. Specifically, when talking about a doctor's busy schedule, more consultations are scheduled in a short amount of time, and the diagnosis is given more importance than the prescription's handwriting. As a result, they frequently have poor handwriting, making it sometimes difficult to read the prescription and recognize the drugs and their possible dosages. It is quite challenging for patients and young pharmacists to distinguish the doctor's handwriting [1]. The spectrum of outcomes from drug errors ranges from no apparent symptoms to

death. It can sometimes result in a new ailment that is either transient or permanent, such as itchy skin, rashes, or skin deformity.

Despite being rare, drug mistakes can seriously harm individuals. According to an Egyptian study [2], almost 96

percent of the public supported a software application that could be used to translate a doctor's handwriting into digital text. In most cases, doctors only indicate the type of medicine, such as tablet, capsule, or syrup, using acronyms and short forms. There are systems that have been suggested that can employ the Deep Convolutional RNN approach to recognize the alphabet and numerals from a written text in English [3]. India is widely renowned for having a wide variety of cultures and languages. Depending on the patient's needs, doctors may occasionally refer to the prescription drugs in regional languages. So, the application will be far more widely utilized by both pharmacists and regular people with regional language support. The primary purpose of this study is to create an application that can actively recognize medical prescription images or scan them for subsequent conversion to digital text.

Researchers have been looking for a solution to this challenge, but no strategy has resulted in complete identification of medical prescriptions. CNN, RNN, were among the methods used. The existing systems have the following drawbacks: One of the main disadvantages of CNNs is that they require a large amount of labeled data to train effectively, which can be costly and time-consuming to obtain and annotate.

In this paper proposed OCR technology is employed in image processing to process data [4]. A customized output is also produced to provide an optimal summary that most consumers may understand even if they have no prior knowledge. The construction procedure is far more convenient for average people to use in order to take their daily dosages as prescribed by their doctors. This also makes it easier for new pharmacists and also consumers to conduct their tasks more efficiently and properly [5-7].

II. REVIEW OF RELATED LITERATURE AND STUDIES

1. Recognition of Doctors' Cursive Handwritten Medical Words by using Bidirectional LSTM and SRP Data Augmentation (2021)

The paper suggests an online handwritten recognition system to identify doctors' handwriting and create a digital prescription using machine learning techniques. The study developed a primary "Handwritten Medical Term Corpus" dataset with 17,431 data samples comprising 480 words from 39 Bangladeshi doctors. On the preprocessed pictures, a new data augmentation technique called SRP is used to increase the number of data samples. Following this, a sequence of line data is extracted from both the original and augmented image data [8-9]. Bidirectional LSTM is applied to the sequential line data derived from the augmented handwritten images to produce complete end-to-end recognition. The model achieved 73.4% accuracy without data expansion and 89.5% accuracy with SRP data expansion.

2. Handwriting Recognition for Medical Prescriptions using a CNN-Bi-LSTM Model (2021)

It is difficult to decipher a doctor's handwriting on a prescription. In this paper, they used neural network techniques such as CNN and BI-LSTM for predicting doctor's handwriting from medical prescriptions. The CTC loss function is used for normalization. This model builds on the IAM dataset. Image acquisition and data augmentation are used for image preprocessing. Furthermore, it is passed as input to 7 convolution layers of a neural network training epochs were used by the training model, which took six hours to complete training and, on a graph, loss values are represented.

3. The approach established a Convolutional Recurrent Neural Network (CRNN) technology.

CRNN technology using Python that can interpret handwritten English prescriptions and translate them into digital text. For this, datasets with 66 different classes, including alphanumeric characters, punctuation, and spaces, were used. Since prescriptions generally contain two or three words, the training was carried out using short texts. Normal handwriting and prescriptions from doctors were used to train the model. The system got a 98% accuracy rate after taking training time and data input into account. This paper further stated that in order to enhance the results, more work is needed on input handling techniques.

4. A method for classifying printed and handwritten texts in doctor's prescription (2021)

Optical Character Recognition (OCR) system is used to convert the document images, either printed or handwritten, into its electronic counterpart. But dealing with handwritten texts is much more challenging than printed ones due to erratic writing style of the individuals. Problem becomes more severe when the input image is doctor's prescription. Before feeding such image to

the OCR engine, the classification of printed and handwritten texts is a necessity as doctor's prescription contains both handwritten and printed texts which are to be processed separately. Much work have been done in the domain of handwritten and printed text separation albeit work related to doctor's handwriting. This dataset consists of various localized and extracted images of handwritten and printed texts from various prescriptions of doctors.

III. DATA COLLECTION

Data is a crucial component of this system for training and testing the deep learning model. As a result, for languages where there is no existing data, the data will be created from scratch. This will be accomplished by physically acquiring the data by scanning physical materials. By doing so, we can retain maximum accuracy in the recognition model, increasing its dependability. However, there is another method by which we may generate a complete prescription data set from scratch by translating the English prescription using Google API and then producing handwritten text in other languages using GAN. However, there will be a loss of precision using this procedure [3].

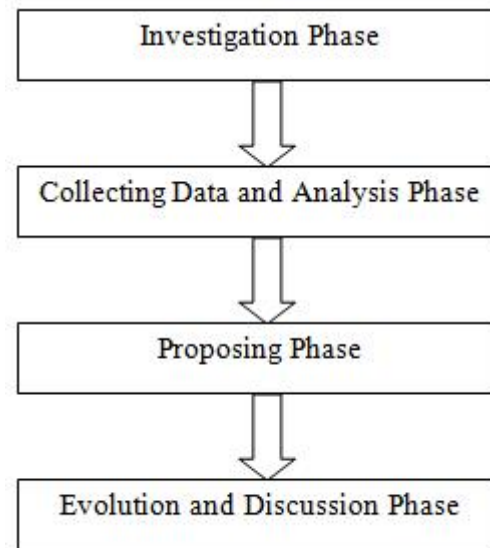
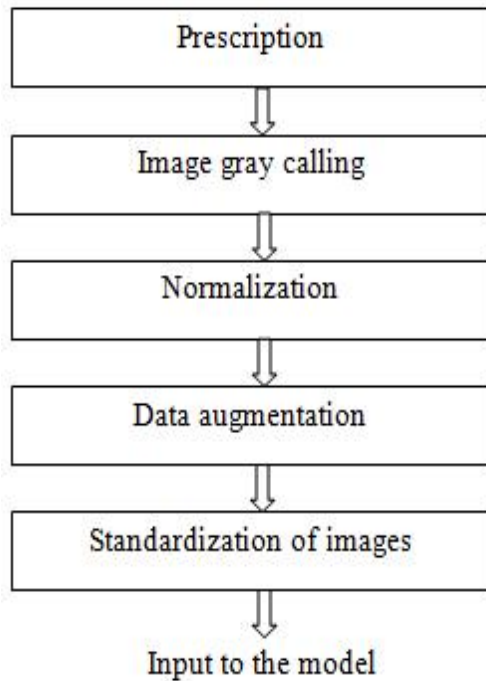


Fig. 1 Phases of Methodology

As shown in Fig.1, these are the methods used to process a physician's handwritten note. It's been discussed shortly below:

A. Data pre-processing and training model:

- **Data Preprocessing:** Following data collection, the gathered data will be unsorted so processed before training the model observer in fig.2. We all know that if we feed the model garbage data, we will get garbage results. As a result, we must tread cautiously when training the model. So, the following data pre-processing sets will be taken:



1	T CERUVIN , A75 OD T.ROSUNAS 20 OD T.ANGISPAN TR BD T.XIRATM 40mg OD JT DILZIM SR 90gm OD T GEMER ing OD T.NUOKIND LC 1 T. CALPOL 650
2	Scalpe shampoo Tab. Roxid 150 mg T Bact cream Darwin cream Eucerine cream Elovera body wash Ten ovate o int
3	Elocon cream od (2) Tab Roxid 150 mg (3) Tab . xyzal (4) cetaphil moisturizing (5) Elovun body wash

Fig. 2 Data pre-processing

Number of try_Initials of the Doctor_Medicine name in the prescription the name of the image file started in a number which could be 1, 2 and 3. This number represented the amount of trials made by the doctor. Since doctors were asked to write each prescription three times, number 1 was used for the image of sample handwritings written for the first try while 2 and 3 were used for the second and third try. The number was followed by an underscore (_) after that, the surname of the doctor was included in naming the file and for those doctors that had the same surname; the initial of their first name was added in the name of the file. Another underscore followed the surname of the doctor, the medicine name in the prescription written was the last one included in naming the image file, the sample of file names used for the images is displayed in Fig. 3 while in Table 1 shows the list of prescription used in this study.



Fig. 3 Sample files names of the captured images

TABLE I

List of Medicine Names with Instruction of Use in the Preset Prescription

Prescription	Medicine
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Grayscale conversion: To prepare the pictures for model training and drawing a conclusion from them, image preprocessing is performed. Gray scaling is the first step in digital image pre-processing that must be done. Here each pixel's value solely encodes the light's intensity information.

The skeleton zed images were the ones used to feed in the training process. There is a square-shaped sliding window used to scan the text-line image and the movement of sliding window is the direction of the writing. The height of the window depends on the size of the image and its pixel is normalized to 64 pixels. To address the change of convolution filters, there is a window overlap of 2 pixels. The researchers used int64 data type for the sequence length.

- *Normalization*: It is done to resize the picture pixels to a preset range where they will be consistent with the data given. And by doing so, the model will perform common learning, avoiding irregularities in training the model.

- *Data Augmentation*: It is used to make slight changes to a picture in order to deliver a diverse range of data in a single identifiable format. And the procedure frequently includes rotation, cropping, shearing, horizontal and vertical flipping, and so on. Furthermore, by doing so, we can keep the neural network from learning from irrelevant data. And followed by fig.4 image stabilization will be performed.

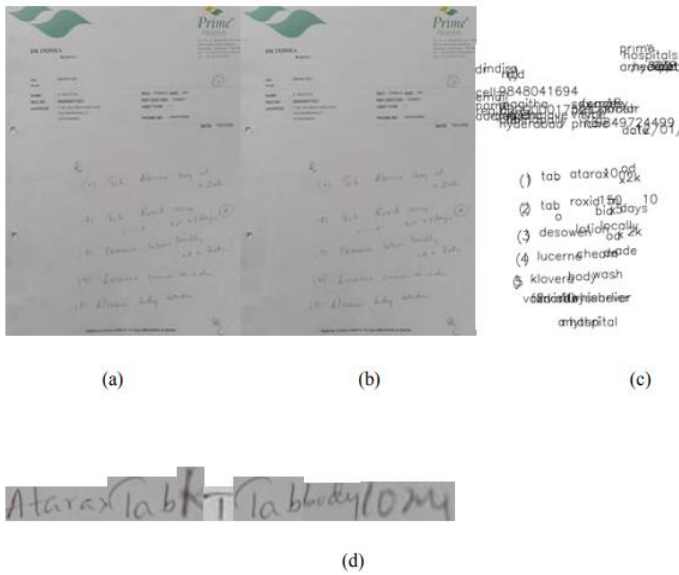


Fig. 4 Original Image

- **Image standardization:** To convert the height and weight of a picture to a common scale, which will convert all of the given data into an appropriate size? We increase the consistency of the given data as well as the quality, which is a priority while completing these activities. Once these processes are in place, there will be an optimal dataset that can be utilised to train the model. As a result, the neural network model will not be trained on irregular data.
- **Training the model:** After processing the handwritten text input, we must train the model using structured data. So, in order to get the optimal recognition model, we need to avoid overtraining the model, which will result in the model being suited only to that particular data. To circumvent this, we will train the model using 50 ecop, which is the appropriate ratio for training the model to recognize the presented information.
- **Fuzzy search:** It is used to deliver the precise predicted tablet word even if the model recognized only a few words in it, whereas fuzzy search would provide the name even if the spelling is incorrect. This is done by using the provided medicine database shown in fig.5.
- **Market basket analysis:** This is used to save time when we detect commonly used drug names and data this may be used to fetch the name faster based on use. So, we conserve the time for analyzing the words.

C. Unicode Data:

Everyone knows that OCR is the finest method for character recognition. Because Indian scripts are difficult to recognize, we are adding a post-processing step to the OCR to achieve valid character recognition. In this method, typical

characters that have already been divided into meaningful parts and used to train the model with unicodes are combined to form a string using mapper. The result will then be classified as valid UAM (unicode Approximation Model) or invalid UAM. The invalid UAM is processed again with a string pattern matching algorithm and cross-checked against legitimate UAM databases, and the map per alters the character or string accordingly to generate the correct UAM.

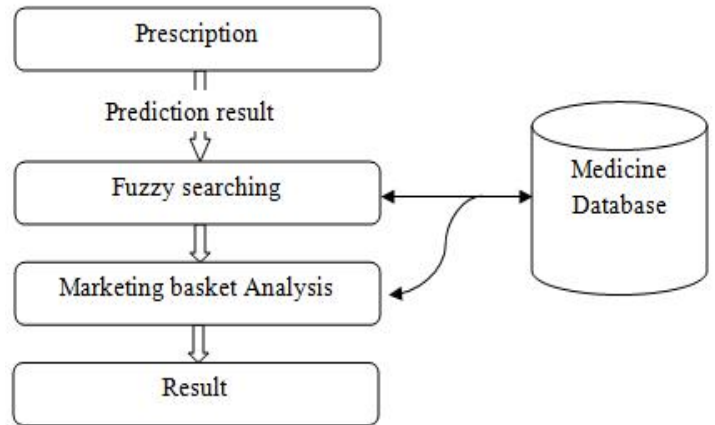


Fig. 5 Prediction Optimizer

D. Application interface:

The processed text will be given in an organized manner in the application interface, along with a brief explanation of the identified medicines. And this application will be autonomous and simple to use, allowing any user to effortlessly upload an image and receive understandable text in return.

IV. RESULTS AND TEST CASES

To achieve the best possible outcome, we ensured that the model's data was correct. To get a favorable result, we trained the model with 50 ecop so that it is not accustomed to the training data and can predict the words. Testing is a vital component that ensures the proposed system's quality and effectiveness fulfilling its goals. Testing is carried out at different phases of the system design and implementation process with the goal of creating a transparent, adaptable, and secure system. Testing is an essential component of software development. The testing procedure verifies whether the produced product satisfies the specifications that it was designed to meet. The creation of test cases against which the product must be evaluated is part of the testing process.

Test Objectives

- the process of running a program to find errors is known as testing. A good case is one in which there is a good chance of finding an unknown flaw.
- a test that finds a mistake that was previously unknown is successful. Deficiencies in the program will be discovered if the testing is successful (in accordance with the objectives).
- the absence of flaws cannot be demonstrated through testing. It can only show that there are software bugs.

Testing Principles

A software engineer must grasp the core idea that leads software testing before using methodologies to construct successful test cases. The client's specifications should be the basis for all testing.

Testing Design

There are two ways to evaluate engineering products:

- White box Testing

Glass box testing is another name for this kind of testing. A test can be carried out to verify that each function is fully operational and to look for flaws in each function by understanding the specific function that a product was designed to perform. Test cases are derived from the control structure of the procedural design in this test case design approach.

Levels of Testing

Multiple levels of SDLC testing are possible. These are the main ones:

- *Unit Testing*

The most fundamental type of testing is unit testing.

The smallest unit of software design that is tested is the module. A white box is always used for the unit test. The requirements that were established during module design are checked against many different modules. The purpose of unit testing is to verify the internal logic of the modules because unit testing is mostly used to validate the code generated during the development process. Usually, the module's programmer does it.

- *Integration Testing*

The second level of testing is integration testing. A methodical approach to software structure construction and interface issue detection is known as integration testing. A lot of tested modules are combined into subsystems, which are then tested. This is done to see if all of the modules can be merged correctly. There are three kinds of integration testing:

Table II

Clinical Note-Based Functional Assessment of an AI System for Substitutable Low-Cost Medication

Test case name	Test case condition	Test procedure	Test status
Upload image	This module is concerned with uploading the image of a doctor's prescription on the project where the images contains prescribed medicine	1. Open the anaconda prompt. 2. Navigate to the project location 3. on terminal type python main _2.py the application will be opened 4. click on get image	PASS
Convert	This module is concerned with converting/reprocessing the uploaded image	Click on convert the preprocessed images is displayed	PASS
Text file	This module is concerned with the generating document of uploaded images	Click on convert the preprocessed images is displayed	PASS
Output	This module is meant for displaying the low cost medicine for prescribed medicine	Prescribed medicine along with the low cost medicine is displayed	PASS

- *Functional test*

System documentation, user manuals, and business and technical requirements are all met by the functionalities tested, and functional tests provide systematic evidence of this. Functional testing focuses on the following aspects:

System Testing and Acceptance Testing

System testing consists of a series of tests designed to fully test the computer-based system. Test for crash recovery, security, and unauthorized user testing, among other things.

Acceptance testing is often conducted using actual customer data to show that the programmer is operating properly. This FDAC testing focuses on the system's outward behavior.

RESULTS

Figure 6 shows the main file being executed.

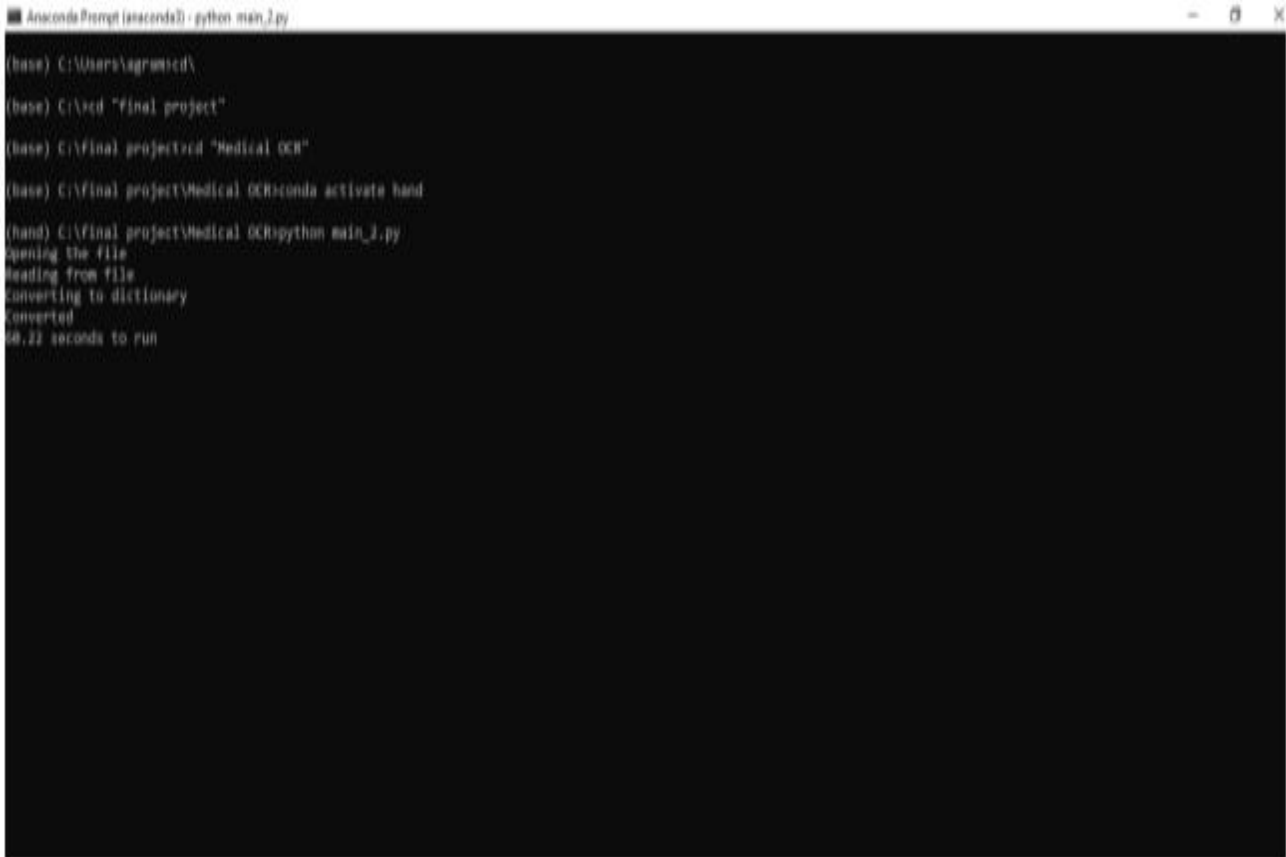


Fig. 6: The main file of the AI System for Substitutable Low Cost Medication Based on Clinical Note is executed.

Figure 6 shows the main file of the project AI System for conversion of the file. The project takes between 55 and 65 Substitutable Low Cost Medication Based on Clinical Note being seconds to complete. Figure 7 shows a pop-up window executed. It denotes the opening of the file, reading of the file, and instructing the user to submit an image of the doctor's prescription.

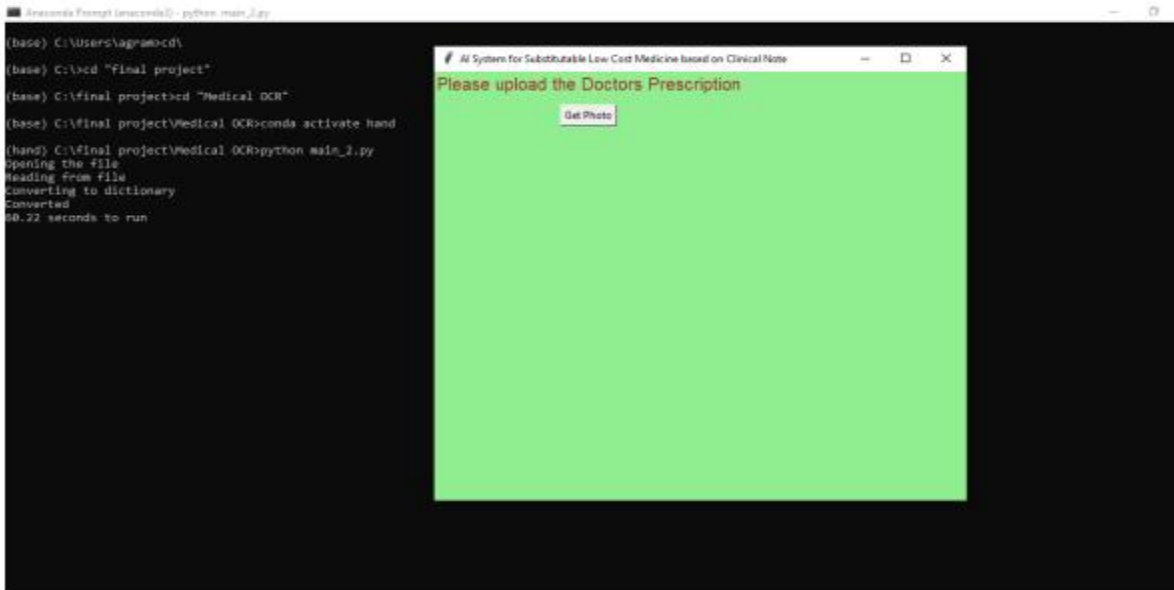


Fig. 7 The popup box prompting the user to submit a picture is shown

The popup box in Fig 7 above asks the user to submit an image of the doctor's prescription of the AI System for Low Cost Medication based on Clinical Note. The project takes around 55 seconds to 70 seconds to complete. After the project is executed, a popup window appears on the screen, prompting the user to submit a picture of the doctor's prescription.

To upload a picture, users must first click the "Get Image" button. When the user clicks on get Image, the system folder is opened in order to upload the picture. The user may submit his or her prescription picture. Figure 8 depicts the window that appears after choosing the picture.

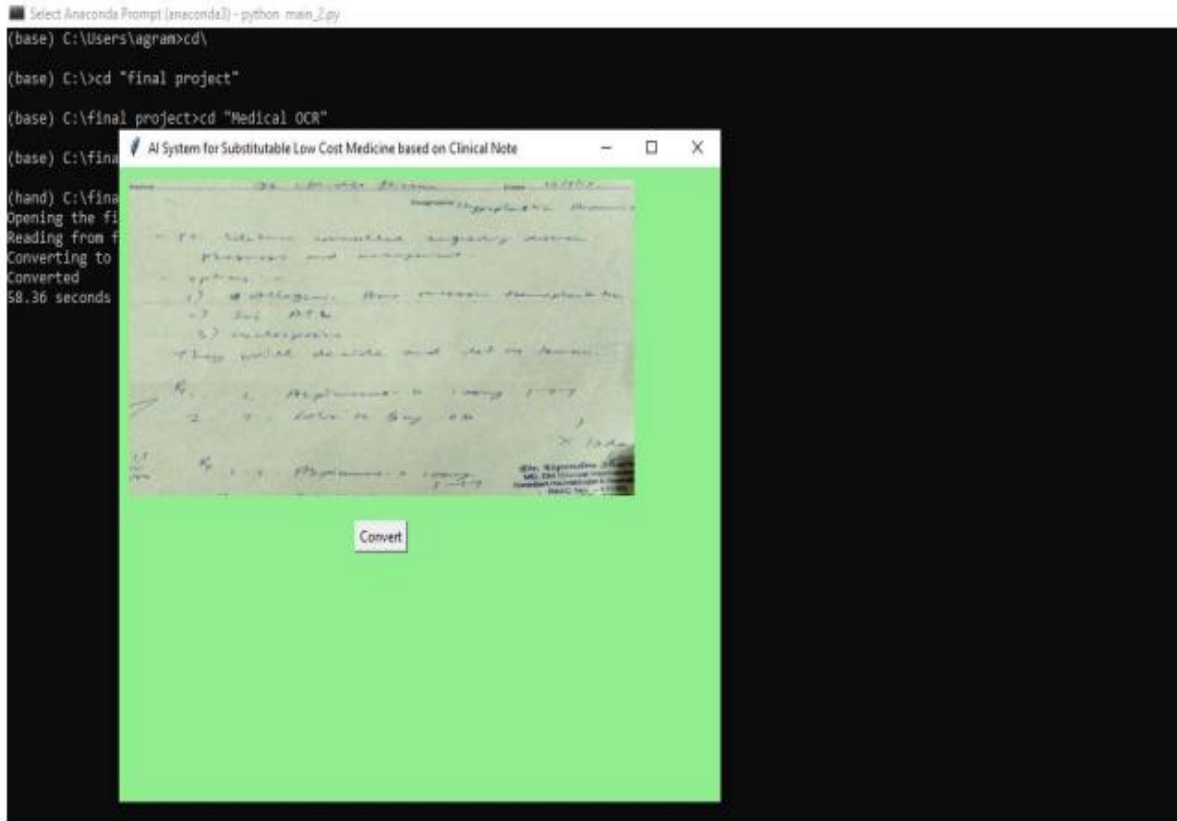
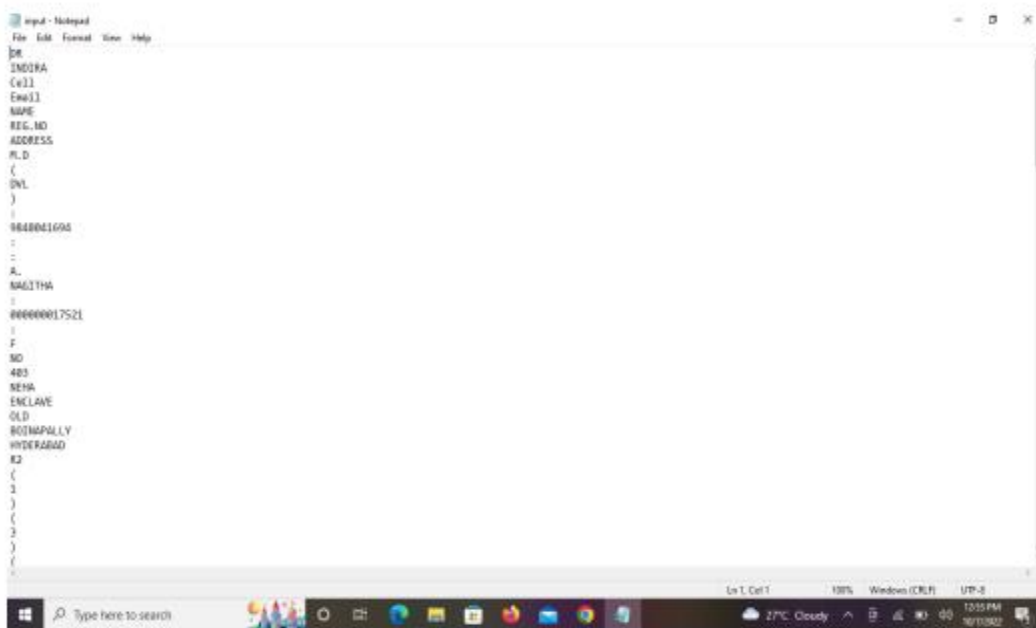
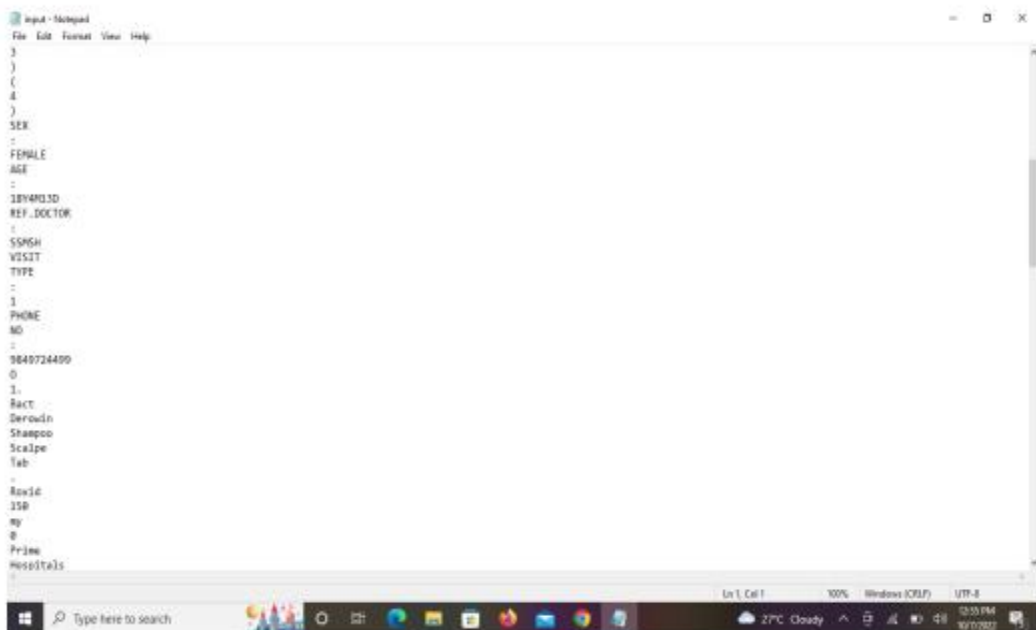


Fig. 8: A user-uploaded picture

The photograph supplied by the user is shown in Fig 8 above. Since the picture submitted by the user may include noise, it is preprocessed. For this procedure. Users should press the "Convert" button.



(a)



(b)

Fig. 9: Google OCR generated a text file from a user-uploaded picture.

Figure 9 shows the text file created by Google OCR for the user-uploaded picture. Users may comprehend the drugs provided by their doctor by using this text file. Since many individuals cannot comprehend the doctor's handwriting, they are unaware of the medications prescribed by the doctor. This text file can help you comprehend your doctor's recommended medications. Figure 10 depicts the outcome if low cost medication for the recommended prescription.

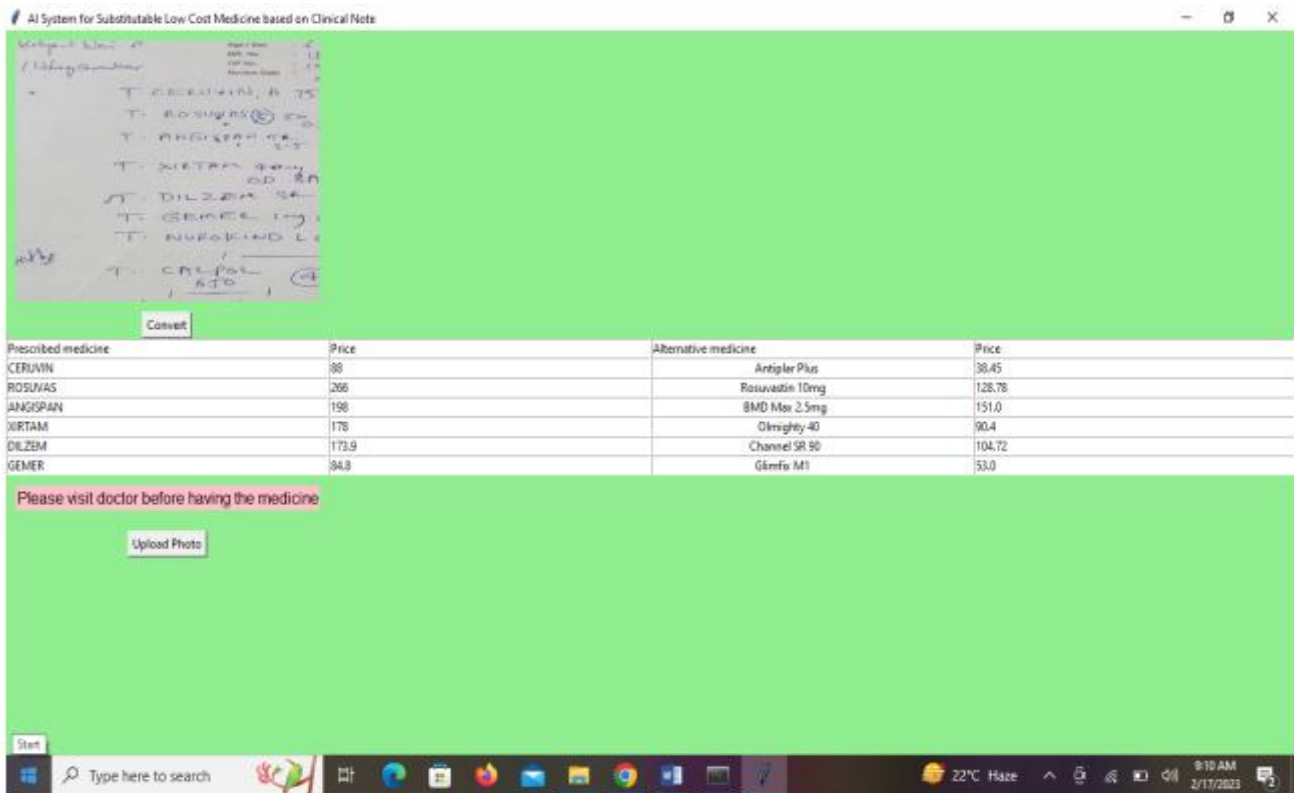


Fig. 10: Alternative low-cost medication for prescription medication

The information about the recommended drug is shown in Fig 10 above. The output is categorized as prescription medication, price, alternate medicine, and price. When a user uploads a picture, it is transformed to a text file. The contents of the text file are compared to the medical dataset given. If any material in the prescription matches the drug in the dataset, the recommended pharmaceutical and its cost, as well as an alternative medicine and

its cost, are presented. It is advised to "Consult doctor before using the alternative medication" to prevent issues. Finally, we have an "Upload Picture" option to submit more images for examination.

Fig. 11 depicts the outcome if no low-cost drug for the requested medication is identified.

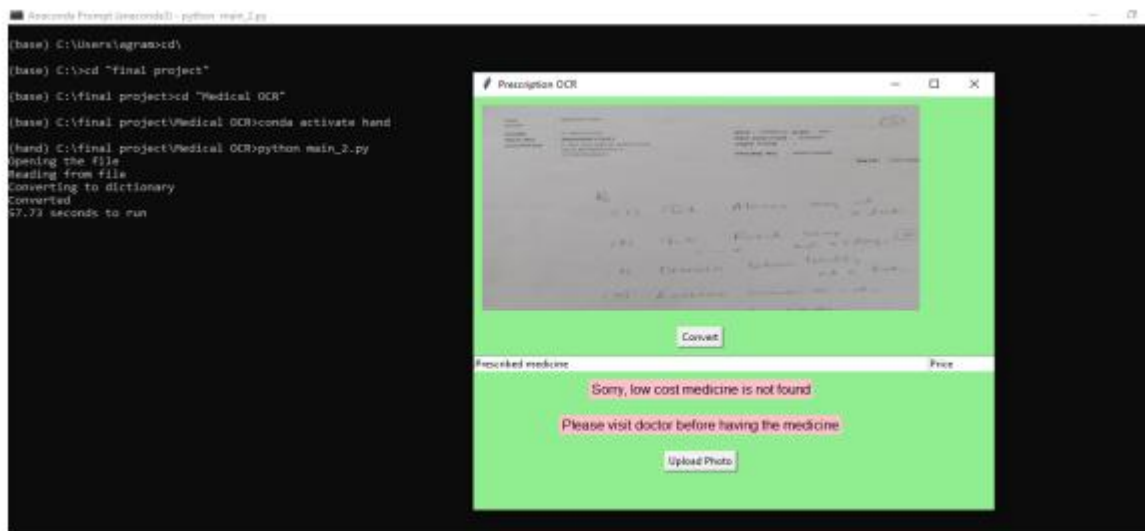


Fig. 11: The notice for the user-uploaded image if a low-cost medicine cannot be located.

The modified picture after preprocessing is shown in Fig 11 above. If the model couldn't identify substitute low cost medication for the recommended drug in its medicine dataset, then it shows "Sorry, low cost medicine is not found".

V. CONCLUSION

This study makes use of a newly constructed medical dataset as well as a lexicon including over 150,000 abbreviations used by physicians. The pharmaceutical dataset includes columns such as Available Brands, Manufacturers, Constituents, and Pricing, as well as Generic/Low Cost Medicine and Price. The Cloud Vision API key is used in this study to detect the content in the picture. The model is educated on various doctors' handwriting. Users may now test the identified output by uploading a picture from the gallery. The detected output includes the recommended medication, its cost, and a substitute low-cost medication, as well as its cost. If an alternative low-cost drug is not accessible, the message "Sorry, no low-cost medicine identified" appears. Google OCR creates a text file in which consumers may check their prescription medications. Future Scope: In the suggested effort, a new dataset linked to low-cost pharmaceuticals was developed by hand and is offered here. This dataset's size may be enhanced in the future by including additional low-cost medications throughout the study. This project may be expanded in the future to include capabilities such as the submission of a zip bundle containing numerous picture files of medical prescriptions at the same time. Web scraping may be used to get material from many medical websites such as Apollo, Med plus, and others. A mobile version of this online application would allow it to reach a larger audience.

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