# MediScan Handwritten Prescription Translator

S.Vidhya, Yukendhira M, Sidharth K
Assistant Professor, Department of Computing Technologies, SRMIST,
Kattankulathur, Chennai, India
vidhyas2@srmist.edu.in
Department of Computing Technologies, SRMIST,
Kattankulathur, Chennai,India
ym5677@srmist.edu.in
Department of Computing Technologies, SRMIST,
Kattankulathur, Chennai,India
sk9569@srmist.edu.in

Yukendhira M, Sidharth K

**Abstract.** The MediScan Handwritten Prescription Translator represents a significant advancement in healthcare technology, aiming to streamline prescription management and improve accessibility for healthcare professionals and patients. Leveraging state-of-the-art technologies such as YOLOv5 for object detection and the recurrent neural networks (RNN) for recognition of text, the system automates the interpretation of handwritten prescriptions, providing comprehensive medication information and empowering patients with multilingual support. Through collaboration with language experts and integration of additional language models, the system offers enhanced multilingual support, catering to diverse linguistic communities..

**Keywords:** We would like to encourage youMediScan Handwritten Prescription Translator, healthcare technology, prescription management, You only look once (YOLOv5) object detection model, recurrent neural network (RNN), text recognition, multilingual support, natural language processing.

## 1 Introduction

Technological advances have become indispensable in revolutionizing patient care, improving operational efficiency, and minimizing errors within the dynamic landscape of healthcare. In this context, the handling of medical prescriptions stands out as a critical area where technological innovations can yield significant benefits. The proposed project—Mediscan Handwritten Prescription Translator—represents a pivotal advancement as it addresses pressing challenges and revolutionizes the management of medical prescriptions. The importance of feasibility studies in the realm of healthcare technology cannot be overstated. Previous studies have demonstrated their pivotal role in informing decision-making processes, guiding project planning, and ensuring the successful implementation of innovative solutions. As we embark on the development of the Mediscan Handwritten Prescription Translator, it is imperative to draw insights from existing feasibility studies to enhance the efficacy and viability of our project.Incorporating state-of-the-art technologies such as deep learning models for text recognition and YOLOv5 for object detection, the Mediscan Handwritten Prescription Translator offers a holistic approach to prescription management, focusing on the following key objectives:

**Enhancing Accuracy and Efficiency**: Leveraging object detection techniques like YOLOv5, the system can accurately identify and locate medication names on prescriptions, thereby minimizing the risk of misinterpretation and ensuring patients receive the intended medications and dosages.

**Improving Accessibility**: Through text recognition and data extraction capabilities, the system facilitates easy access to prescription information, enabling healthcare professionals to quickly retrieve essential details and empowering patients to understand their prescribed medications comprehensively.

**Empowering Patients**: By providing patients with detailed information about their treatment regimens, including medication details and pricing options, the system empowers them to make informed decisions about their health and financial well-being.

**Streamlining Healthcare Processes**: Automating the prescription interpretation process decreases the time taken and effort for prescription management, allowing healthcare providers to focus on delivering high-quality patient care.

Against the backdrop of a rapidly evolving healthcare landscape, characterized by the increasing importance of data-driven decision-making, the Mediscan Handwritten Prescription Translator holds immense potential to enhance patient safety, improve healthcare delivery quality, and alleviate administrative burdens on healthcare professionals. By leveraging cutting-edge technology to address fundamental challenges in prescription management, this project not only showcases technical prowess but also makes a significant contribution to the broader field of healthcare technology.

## Discussion

Feasibility studies play a crucial role in the successful development and implementation of healthcare technology solutions. By examining the experiences and insights gained from previous feasibility studies, we can glean valuable lessons and best practices that inform our approach to the development of the Mediscan Handwritten Prescription Translator. In this discussion, we highlight key findings from relevant feasibility studies and explore their implications for our project.

The literature review presented in the "Related Work" section provides a comprehensive overview of research that is already present on handwritten recognition and text translation in healthcare settings. Studies such as those by Dr. J. Miraclin Joyce Pamila et al., Pavithiran et al., and G.R. Hemanth et al. underscore the importance of leveraging deep learning techniques for accurate and efficient handwritten text recognition. These studies demonstrate the feasibility of employing convolutional neural networks (CNNs), recurrent neural networks (RNNs), and connectionist temporal classification (CTC) to achieve high levels of accuracy in text recognition tasks.

Furthermore, the introduction of novel approaches like rotation of the stroke and parallel shift (SRP) augmentation, as discussed in the study by Shaira Tabassum et al., highlights the potential for innovative data augmentation techniques to enhance recognition performance. By incorporating insights from these studies into the development of the Mediscan Handwritten Prescription Translator, we can explore the feasibility of implementing similar techniques to improve the accuracy and reliability of our text recognition algorithms.

## 2 Related Work

The different handwriting detection models that have been developed in recent years are covered in this literature review, along with a thorough discussion of the features and methodology of previous studies.

Dr. J. C. Miraclin Joyce Pamila et.al., (2020) presents a paper that delves into handwritten recognition using CNN in deep learning. Addressing challenges in real-time applications, especially in digital conversion and signature verification, it explores both Online and Offline Handwritten Recognition. Leveraging the MNIST dataset with 70,000 handwritten digits, the study focuses on the efficacy of CNN. Implementing TensorFlow and Anaconda, the proposed CNN-based approach achieves an impressive 93% overall accuracy.

Pavithiran et.al (2020) presents a system for recognizing doctors' handwritten prescriptions in multiple languages using deep learning techniques. The motivation behind this system stems from the difficulty patients and pharmacists face in deciphering doctors' handwriting, which can lead to medication errors. The system aims to translate handwritten prescriptions into digital text, making it simpler to understand for pharmacists and patients alike.

G.R. Hemanth et.al., (2021) presented a paper that addresses the challenges posed by handwritten scripts, emphasizing the need for efficient handwritten text recognition (HTR) systems. Offline Handwritten Text Recognition (OHTR) has gained significant research attention due to its applications in eliminating errors arising from misinterpretation and enhancing automation efficiency. The study proposes an OHTR system utilizing RNN, CNN with Long Short-Term Memory LSTM, and Connectionist Temporal Classification (CTC). Training and testing are conducted on the IAM database, a dataset containing handwritten English text. Image segmentation-based text recognition is implemented using OpenCV for image processing and TensorFlow for training. The model demonstrates promising results with an overall accuracy of 98%.

J. Pradeep et.al., (2011) presented a paper that delves on a neural network-based offline handwritten character recognition system that does not involve feature extraction. The system aims to recognize English alphabets using a multilayer feedforward neural network. Each character is resized into a 30x20-pixel image, and these pixels serve as features for training the neural network. The proposed system undergoes stages of image acquisition, preprocessing, segmentation, classification, and post-processing.

Shaira Tabassum et.al, (2021) presented a paper that proposes an online system to recognize doctors' illegible handwritten prescriptions, aiming to improve accuracy.

It introduces the "Handwritten Medical Term Corpus" dataset, comprising 17,431 samples of 480 medical words from Bangladeshi doctors. A new data augmentation technique, Stroke Rotation and Parallel-shift (SRP), enhances sample variety. The recognition process involves data preprocessing, SRP augmentation, and a bidirectional LSTM model trained on sequential line data. Results show a significant accuracy improvement (89.5%) with SRP augmentation. The paper emphasizes the potential to reduce medical errors and suggests future research directions for further improving recognition performance.

In a paper published prior to OCR processing, Bala Mallikarjunarao Garlapati et al., (2017) present a method for differentiating between handwritten and machine-printed text in scanned documents. A feature-based approach is proposed, which makes use of structural features such as shape and intensity. The procedure consists of feature extraction, text localization, and SVM classification. The experimental outcomes pertaining to the IAM dataset indicate that various features, including pixel density, variance, mean, standard deviation, upper quarter intensity, and Otsu's threshold, exhibit notable efficacy in facilitating differentiation. The proposed method surpasses prior approaches with an overall accuracy of 98.6%. Furthermore, it establishes a foundation for potential future improvements, such as the integration of supplementary functionalities and expansion to encompass other language scripts.

Praveen Krishnan et.al., (2016) published a paper describing a novel approach for word spotting and recognition in handwritten images that uses deep convolutional feature representations and an embedded attribute framework. The proposed method outperforms state-of-the-art methods on datasets like the IAM, with a mean Average Precision (mAP) of 91.58% for word spotting and a mean word error rate of 6.69% for recognition. Our method improves discriminative ability and allows for efficient query-by-string retrieval by embedding both image and text labels in the same subspace. These findings show that deep learned features and the embedded attribute framework can effectively address the challenges of word spotting and recognition in handwritten text.

## 4 Objective

Our project endeavors to address the critical need for accessible prescription management by developing a multifaceted website capable of recognizing and translating medical prescriptions into indian regional languages. With a focus on leveraging advanced optical character recognition (OCR) technology and state-of-the-art translation algorithms, our platform aims to revolutionize the way prescriptions are handled in healthcare settings. Beyond mere recognition, our system seeks to ensure accurate translation of prescription details, including medication names, dosages, and instructions, into languages beyond the original text. By facilitating seamless communication across language barriers, our initiative not only enhances the accessibility of healthcare information but also empowers patients to actively engage in their treatment plans. Through this comprehensive approach, we aim to promote equitable healthcare access for individuals of diverse linguistic backgrounds, ultimately fostering better patient outcomes and driving efficiency in healthcare delivery systems worldwide.

## 5 Existing System

The existing system for handwritten recognition and related systems is enhanced by the insights gleaned from the research conducted by Fajardo et al. The study addresses the critical issue of illegible cursive handwriting among doctors in medical prescriptions, proposing a novel solution in the form of a Deep Convolutional Recurrent Neural Network (CRNN) model. Through comprehensive data collection, preprocessing, and model training, the researchers achieved significant advancements in accurately identifying handwritten text, particularly within medical prescriptions. The integration of CRNN, combining CNNs for image feature extraction and RNNs for sequence modeling, yielded promising results, showcasing improved recognition accuracy.

Furthermore, the implementation of the developed model in a mobile application, 'Doctors' Cursive Handwriting Recognition System' (DCHRS), provides a practical solution for translating handwritten prescriptions into digital text, enhancing accessibility, and reducing errors in medication management. By incorporating these findings into our existing system, we aim to leverage the advancements in deep learning techniques to enhance the effectiveness and usability of our handwritten recognition system.

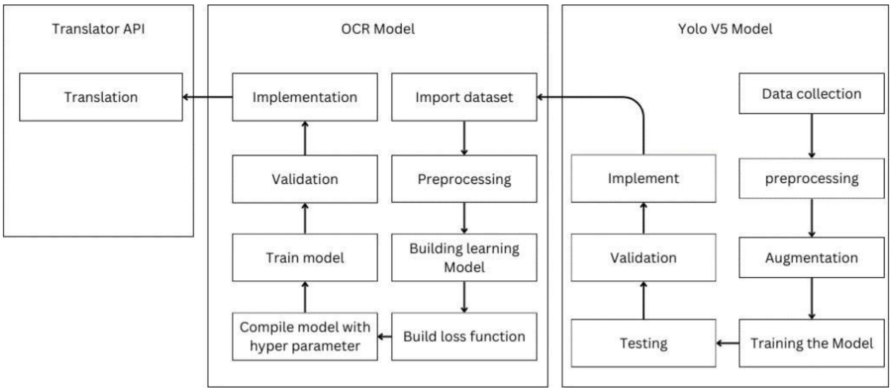
## 6 Proposed Work

Technological advancements are crucial for reducing errors, enhancing efficiency, and enhancing patient care in the rapidly evolving healthcare landscape of the present era. The MediScan Handwritten Prescription Translator project intends to transform the way medical prescriptions are managed by utilising advanced technology in optical character recognition (OCR) and deep learning. This system tackles crucial concerns related to the management of prescriptions, providing a comprehensive solution to optimise workflows, enhance availability, bolster patient safety, and offer multilingual assistance by translating into many regional Indian languages. This technology has the potential to revolutionise the handling of medical prescriptions by automating prescription interpretation, presenting comprehensive pharmaceutical information, empowering patients to make educated choices, and providing multilingual support.

Upon comparing the suggested design with the present system, both have the objective of tackling issues related to the recognition of handwritten prescriptions and enhancing drug management procedures. The current approach, as described in the study conducted by Fajardo et al., utilizes a Deep Convolutional Recurrent Neural Network (CRNN) model to precisely detect handwritten text, specifically in medical prescriptions. This strategy greatly improves the accuracy of recognition, making it easier to access and decreasing errors in drug administration. On the other hand, the MediScan Handwritten Prescription Translator has unique characteristics that set it apart from current solutions. Upon identifying the handwritten prescription, the proposed system proceeds to compare the predicted pharmaceutical name with a dataset obtained from Kaggle. This dataset includes medicine names, pricing, and business names. The system retrieves the most similar pharmaceutical name from the dataset and presents the result, including the price and firm name. In addition, the proposed system provides translation of pharmaceutical names and corporate names into four distinct Indian languages—Tamil, Malayalam, Hindi, and Kannada—offering multilingual support that is currently lacking in the existing system. This innovation improves the ease of use and availability, giving both patients and healthcare professionals the capacity to make well-informed choices and enhancing the quality of patient care in the quickly changing healthcare environment. With these developments, the suggested system has the potential to completely transform the management of medical prescriptions. It offers a holistic solution to make procedures more efficient, improve patient safety, and give multilingual support to various populations.

## A Architecture

**Fig. 1.** Text Recognition System




## 7 System Design

### 7.1 Image Processing

Image processing serves as the cornerstone of the MediScan Handwritten Prescription Translator project, enabling the conversion of handwritten prescription images into machine-readable text. This critical component encompasses a series ofoperations aimed at enhancing the quality, consistency, and interpretability of the input data, ultimately facilitating accurate text recognition and extraction.

**Image Preprocessing Pipeline**: The image preprocessing pipeline, implemented through the Preprocessor class, encompasses several key stages:

Standardization: Input images are resized to a standardized dimension, ensuring uniformity across the dataset, and facilitating efficient processing by subsequent model components.

**Data Augmentation**: Techniques such as blurring, dilation, erosion, and contrast adjustment are applied to augment the dataset, enhancing model robustness and generalization capabilities. Augmented data enables the models to learn diverse patterns and variations present in handwritten prescriptions.

**Normalization**: Pixel values are normalized to a standardized range, ensuring consistency in data representation, and improving model convergence during training.

**Dynamic Width Adjustment**: Enables adaptive resizing of images based on their aspect ratio, preserving the spatial integrity of handwritten text, and optimizing utilization of available image space.

**Batch Processing**: Supports batch processing of images and corresponding ground truth texts, streamlining data handling and accelerating model training and inference.

Importance in Text Recognition

**Effective image processing** is fundamental to the success of text recognition tasks, as it directly impacts the quality and suitability of input data for subsequent processing stages. By preprocessing handwritten prescription images, the system enhances the readability and interpretability of text regions, thereby enabling the text recognition model to accurately transcribe handwritten text into machine-readable format.

**Integration with Object Detection**: Image processing also interfaces with the object detection component of the system,providing preprocessed images as input for detecting text regions and other criticaldetails within handwritten prescriptions. By standardizing and enhancing the qualityof input images, image processing lays the foundation for precise object detection and subsequent text recognition.

## 7.2 YOLOv5 Model

The MediScan Handwritten Prescription Translator employs a sophisticated system architecture that combines YOLOv5 for object detection and RNN for text recognition, enabling accurate interpretation of handwritten prescriptions.

YOLOv5, an advanced object recognition system algorithm renowned for its precision and effectiveness. It works by first splitting the input image as a grid and then estimating the class probabilities and bounding boxes for every grid cell. YOLOv5 introduces a more simplified architecture, improved performance, and greater versatility compared to its predecessors. YOLOv5 is used in the setting of the MediScan system to identify and locate medication names and other important information on handwritten prescriptions. By accurately identifying regions of interest within the prescription image, YOLOv5 lays the foundation for precise text recognition and data extraction.

### 7.3 Recurrent Neural Network(RNN)

An artificial neural network type called an RNN is made to process data sequences. making it especially suitable for sequential information-based tasks like natural language processing. RNNs have interconnections that keep looping back on themselves, in contrast with conventional feedforward neural network designs, which enables them to retain a memory of prior inputs. RNNs can recognize patterns and temporal dependencies in sequential data thanks to this memory. An RNN is used in the MediScan system's text recognition context to transform the machine-readable format of the text regions that are detected in the prescription image. By leveraging thesequential nature of handwritten text, the RNN processes each character or word incontext, enabling accurate transcription and extraction of medication information.

The integration of YOLOv5 for object detection and RNN for text recognition forms the backbone of the MediScan Handwritten Prescription Translator system. Upon receiving a prescription image as input, the system first applies YOLOv5 to detect regions containing text, medicine names. Once the region is identified, the system utilizes an RNN to transcribe and extract the text from the region, converting it into a machine-readable format. This extracted information is then displayed in a user-friendly interface, providing healthcare professionals and patients with comprehensive medication details. Through the seamless integration of YOLOv5 and RNN, the MediScan system achieves high accuracy and efficiency in interpreting handwritten prescriptions, ultimately enhancing prescription management in healthcare.

### 7.4 Google Translate API

In our project, we leverage the Google Translate API to facilitate language translation, enabling the conversion of text from one language to another. The Google Translate API, provided by Google LLC, offers a robust and scalable solution for language translation tasks, with support for over 100 languages and advanced translation features.

**Functionality**: The Google Translate API operates by sending text inputs to Google's cloud-based translation service, which then returns the translated text in the desired target language. It employs sophisticated machine learning algorithms to analyze and translate text accurately, considering linguistic nuances, context, and language-specific conventions.

**Integration:** To integrate the Google Translate API into our project, we utilize the Google Cloud client libraries and APIs, which provide a seamless interface for interacting with Google Cloud services. This integration involves the following steps:

**Authentication**: We obtain authentication credentials, such as API keys or service account credentials, to authenticate our requests to the Google Translate API. This ensures secure communication with the translation service.

**API Requests**: When a language translation task is initiated within our application, we construct HTTP requests containing the text to be translated, along with parameters specifying the source and target languages. These requests are sent to the Google Translate API endpoint using standard HTTP protocols.

**Response Handling**: Upon receiving a response from the Google Translate API, we parse the translated text from the JSON or XML format and incorporate it into our application's output. We handle any errors or exceptions gracefully to ensure robustness and reliability.

The proposed study, holds significant potential for both future research and real-time implementation due to several key factors:

**Innovative Technology Integration**: The study integrates cutting-edge technologies such as YOLOv5 for object detection and recurrent neural networks (RNN) for text recognition. This integration showcases a novel approach to prescription management, providing a foundation for further research into improving the accuracy and efficiency of OCR systems in healthcare.

**Multifaceted Approach**: The proposed system addresses multiple aspects of prescription management, including object detection, text recognition, language translation, and user interface design. This multifaceted approach opens avenues for future research into optimizing each component individually and exploring their synergies for enhanced performance.

**Multilingual Support and Accessibility**: By offering translation capabilities into regional Indian languages, the system enhances accessibility to healthcare information for diverse linguistic communities. Future research can explore expanding multilingual support to include additional languages and dialects, catering to a broader user base and improving inclusivity in healthcare services.

**Patient-Centered Design**: The emphasis on empowering patients with detailed medication information and options for finding competitive prices fosters a patient-centered approach to healthcare. Further research could focus on user experience design, patient engagement strategies, and the impact of improved medication accessibility on patient outcomes.

**Real-Time Implementation Potential**: The proposed system is designed with practicality in mind, aiming for real-time implementation in healthcare settings. Its ability to automate prescription interpretation, provide comprehensive medication details, and facilitate language translation makes it suitable for integration into existing healthcare workflows.

**Scalability and Adaptability**: The architecture of the proposed system is scalable and adaptable, allowing for future enhancements and customization to meet evolving healthcare needs. Research efforts can focus on scalability testing, performance optimization, and adapting the system to different healthcare contexts and regions.

## 8 Result Analysis

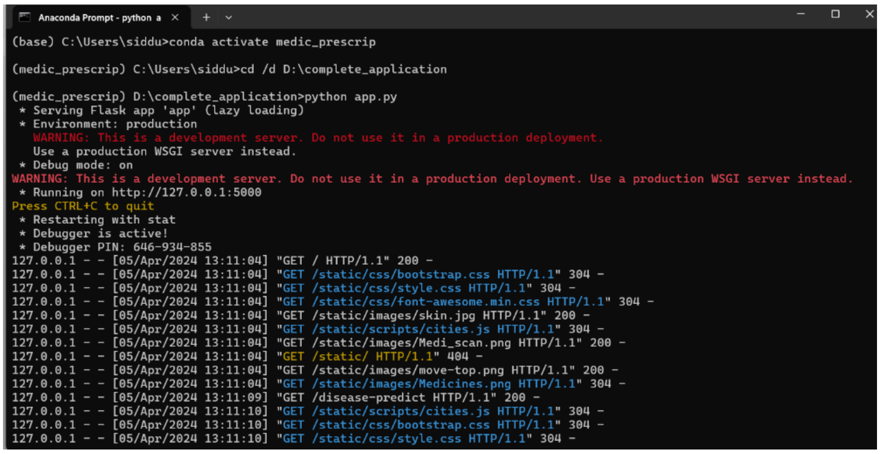



**Fig 2**: Running the Python script app.py within the virtual environment named medic_prescrip

In Fig 2 the provided Anaconda prompt output exemplifies the execution of a Flask web application within a virtual environment titled medic_prescrip. Upon invoking the python app.py command, the server initiates, indicating its operational status through messages such as "Serving Flask app 'app'" and "Running on http://127.0.0.1:5000". However, noteworthy warnings follow, cautioning against deploying the server in a production environment due to its developmental nature. The debug mode is enabled, facilitating debugging functionalities, while the active debugger is assigned a PIN for diagnostic purposes. The subsequent log entries delineate HTTP requests received by the server, denoted by their respective methods, URIs, and response status codes. These entries signify the server's responsiveness to client requests, including fetching static resources like CSS files and images, alongside serving dynamic content. Overall, the Anaconda prompt output encapsulates the setup and operation of a Flask web server, highlighting its developmental nature and interaction with client requests during runtime.

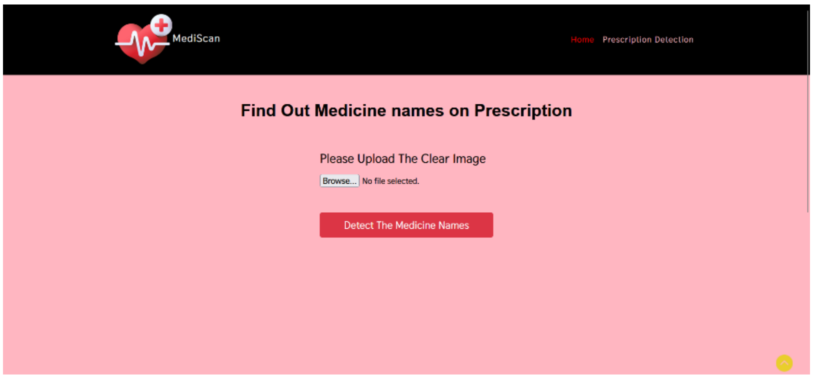



**Fig 3**: Page that allows the user to upload prescription

As shown in Fig 3, users can easily upload prescription images directly from their local machines using the intuitive file upload feature. Once the prescription image is uploaded, users have the option to initiate the medication name detection process by clicking the 'detect the medicine names’ button.

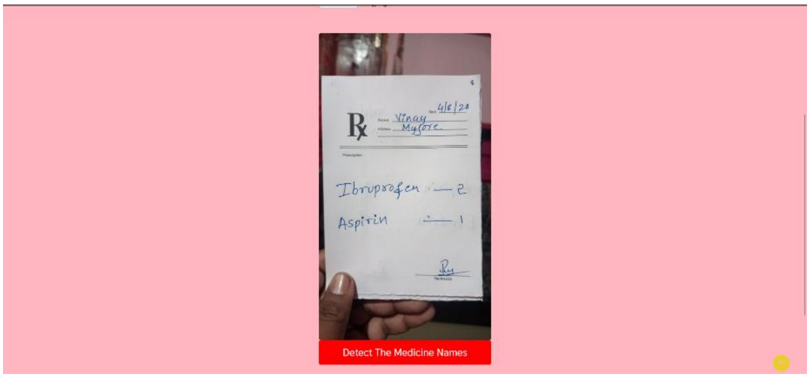



**Fig 4**: The prescription of our choice has been uploaded.

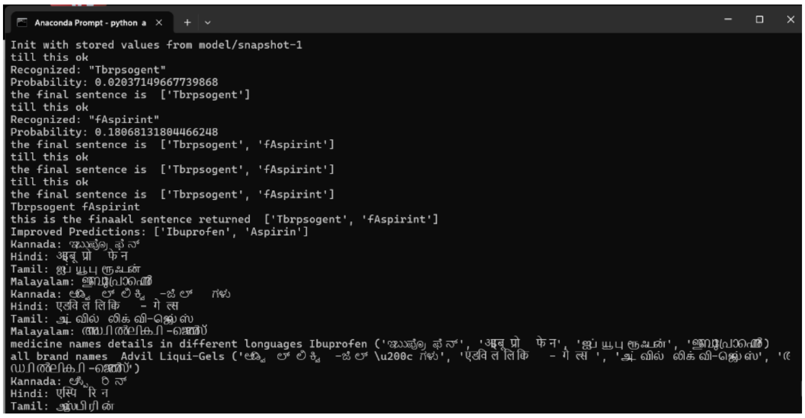



**Fig 5:** Anaconda prompt after execution

As seen in Fig 4, the prescription that has been uploaded contains two Medicines, ‘Ibuprofen’ and ‘Aspirin’. The Fig 5 shows the Anaconda prompt after the execution. It first recognizes the medicine names as “Tbrpsogent” and “fAspirint”, and the probability for this medicine name to be correct is shown as 0.02 and 0.18 respectively. These recognized medicine names are then compared with a csv file (medicine_dataset.csv) that contains the fields “Medicine name”, “Company name” and “price”. After comparing and finding similarity between the detected Medicine and the actual Medicine names, the Final prediction is shown.

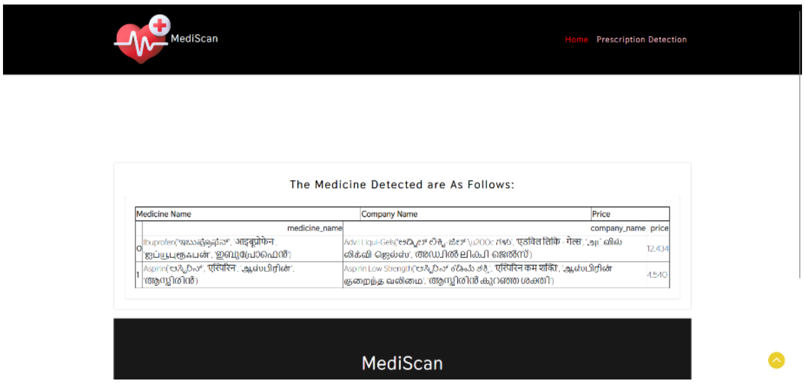



**Fig 6**: Final Display of Medicine names and Translation

Fig 5, Displays the final result, Where the Medicine names that are recognized are displayed in one column along with the company name and the price of the corresponding Medicines.

The translations of the Medicine names and the company names are also being displayed. As seen in the anaconda prompt in Fig 4, The recognized Medicine names are translated to 4 different Indian regional languages which are Hindi, Malayalam, Tamil and Kannada. The translation is done using Google translate API.

**Automation and Efficiency**: The process of prescription interpretation has been automated by the use of YOLOv5, an advanced object identification system, and deep learning models for word recognition. By automating the process, the likelihood of human errors related to manual interpretation is greatly reduced, resulting in improved efficiency in prescription management.

**Improved Access to Medication Information**: The solution guarantees enhanced accessibility to complete drug information for healthcare professionals and patients, encompassing details such as chemical makeup, dosages, precautions, and probable adverse effects. This not only enhances patient safety but also cultivates a more comprehensive comprehension of prescribed treatments.

**Patient Empowerment**: The project aims to empower patients by providing them with comprehensive information on their medications and the ability to compare pricing for prescribed medicines. Patients can actively participate in their well-being by making informed decisions regarding their treatment.

**Data Privacy and Security**: Ensuring the safeguarding of sensitive medical information is achieved by the installation of strong data privacy and security measures. Adhering to data privacy legislation is essential for upholding trust and ethical norms.

**User-Friendly Interface**: The creation of a web application that is easy to use ensures a smooth and effortless experience for healthcare professionals and patients. The user-friendly interface streamlines the process of inputting prescriptions and displaying the results.

**Educational Value**: The system is a wonderful resource for showcasing the potential of deep learning and optical character recognition in educational initiatives. It emphasizes the capacity of technology to enhance healthcare processes and improve patient care.

**Probability**: Recognition of the words may not always be accurate. In the sample input, the recognized words is first shown as “Tbrpsogent” and “fAspirint”, and the probability is shown as 0.0203714 and 0.1806813 respectively. This means that the probability for that recognized words (“Tbrpsogent” and “fAspirint”) to be correct is 0.0203714 and 0.1806813 respectively.

## 10 Conclusion

Ultimately, the Mediscan Handwritten Prescription Translator serves as a connection between conventional manual prescription management and contemporary, streamlined, and patient-focused healthcare procedures. This project exemplifies the potential of technology to enhance patient safety, optimize healthcare processes, and actively include patients in their treatment. As it transitions from the development stage to practical implementation, this technology has the potential to revolutionise the management of medical prescriptions, establishing a model for a healthcare system that is more streamlined and patient centric. In addition, translating prescription information into regional Indian languages allows for greater accessibility and comprehension, serving varied linguistic populations and promoting inclusivity in healthcare services.

## 11 Future Works

The current version of the MediScan Handwritten Prescription Translator system can translate into more languages. However, there is a great opportunity to increase multilingual support and cater to a wider range of linguistic communities. Expanding the system to incorporate more languages would not only enhance accessibility for a wider range of users but also address the linguistic diversity commonly found in healthcare environments. To accomplish this extension, future efforts will entail partnering with linguistic specialists and including supplementary language models that are customized for certain languages or dialects. This joint endeavor will guarantee the accuracy and smoothness of translations, taking into consideration subtleties in language structure, syntax, and terminology. In addition, investigating methods for unsupervised or semi-supervised learning could aid in the system's ability to adjust to languages that have little or scarce training data. The expanded multilingual support will enhance the impact and reach of the MediScan system by embracing linguistic diversity and promoting inclusivity. This will improve healthcare accessibility and patient outcomes in diverse cultural and linguistic contexts, making the system a more versatile tool.

## 10 References

[1] Shaira Tabassum1, Ryo Takahashi 1, Md Mahmudur Rahman “Recognition of Doctors’ Cursive Handwritten Medical Words by using Bidirectional LSTM and SRP Data augmentation”,IEEE .

[2] Tanvish Jain,Rohan Sharma,Ruchika Malhotra,” Handwriting Recognition for Medical Prescriptions using a CNN-Bi-LSTM Model” .

[3] Lovely Joy Fajardo 1, Niño Joshua Sorillo , Jaycel Garlit , Cia Dennise Tomines , Mideth B. Abisado , Joseph Marvin R. Imperial , Ramon ,” Doctor’s Cursive Handwriting Recognition System Using Deep Learning”.

[4] Leonidas Lefakis and MA Wiering. 2007. Semi-Supervised Methods for Handwritten Character Recognition using Active Learning. Proc. Belgium–Netherlands Conf. Artif. Intell. (2007), 205–212.

[5] D. Dhar, A. Garain, P. Singh, and R. Sarkar, “Hp docproc: a method for classifying printed and handwritten texts in doctor’s prescription,” Multimedia Tools and Applications, pp. 1–34, 11 2020.

[6] Mohamad Ivan Fanany Darmatasia, "Handwriting Recognition on Form Document Using Convolutional Neural Network and Support Vector.

[7] D. Prabha Devi, R. Ramya, P.S. Dinesh, C. Palanisamy and G. Sathish Kumar, "Design and simulation of handwritten recognition system.

[8] R. J. Milewski, V. Govindaraju, and A. Bhardwaj, “Automatic recognition of handwritten medical forms for search engines,” IJDAR, 2009.

[9] T. M. Rath and R. Manmatha, “Word spotting for historical documents,” IJDAR, 2007.

[10] P. Krishnan and C. Jawahar, “Generating Synthetic Data for Text Recognition,” in CoRR, 2016.

[11] M. Jaderberg, K. Simonyan, A. Vedaldi, and A. Zisserman, “Reading text in the wild with convolutional neural networks,” IJCV, 2016.

[12] Purohit, A., & Chauhan, S.S. (2016). A Literature Survey on Handwritten

Character Recognition. (IJCSIT) International Journal of Computer Science and Information Technologies, 7(1), 1-5.

[13] Singh, V., & Lal, S. P. (2014, November). Digit recognition using single layer neural network with principal component analysis. In Asia-Pacific World Congress on Computer Science and Engineering (pp. 1-7). IEEE.

[14] C Yadav, P., & Yadav,N. (2015). Handwriting recognition system- A review. International Journal of Computer Applications, 114(19), 36-40.

[15] N. Arica and F. Yarman-Vural, “An Overview of Character Recognition Focused on Off-line Handwriting”, IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews, Vol.31 (2), pp. 216 - 233. 2001.