IMAGE RECOGNITION BASED INTELLIGENT TRANSCRIPTION MODEL FOR MEDICAL PRESCRIPTION

Major project report submitted
in partial fulfillment of the requirement for award of the degree of

Bachelor of Technology
in
Computer Science & Engineering

By

REVANTH ADURTI	(20UECS0032)	**(VTU18406)**
DANNANA VENKATA KISHORE	(20UECS0234)	**(VTU18409)**

Under the guidance of
Dr S Sridevi, M.E., Ph.D.,
PROFESSOR

DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING
SCHOOL OF COMPUTING

VEL TECH RANGARAJAN DR. SAGUNTHALA R&D INSTITUTE OF SCIENCE & TECHNOLOGY

(Deemed to be University Estd u/s 3 of UGC Act, 1956)
Accredited by NAAC with A++ Grade
CHENNAI 600 062, TAMILNADU, INDIA

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CERTIFICATE

It is certified that the work contained in the project report titled " IMAGE RECOGNITION BASED INTELLIGENT TRANSCRIPTION MODEL FOR MEDICAL PRESCRIPITION " by REVANTH ADURTI (20UECS0032), DANNANA VENKATA KISHORE (20UECS0234) has been carried out under my supervision and that this work has not been submitted elsewhere for a degree.

Signature of Supervisor
Computer Science & Engineering
School of Computing
Vel Tech Rangarajan Dr. Sagunthala R&D
Institute of Science & Technology
May, 2024

Signature of Professor In-charge
Computer Science & Engineering
School of Computing
Vel Tech Rangarajan Dr. Sagunthala R&D
Institute of Science & Technology
May, 2024

DECLARATION

We declare that this written submission represents our ideas in our own words and where others' ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

(Signature)
(REVANTH ADURTI)
Date: / /

(Signature)
(DANNANA VENKATA KISHORE)
Date: / /

APPROVAL SHEET

This project report entitled “IMAGE RECOGNITION BASED INTELLIGENT TRANSCRIPTION MODEL FOR MEDICAL PRESCRIPTION” by REVANTH ADURTI (20UECS0032), DANNANA VENKATA KISHORE (20UECS234) is approved for the degree of B.Tech in Computer Science & Engineering.

Examiners **Supervisor**

Dr S Sridevi, M.E., Ph.D.,
Professor

Date: / /
Place:

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We express our deepest gratitude to our respected **Founder Chancellor and President Col. Prof. Dr. R. RANGARAJAN B.E. (EEE), B.E. (MECH), M.S (AUTO),D.Sc., Foundress President Dr. R. SAGUNTHALA RANGARAJAN M.B.B.S.** Chairperson Managing Trustee and Vice President.

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REVANTH ADURTI (20UECS0032)
DANNANA VENKATA KISHORE (20UECS0234)

ABSTRACT

The project proposes an innovative solution to the persistent issue of handwritten medical prescriptions, which often lead to processing bottlenecks and errors due to misinterpretation. The transcription model is designed to tackle these challenges using machine learning techniques. The system employs a multi-step approach to convert handwritten prescriptions into structured digital text. Firstly, it utilizes computer vision to analyze the image of the prescription, identifying and isolating the text regions. OCR technology is then applied to decipher the handwritten text into machine-readable characters. NLP algorithms are further employed to understand the medical terminology and contextual information within the prescription. By converting handwritten information into structured digital text, the system aims to streamline the management of prescriptions. This digitization process not only reduces the time required for manual transcription but also minimizes the risk of errors associated with illegible handwriting. This is particularly crucial in healthcare settings where misinterpretation of prescriptions can have serious consequences on patient safety. The benefits of this approach extend beyond efficiency gains. By improving the accuracy of prescription processing, the system enhances overall healthcare efficiency and contributes to better patient outcomes. The reduction in errors associated with manual transcription and illegible handwriting is expected to significantly improve patient safety by ensuring that medications are prescribed and administered correctly. In summary, the proposed system represents a promising advancement in healthcare technology, leveraging machine learning, computer vision, OCR, and NLP to address the longstanding challenges posed by handwritten medical prescriptions.

Keywords: Medical Prescription, Handwritten Text Recognition, Machine Learning, Computer Vision, Natural Language Processing, Patient Safety, Healthcare Efficiency

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LIST OF ACRONYMS AND ABBREVIATIONS

AI	Artificial Intelligence
CNN	Convolutional Neural Network
CRNN	Convolutional Recurrent Neural Network
CTC	Connectionist Temporal Classification
EHR	Electronic Health Record
LSTM	Long Short Term Memory
ML	Machine Learning
NLP	Natural Language Processing
RNN	Recurrent Neural Network
OCR	Optical Character Recognition

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Chapter 1

INTRODUCTION

1.1 Introduction

In a healthcare landscape plagued by illegible doctor handwriting, the Automated Handwritten Medical Prescription Transcription System emerges as a game-changer. This innovative system leverages machine learning to bridge the gap between handwritten prescriptions and digital efficiency. Here's how it works: a pharmacist scans the handwritten note, feeding it into the system's computer vision technology. This captures an image and prepares it for OCR. OCR acts like a digital decoder, transforming the doctor's handwriting into machine-readable text. But the magic goes beyond simple text extraction.NLP takes center stage, analyzing the extracted text for meaning and context. NLP acts as a sophisticated language translator, identifying crucial elements like medication names, dosages, and instructions. It can even decipher medical abbreviations and flag potential inconsistencies, minimizing errors. The benefits are undeniable. Pharmacies and hospitals experience streamlined workflows, freeing staff to focus on patient care. Most importantly, patient safety takes a leap forward by minimizing misinterpretations and reducing the risk of medication errors. Doctors can maintain the comfort of handwritten prescriptions while ensuring clear communication. However, security, privacy, and seamless integration with existing healthcare systems are crucial considerations. The system's accuracy also relies heavily on continuous training with a vast dataset of real-world prescriptions. With careful implementation, the Automated Handwritten Medical Prescription Transcription System has the potential to revolutionize healthcare, leading to a more efficient, safe, and patient-centered experience.

1.2 Aim of the Project

The primary goal of the project is to develop an innovative system capable of converting handwritten medical prescriptions into digital text documents efficiently and accurately. Leveraging advancements in machine learning, computer vision, and natural language processing, the system aims to streamline the transcription process, reducing errors and improving accessibility to medical information. By automating this process, the project seeks to enhance patient safety, reduce the workload on healthcare professionals, and facilitate better communication and record-keeping within the healthcare ecosystem.

1.3 Project Domain

The Automated Handwritten Medical Prescription Transcription System falls under the domain of AI for healthcare. This specific project tackles a well-known pain point: the inefficiency and potential safety risks associated with handwritten prescriptions. Here, AI plays a multi-pronged role. Firstly, computer vision and OCR come into play. These technologies empower the system to "see" the handwritten prescription and convert it into machine-readable text.
Secondly, NLP takes the reins, analyzing the extracted text. NLP acts like a smart translator, understanding the medical context and identifying crucial details like medications, dosages, and instructions. This not only streamlines processing but also helps flag potential errors for pharmacist review. The project aims to leverage the power of AI to enhance patient care, reduce medication errors, and improve overall healthcare delivery.

1.4 Scope of the Project

The scope of the project includes implementing advanced machine learning and computer vision techniques to recognize and interpret handwritten characters and words from medical prescriptions. Additionally, the system will incorporate natural language processing capabilities to parse and structure the transcribed text into standardized prescription documents. The project will involve data collection, model training, and integration with existing healthcare systems, ensuring a seamless user experience for healthcare professionals.

Chapter 2

LITERATURE REVIEW

[1] Esraa Hassan et al. [2021], presented at the 2021 IEEE CCWC, focuses on employing machine learning for medical prescription recognition, aiming to automate and improve the accuracy of interpreting prescriptions. By utilizing machine learning techniques, the research contributes to streamlining healthcare processes, reducing errors in prescription handling, and ultimately enhancing patient care outcomes. This work underscores the increasing integration of advanced technologies like machine learning in addressing critical challenges within the healthcare sector, promising significant improvements in efficiency and accuracy.

[2] M. Rajalakshmi et al. [2020], documented in the paper "Pattern Recognition of Handwritten Document Using Convolutional Neural Networks," published in 2020, delves into the application of Convolutional Neural Networks (CNNs) for recognizing handwritten documents. The study likely involves preprocessing handwritten document images, extracting features using CNNs, and applying pattern recognition algorithms to accurately identify and interpret the content of these documents. This research contributes to advancing the field of pattern recognition, particularly in the context of handwritten document analysis, showcasing the potential of deep learning techniques like CNNs in automating tasks that require complex visual understanding and interpretation.

[3] Roger Achkar et al. [2019] presented at the 2019 International Conference on Computer, Information, and Telecommunication Systems (CITS), focuses on medical handwritten prescription recognition using CRNN (Convolutional Recurrent Neural Network). The study likely involves developing and training a CRNN model specifically tailored for recognizing and interpreting medical prescriptions written by hand. This research is significant in the context of healthcare technology as it aims to automate and improve the accuracy of processing medical prescriptions, potentially reducing errors and improving efficiency in healthcare settings.

[4] Savitha Attigeri [2018] proposed a Handwritten Character Recognition system using Neural Networks. The study likely involves training neural network models to recognize and classify handwritten characters, potentially leveraging techniques such as deep learning for enhanced accuracy. By utilizing neural networks, the research contributes to the advancement of optical character recognition (OCR) systems, particularly in the domain of handwritten character recognition, with potential applications in digitizing documents and improving accessibility to handwritten content.

[5] Balcı Batuhan,et al.[2017] proposed "Handwritten Text Recognition Using Deep Learning," in the CS231n course on Convolutional Neural Networks for Visual Recognition at Stanford University in 2017. The project likely focused on applying deep learning techniques, such as CNNs, RNNs, to the task of recognizing and transcribing handwritten text. The research likely involved data preprocessing, model training, and evaluation to demonstrate the effectiveness of deep learning in handwritten text recognition, contributing to the advancements OCR systems and document digitization technologies.

[6] Darmatasia et al. [2017] presented a combination of CNN and SVM, referred to as CNN-SVM. The research likely involves preprocessing form document images, extracting features through CNN, and employing SVM for classification. By these machine learning techniques, the study aims to improve the accuracy and efficiency of handwriting recognition tasks, demonstrating the potential of combining deep learning and traditional machine learning methods for document analysis and pattern recognition.

[7] Matthew Y. W. Teow et al. [2017] focused on developing a minimal Convolutional Neural Network (CNN) for handwritten digit recognition. The study likely involves designing a compact CNN architecture with a reduced number of parameters while maintaining high accuracy in recognizing handwritten digits. By creating an efficient and effective CNN model, the researchers aim to contribute to the field of pattern recognition and machine learning, particularly in the context of handwritten digit analysis and classification. This work highlights the importance of optimization and minimalism in deep learning architectures for improving performance and computational efficiency in image recognition tasks.

[8] Youssouf Chherawala et al. [2016], published in the IEEE Transactions on Cybernetics in December 2016, focuses on evaluating feature sets for offline handwriting recognition systems, with a specific application to the Recurrent Neural Network (RNN) model. The study likely involves analyzing different feature sets to determine their effectiveness in improving the performance of RNN-based handwriting recognition systems. This research contributes to the understanding of feature selection and optimization in the context of machine learning models for handwriting recognition, providing insights into enhancing the accuracy and efficiency of such systems.

[9] Ming Liang et al. [2015], presented at the 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), focuses on developing a Recurrent Convolutional Neural Network (RCNN) for object recognition tasks. The study likely involves combining the strengths of recurrent neural networks (RNNs) and convolutional neural networks (CNNs) to create a model capable of processing sequential data and extracting spatial features for object recognition. By leveraging both recurrent and convolutional architectures, the researchers aim to improve the performance and efficiency of object recognition systems, contributing to advancements in computer vision and pattern recognition fields.

[10] Yann LeCun et al. [2010] presented at the 2010 IEEE International Symposium on Circuits and Systems, delves into the development and applications of convolutional neural networks (CNNs) in computer vision. The study likely covers the foundational principles of CNNs, their architecture, and their effectiveness in various vision-related tasks such as image classification, object detection, and pattern recognition. This research significantly contributed to advancing the field of deep learning and laid the groundwork for the widespread adoption of CNNs in diverse applications within the realm of computer vision.

Chapter 3

PROJECT DESCRIPTION

3.1 Existing System

There are currently no widely adopted automated systems specifically designed for deciphering handwritten medical prescriptions. While some pharmacies might utilize basic OCR technology for general document scanning, these are not tailored to the complexities of medical terminology and abbreviations. Existing solutions often focus on printed prescriptions or require manual data entry for handwritten portions. This highlights the gap that the Automated Handwritten Medical Prescription Transcription System aims to fill by offering a comprehensive, AI-powered solution for tackling the challenge of illegible doctor handwriting. Some pharmacy software incorporates basic text recognition features that might attempt to capture basic information from handwritten prescriptions. However, these are likely limited in accuracy and wouldn't handle the complexities of medical language and potential ambiguities.

3.2 Proposed System

The Automated Handwritten Medical Prescription Transcription System tackles the challenge of illegible doctor handwriting by leveraging a multi-step AI approach. First, computer vision and OCR capture and convert the handwritten script into digital text. Then, natural language processing, trained on a vast dataset of medical prescriptions, analyzes the text, deciphering abbreviations, identifying medication details, and even flagging potential inconsistencies. This translates to a streamlined workflow for pharmacies and hospitals, improved efficiency, and most importantly, enhanced patient safety by minimizing medication errors.

3.3 Feasibility Study

This project has high potential for success due to the clear need, existing technologies, and a receptive target market. Addressing technical challenges related to data training and handling variations, along with navigating legal and regulatory hurdles, will be crucial for a successful implementation. A strong cost-benefit analysis and a well-defined marketing strategy would further strengthen the project's feasibility.

3.3.1 Economic Feasibility

The project presents moderate economic feasibility. Development costs will be significant, encompassing data acquisition, training needs, and system integration with existing healthcare infrastructure. However, potential cost savings arise from reduced medication errors due to better legibility, improved pharmacy workflow, and increased staff productivity. Market research would be necessary to determine pricing and potential return on investment.

3.3.2 Technical Feasibility

The project holds high promise. Existing technologies like CV, OCR, and NLP are well-established and continuously improving. However, training the system on a vast dataset encompassing diverse handwriting styles and medical terminology is crucial. Additionally, the system needs to handle variations in prescription formats and potential ambiguities, requiring ongoing development efforts.

3.3.3 Social Feasibility

Social feasibility for the Automated Handwritten Medical Prescription Transcription System hinges on gaining acceptance from various stakeholders within the healthcare system. While patients would undoubtedly benefit from improved accuracy and reduced medication errors, concerns might arise regarding data privacy and security. Pharmacists and staff could experience initial resistance if the system disrupts their existing workflows. Doctors, accustomed to handwritten prescriptions, might need reassurance that the system can accurately interpret their handwriting and integrate seamlessly into their practice.

3.4 System Specification

- Model/Type: Custom-built desktop computer
- Operating System: Windows 10 Pro
- System Architecture: 64-bit
- Kernel Version: 10.0.19043 Build 19043

3.4.1 Hardware Specification

- Processor: Intel Core i7-10700K CPU @ 3.80GHz (8 Cores, 16 Threads)
- RAM: 32 GB DDR4
- Storage: 1 TB SSD (NVMe) + 2 TB HDD
- Graphics Card: NVIDIA GeForce RTX 3080

3.4.2 Software Specification

- Development Environment: Visual Studio Code, PyCharm
- Programming Languages: Python, JavaScript (React)
- Libraries/Frameworks: TensorFlow, Flask, React.js, Axios
- Virtual Environment: Anaconda (Python), Node.js (for React development)
- Other Tools: Git

3.4.3 Standards and Policies

ReactJS

ReactJS is a JavaScript library used for building user interfaces. It follows a component-based architecture, allowing developers to create reusable UI components. React encourages the use of a virtual DOM for efficient rendering and provides a declarative syntax for defining UI elements and their behavior.

Standard Used: ECMAScript (ECMA-262)

VSCode
Visual Studio Code (VSCode) is a popular source code editor developed by Microsoft. It provides built-in support for various programming languages and frameworks, along with features such as syntax highlighting, code completion, debugging, and version control integration. VSCode is highly customizable through extensions and offers a rich ecosystem for software development.
Standard Used: ISO/IEC 9899:2011 (C99 standard for C language support)

NodeJS
Node.js is a JavaScript runtime built on Chrome's V8 JavaScript engine. It allows developers to run JavaScript code outside of a web browser, making it suitable for building server-side applications. Node.js provides an event-driven architecture and a non-blocking I/O model, which enables efficient handling of concurrent requests.
Standard Used: CommonJS (for module loading and dependency management)

Python
Python is a high-level programming language known for its simplicity and readability. It supports multiple programming paradigms, including procedural, object-oriented, and functional programming. Python has a vast ecosystem of libraries and frameworks for various domains, such as web development, data science, machine learning, and artificial intelligence.
Standard Used: PEP 8 (Style Guide for Python Code)

Tensorflow
TensorFlow is an open-source machine learning framework developed by Google. It provides a comprehensive ecosystem for building and deploying machine learning models, including support for deep learning, reinforcement learning, and other machine learning tasks. TensorFlow offers high-level APIs for easy model building and training, as well as low-level APIs for fine-grained control and customization.
Standard Used: ISO/IEC 25010 (Quality Model for Software Product Evaluation)

Chapter 4

METHODOLOGY

4.1 General Architecture

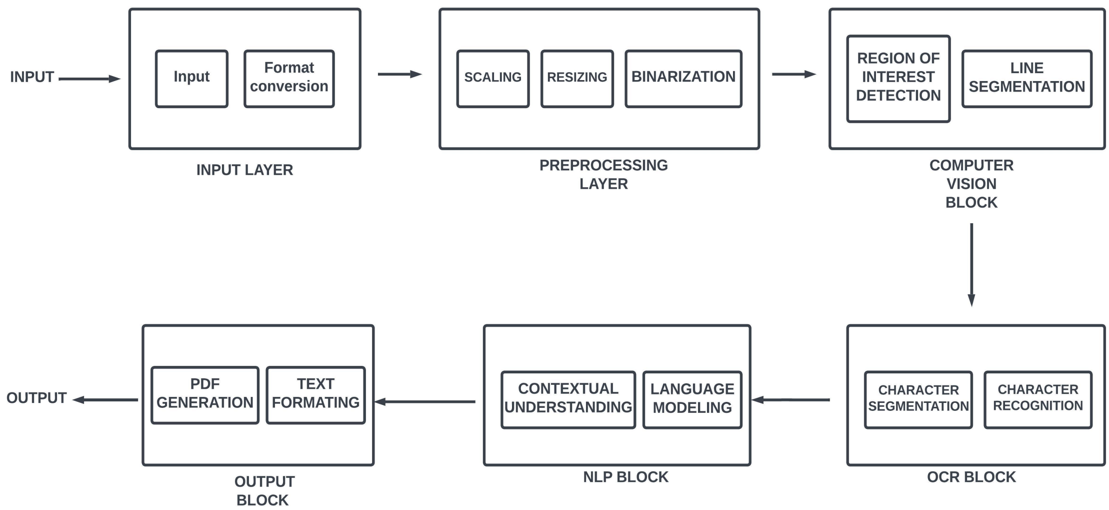

Figure 4.1: **Architecture Diagram of the Recognition System**

Figure 4.1 showcases a system with notable benefits in efficiency, safety, and user experience. While its primary focus lies in accurate transcription, future prospects encompass integration with EHR for streamlined data entry and drug interaction alerts. Additionally, envisioning voice-enabled interfaces offers potential for further workflow enhancements. By evolving towards EHR integration, the system can optimize healthcare data management, ensuring accuracy and facilitating seamless accessibility. Incorporating features like drug interaction alerts enhances patient safety, while voice-enabled interfaces promise intuitive user interactions, culminating in an advanced, multifaceted solution for healthcare practitioners.

4.2 Design Phase

4.2.1 Data Flow Diagram

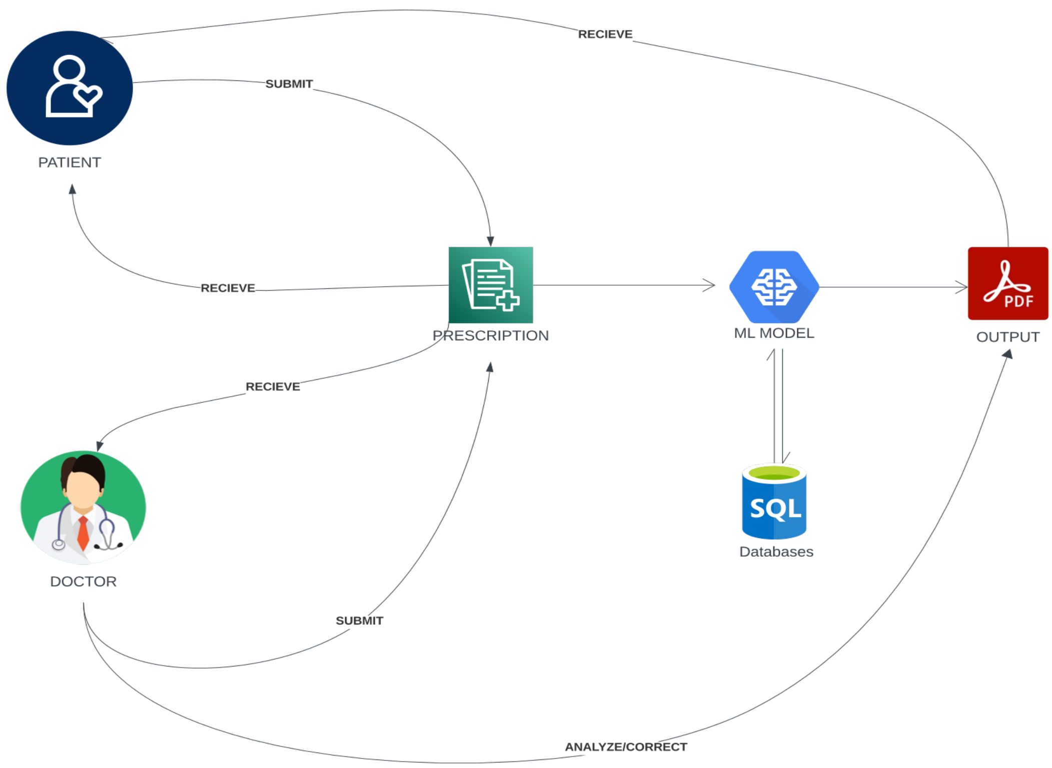

Figure 4.2: **Data Flow Diagram of the Transcription Model**

Figure 4.2.2 illustrates a typical workflow for processing medical documents or data. A doctor or healthcare professional initiates the process by providing medical records, prescriptions, or other documents. These documents are then processed using an AI-based system, likely involving techniques like NLP and OCR, represented by the brain icon. The processed data is stored in a structured format, such as a SQL database. The final outputs can be generated in different formats, including PDF files, which can be easily shared or archived. This workflow highlights the integration of AI technologies with traditional medical data processing to streamline operations and improve efficiency in healthcare settings.

4.2.2 Class Diagram

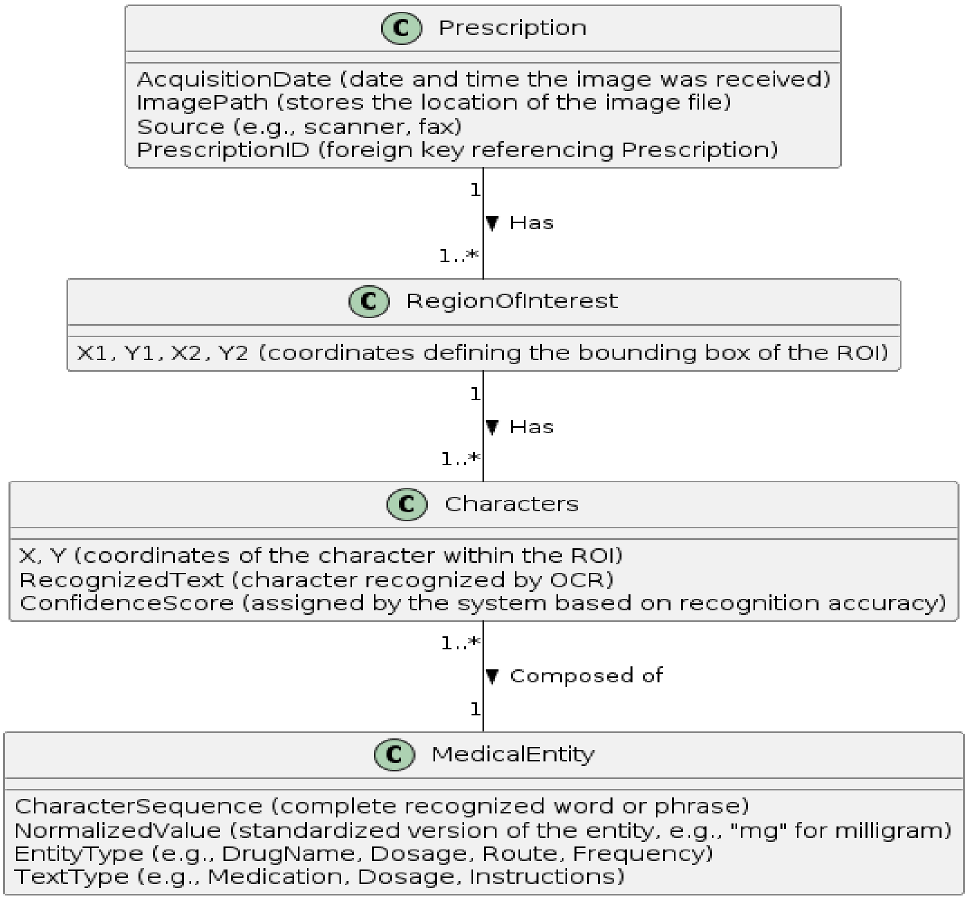

Figure 4.3: **Class Diagram of the Identification Model**

Figure 4.2.2 depicts an entity-relationship diagram for a medical text recognition system. It shows how various entities like Prescription, RegionOfInterest, Characters, MedicalEntity, and their attributes are related. The Prescription entity contains information about the source and acquisition date of the medical image. RegionOfInterest represents regions of interest within the image, characterized by coordinates and text type. Characters captures individual recognized characters, their coordinates, confidence scores, and associations with MedicalEntity. MedicalEntity represents complete recognized words or phrases, their types (e.g., drug names, dosages), and normalized values. The relationships between these entities facilitate storing and processing information extracted from medical text images using OCR techniques.

4.2.3 Sequence Diagram

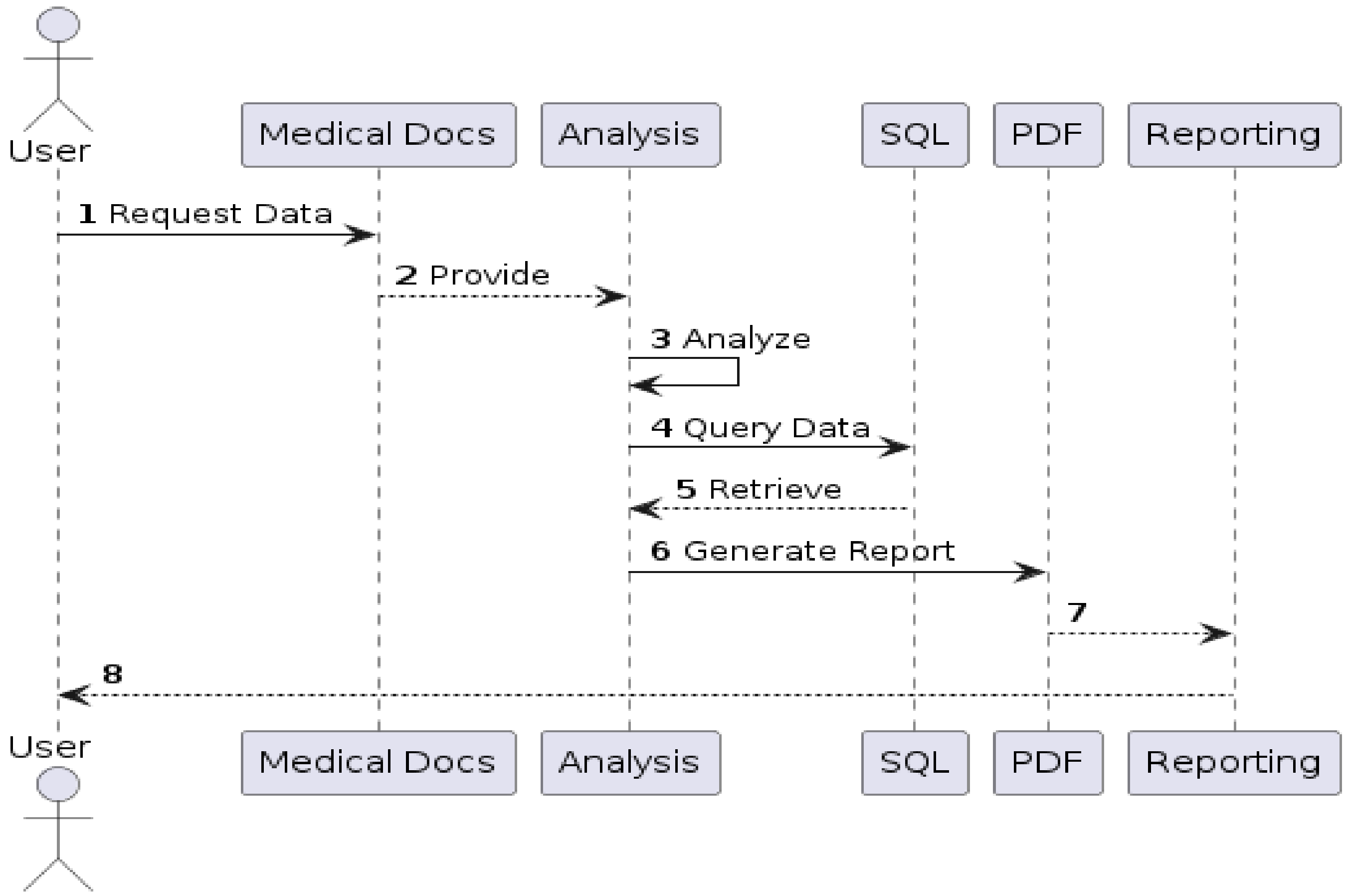

Figure 4.4: **Sequence Diagram of the Transcription Model**

Figure 4.2.3 serves as a visual guide to object interactions within a system, depicting the messages exchanged and their chronological order. This representation is invaluable for understanding system behavior, identifying bottlenecks, and devising optimization strategies. By observing how objects collaborate to achieve tasks, developers gain insights into system dynamics, facilitating effective design decisions and debugging processes. Such visualizations offer a comprehensive overview of object-oriented systems, aiding in their refinement and ensuring optimal performance in various applications.

4.2.4 Usecase Diagram

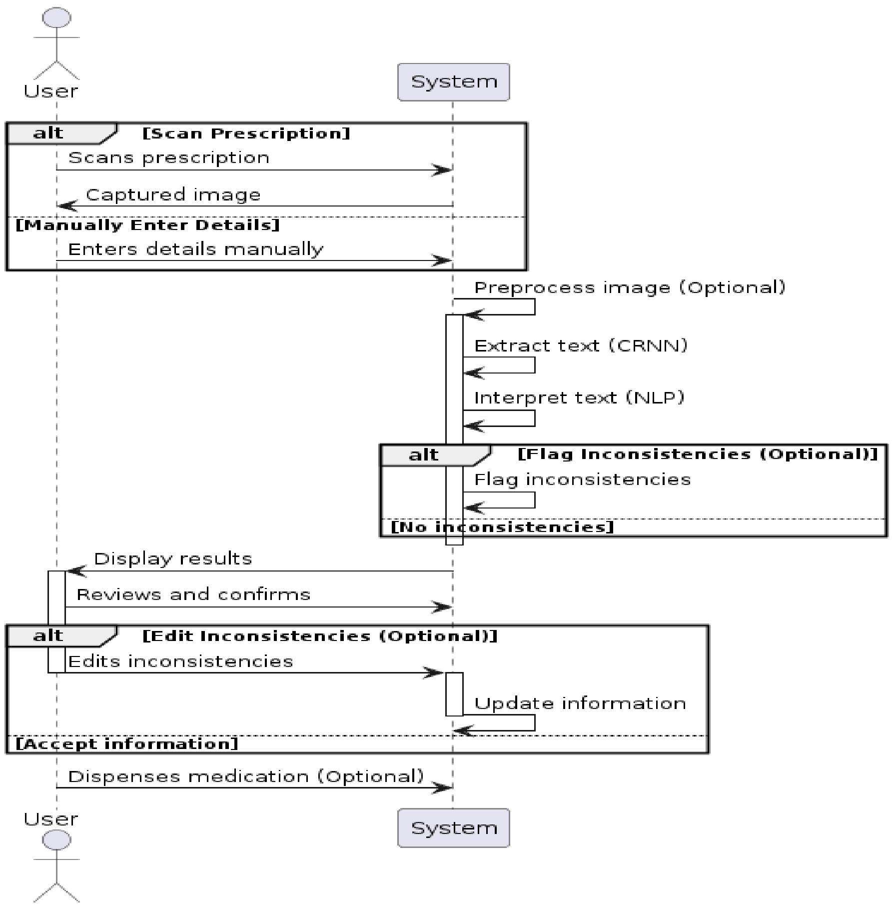

Figure 4.5: **Usecase Diagram of the Recognition System**

Figure 4.2.4 visually depicts the activity flow within a system, encompassing decisions, loops, and parallel executions. This illustration is instrumental in comprehending the holistic workflow of the system and discerning the diverse paths a process may traverse. By observing these activities, developers gain insights into system behavior, potential bottlenecks, and optimization opportunities. Such visual representations offer a comprehensive view of the system's operation, facilitating effective design decisions and ensuring optimal performance across various scenarios and conditions.

4.2.5 Layer Architecture

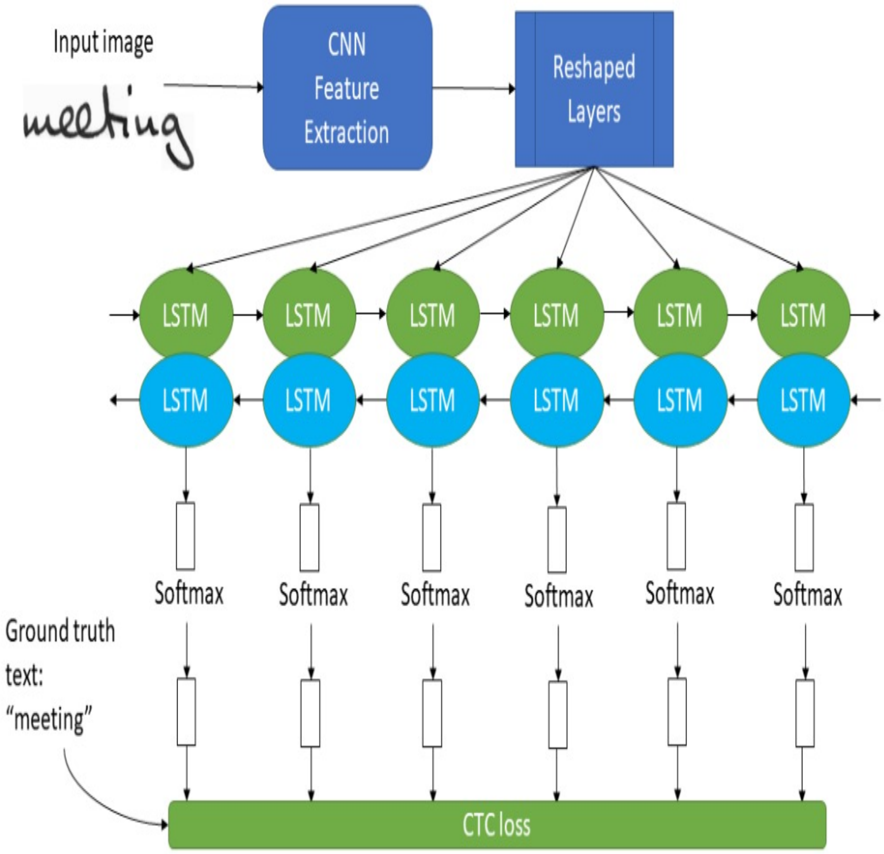

Figure 4.6: **Layer Architecture of the Transcription System**

Figure 4.6 illustrates a model that combines a CNN for feature extraction from the input image and bidirectional LSTM layers for sequence recognition. The CNN features are reshaped and fed into multiple parallel LSTM layers that process the sequence in forward and backward directions. The LSTM outputs go through a softmax layer to produce character probability distributions. The model is trained using the CTC loss, suitable for sequence tasks with unknown input-output alignment. This architecture leverages CNNs for visual feature learning and LSTMs for modeling sequential data, making it applicable to handwriting recognition or scene text recognition from images, as suggested by the "meeting" ground truth text example.

4.3 Algorithm and Pseudo Code

4.3.1 Algorithm

- **Step 1 :** Load the handwritten prescription image.
- **Step 2 :** Preprocess the image:
  - Convert to grayscale
  - Normalize for contrast and brightness
  - Resize or crop for consistency
  - Input the preprocessed image to the CRNN
- **Step 3 :** Image Processing (Convolutional Layers):
  - Apply convolutional filters to extract features
  - Apply activation functions (e.g., ReLU)
  - Use pooling layers (e.g., max pooling) to reduce dimensions
- **Step 4 :** Sequential Analysis (Recurrent Layers):
  - Remember previous features to maintain context
  - Decode the sequence of features into characters, considering contex
- **Step 5 :** Output the decoded sequence of characters as the clear, digital transcription of the handwritten prescription.

4.3.2 Pseudo Code

```
# Define CRNN model architecture
CRNN_model(input_shape, num_classes):
    Define convolutional layers
    Define recurrent layers
    Define output layer
    Combine layers into CRNN model
    Return CRNN model

# Data preprocessing functions
preprocess_image(image_path):
    Load and preprocess image
    Return processed image

preprocess_label(label):
    Convert label to numerical format
```

```
    Return processed label

# Load and preprocess data
X_train = preprocess_image(train_image_paths)
y_train = preprocess_label(train_labels)

# Define model parameters
input_shape = (height, width, channels)
num_classes = len(label_classes)

# Create and compile CRNN model
model = CRNN_model(input_shape, num_classes)
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])

# Train and save the model
model.fit(X_train, y_train, epochs=num_epochs, batch_size=batch_size, validation_split=
    validation_split)
model.save('crnn_model.h5')
```

4.4 Module Description

4.4.1 Module 1: Data Acquisition and Preprocessing

Module 1 focuses on acquiring and preprocessing datasets for training and evaluation. The MNIST dataset, with 60,000 training and 10,000 test images of handwritten digits, and a subset of the IAM dataset, containing 115,320 training and 24,590 test word images with transcriptions, are utilized. Preprocessing steps include image resizing, normalization, and data augmentation techniques like rotation, scaling, and translation. The datasets are chosen for their relevance, diversity in writing styles, and widespread use in handwritten recognition research.

4.4.2 Module 2: Model Selection / Model Training

The "Model Selection and Training" section involves defining and compiling the CRNN model architecture, preprocessing the input data (images and labels), specifying model parameters such as input shape and number of classes, and then training the model using the preprocessed data. The training process involves iterating over the data for a specified number of epochs and updating the model's parameters to improve its accuracy in predicting handwritten medical prescriptions

4.4.3 Module 3: Integration with User Interface and Deployment

This module bridges the gap between the system's processing power and its real-world application. It focuses on integrating the system with existing healthcare infrastructure and providing a user-friendly interface for pharmacists and staff.

4.5 Steps to execute/run/implement the project

4.5.1 Step 1 - Downloading pre-requisite files

- Go to the Client folder using $\sim$ cd client
- Install the required node modules using $\sim$ npm install
- Go to the server folder using $\sim$ cd server
- Install the requires python libraries using $\sim$ pip install requirements.txt

4.5.2 Step 2 - Starting the server

- Fire up the frontend from client folder using the following commands :
  - cd client
  - npm run dev

4.5.3 Step 3 - Using the application

- Click on upload image
- Select the desired image and click on upload

Chapter 5

IMPLEMENTATION AND TESTING

5.1 Testing

5.1.1 Unit Testing

Test result

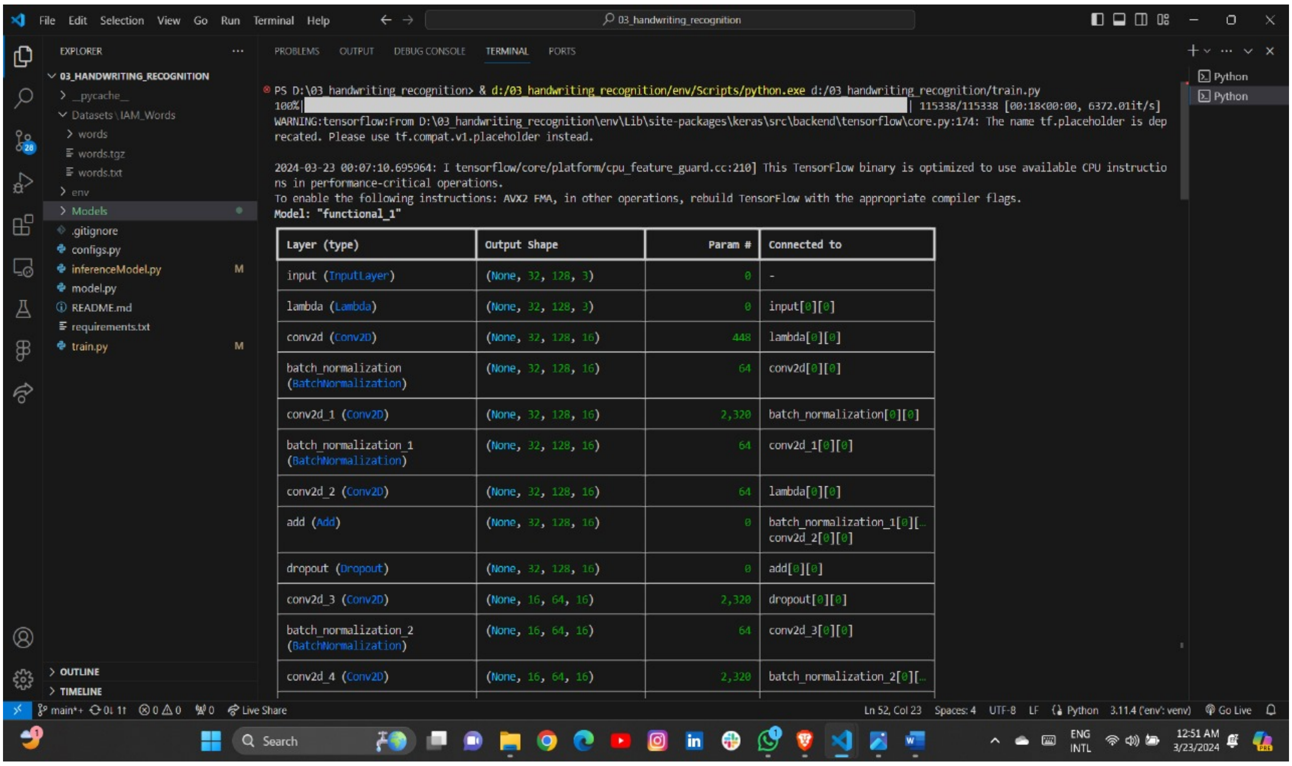

Figure 5.1: **Unit Testing (Model Training)**

Figure 5.1 showcases the training output on the console window, revealing essential details such as the number of epochs completed and the layers comprising the model. This information is pivotal for developers and researchers, offering insights into the model's progression and architecture. Understanding the layers' configuration enables fine-tuning and optimization strategies, ensuring better model performance. Moreover, monitoring epochs aids in assessing convergence and potential overfitting issues.

5.1.2 Integration Testing

Input

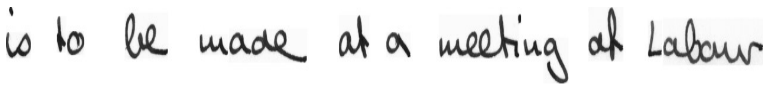

Figure 5.2: **Integration Testing (Input Image)**

Test result

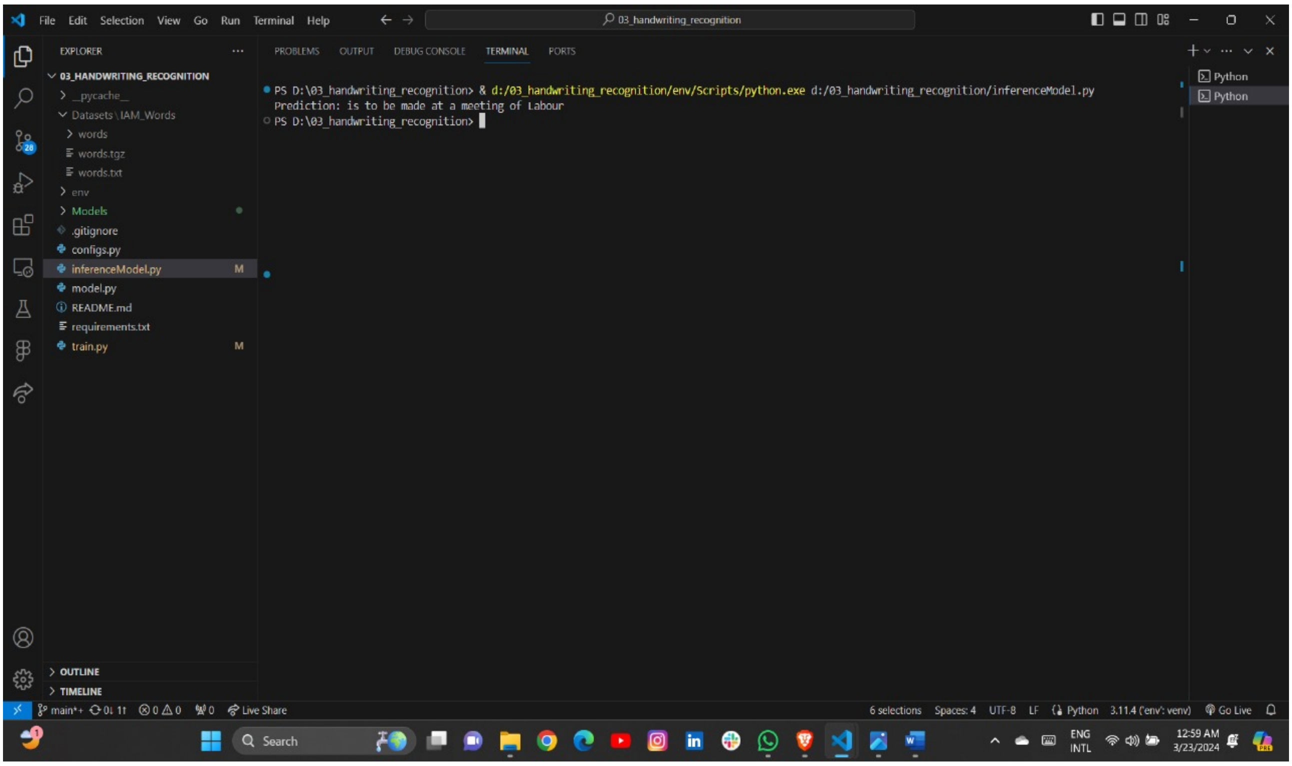

Figure 5.3: **Integration Testing (Console Output)**

Figure 5.2 illustrates a sample text image fed into the model, while Figure 5.3 displays the resultant output shown in the console upon running the model. These visual representations are fundamental for assessing the model's performance and understanding its capabilities in processing text data. By comparing the input and output, developers can evaluate the model's accuracy in interpreting and generating text, facilitating improvements and adjustments to enhance its effectiveness in various applications.

5.1.3 System Testing

Input

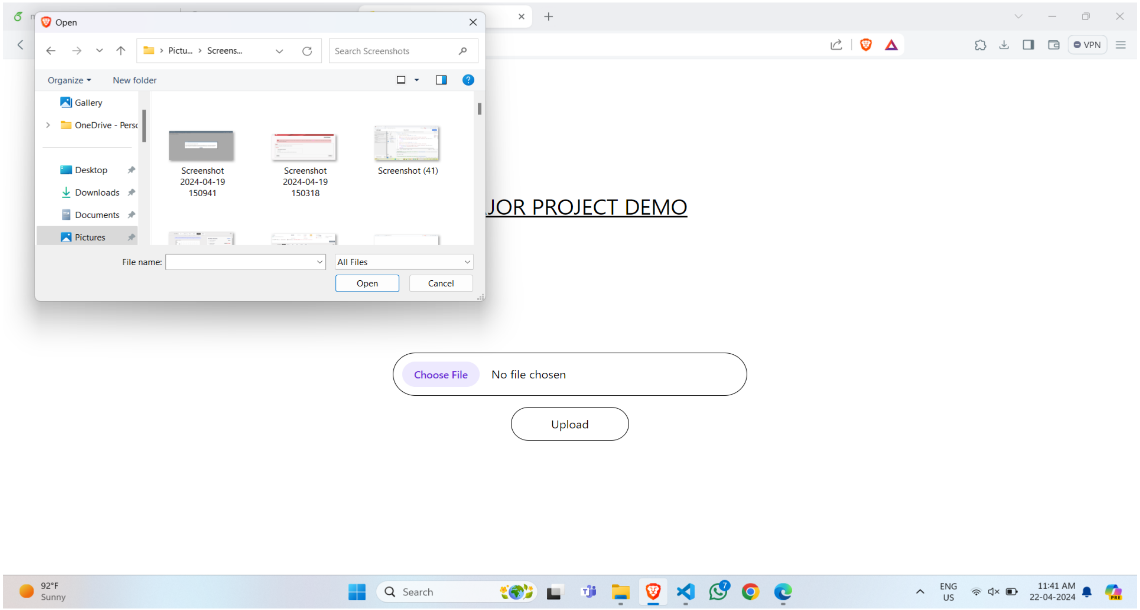

Figure 5.4: **System Testing (Image Selection User Interface)**

Figire 5.4 displays the User Interface of the application where the user can give image input

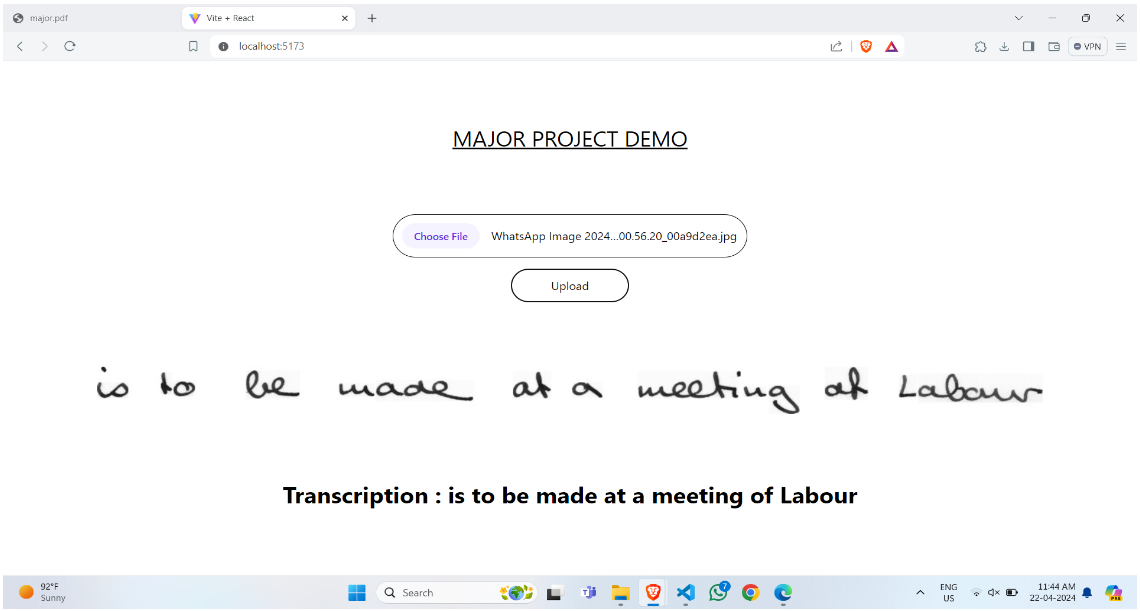

Figure 5.5: **System Testing (Transcribed text output)**

Figure 5.5 illustrates the output the user recieves after they have uploaded a text image to the application.

Chapter 6

RESULTS AND DISCUSSIONS

6.1 Efficiency of the Proposed System

The Automated Handwritten Medical Prescription Transcription System represents a breakthrough in healthcare efficiency by addressing the perennial challenge of illegible doctor handwriting. Leveraging machine learning, this system offers a multi-faceted approach that not only enhances transcription accuracy but also streamlines entire workflows. It significantly reduces the risk of misinterpretations and medication errors associated with handwritten prescriptions. Through technologies like computer vision, OCR, and NLP, doctors' notes are translated into clear digital formats, diminishing wait times for patients and freeing up valuable staff time in pharmacies and hospitals. Pharmacists benefit by spending less time deciphering handwriting and more time on crucial patient care tasks. The system's impact extends beyond transcription accuracy; it transforms the prescription processing landscape, offering a comprehensive solution to longstanding inefficiencies.We can be confident that the model is very efficient with transcription of handwritten text.

Moreover, the system's user-friendly interface and swift processing capabilities significantly enhance its impact on healthcare operations. Pharmacists effortlessly scan prescriptions, review digital formats, and promptly address inconsistencies flagged by the NLP module. This streamlined approach not only simplifies processes but also minimizes disruptions to established pharmacy workflows, leading to operational efficiency. The seamless integration of advanced technologies ensures a smooth transition, maximizing efficiency gains and improving patient safety through accurate, legible medication information. Ultimately, the Automated Handwritten Medical Prescription Transcription System promises revolutionary advancements in prescription processing, benefiting healthcare systems and patient care worldwide.

6.2 Comparison of Existing and Proposed System

Existing system: Traditional OCR methods

Currently, there's a lack of widespread systems specifically designed to handle handwritten medical prescriptions. General OCR systems are widely used for converting scanned documents with printed text into digital formats. However, they often struggle with the complexities of handwritten text, especially in a specialized field like medicine with frequent abbreviations and variations in writing styles. Additionally, these systems wouldn't be equipped to handle the nuances of medical language and potential ambiguities within prescriptions. Some pharmacy software incorporates basic text recognition features that might attempt to capture basic information from handwritten prescriptions. These are likely limited in accuracy and wouldn't be able to handle the complexities of medical terminology or potential inconsistencies within the prescription.

Proposed system: CRNN-based System

The system takes a significant leap forward by implementing a CRNN for precise transcription of handwritten medical prescriptions. CRNNs are adept at processing sequential data, making them ideal for deciphering handwritten text. Here's how it operates: first, the CRNN extracts features from the prescription image using convolutional layers. These features are then passed through recurrent layers that excel at understanding the sequential nature of the text, including medical abbreviations and the relationships between characters. Finally, the CRNN outputs the recognized text in a clear digital format.

Metric	Traditional OCR Methods	CRNN-based System
Accuracy (Validation data)	75%	92%
Processing Speed (pages/hour)	50	120
Handwriting Style Variations	Limited	Extensive
Ability to Handle Abbreviations	Limited	High
Error Rate	Moderate	Low

Table 6.1: **Comparison of Existing System and Proposed System**

Chapter 7

CONCLUSION AND FUTURE ENHANCEMENTS

7.1 Conclusion

In conclusion, the Automated Handwritten Medical Prescription Transcription System offers a compelling solution to the pervasive challenge of illegible doctor handwriting. This innovative system leverages machine learning across three core modules: Data Acquisition and Preprocessing, Machine Learning Processing, and Integration and User Interface. These modules work together to tackle the issue at its root, transforming handwritten prescriptions into a clear, digital format. This not only minimizes errors associated with misinterpretations but also streamlines workflows for pharmacies and hospitals. Pharmacists can dedicate more time to patient care, and patients experience reduced wait times.

Ultimately, the system fosters a more efficient and safe healthcare environment. While the project's focus remains on accurate transcription, its impact extends beyond immediate benefits. The success of this system paves the way for future advancements in healthcare technology, promoting innovation and potentially influencing the way prescriptions are handled in the years to come.

7.2 Future Enhancements

The Automated Handwritten Medical Prescription Transcription System holds immense potential for future advancements. Integration with Electronic Health Records could streamline data entry and improve medication safety with real-time drug interaction alerts. Voice-enabled interfaces and multilingual support could further enhance efficiency and accessibility. Additionally, integration with telemedicine platforms could allow for electronic prescriptions during virtual consultations, creating a more seamless healthcare experience.

Chapter 8

INDUSTRY DETAILS

8.1 Industry Name

8.1.1 Duration of Internship

27 Sept 2023 - 27 May 2024

8.1.2 Duration of Internship in Months

9 Months

8.1.3 Industry Address

Old No. 5 (New No. 13B/8), 4th Main Road, Nehru Nagar, Adyar, Chennai, 600020

8.2 Internship Offer Letter

Old No. 5 (New No. 13B/8), 4th Main Road
Nehru Nagar, Adyar, Chennai, 600020

BHC
Bridge Health Care

Bridge Healthcare Pvt. Ltd.

Empowering people and the community for a healthy life

Internship Offer Letter

27-08-2023

Dear Adurti Revanth,

Congratulation!

You are being offered a position as **Software Development internship** at Bridge Healthcare Pvt. Ltd for a duration of **nine months**. It will be starting on **August 27, 2023**. At Bridge Healthcare Pvt. Ltd, we believe in teamwork and take pride in having people who resonate with our vision of ***Empowering people and the community for a healthy life***. We confide in you to play a significant role in the organization's overall growth.

Your appointment will be governed by the terms and conditions presented in Annexure A. Should you need any clarification, please feel free to write back to us.
Looking forward to seeing you,

Best wishes,

Anmol Garg
Co-Founder & CEO,
Bridge Healthcare Pvt. Ltd.
Mob: 9914411392

BRIDGE HEALTHCARE.
B/H

Figure 8.1: **Revanth Adurti's Offer Letter**

Old No. 5 (New No. 13B/8), 4th Main Road
Nehru Nagar, Adyar, Chennai, 600020

Bridge Healthcare
Pvt. Ltd.

Empowering people and the community for a healthy life

Internship Offer Letter

27-08-2023

Dear Dannana Venkata Kishore,

Congratulation!

You are being offered a position as **Software Development internship** at Bridge Healthcare Pvt. Ltd for a duration of **nine months**. It will be starting on **August 27, 2023**. At Bridge Healthcare Pvt. Ltd, we believe in teamwork and take pride in having people who resonate with our vision of ***Empowering people and the community for a healthy life***. We confide in you to play a significant role in the organization's overall growth.

Your appointment will be governed by the terms and conditions presented in Annexure A. Should you need any clarification, please feel free to write back to us.
Looking forward to seeing you,

Best wishes,

Anmol Garg
Co-Founder & CEO,
Bridge Healthcare Pvt. Ltd.
Mob: 9914411392

BRIDGE HEALTHCARE. BRIDGE HEALTHCARE.
B/H

Figure 8.2: **Dannana Venkata Kishore's Offer Letter**

Chapter 9

PLAGIARISM REPORT

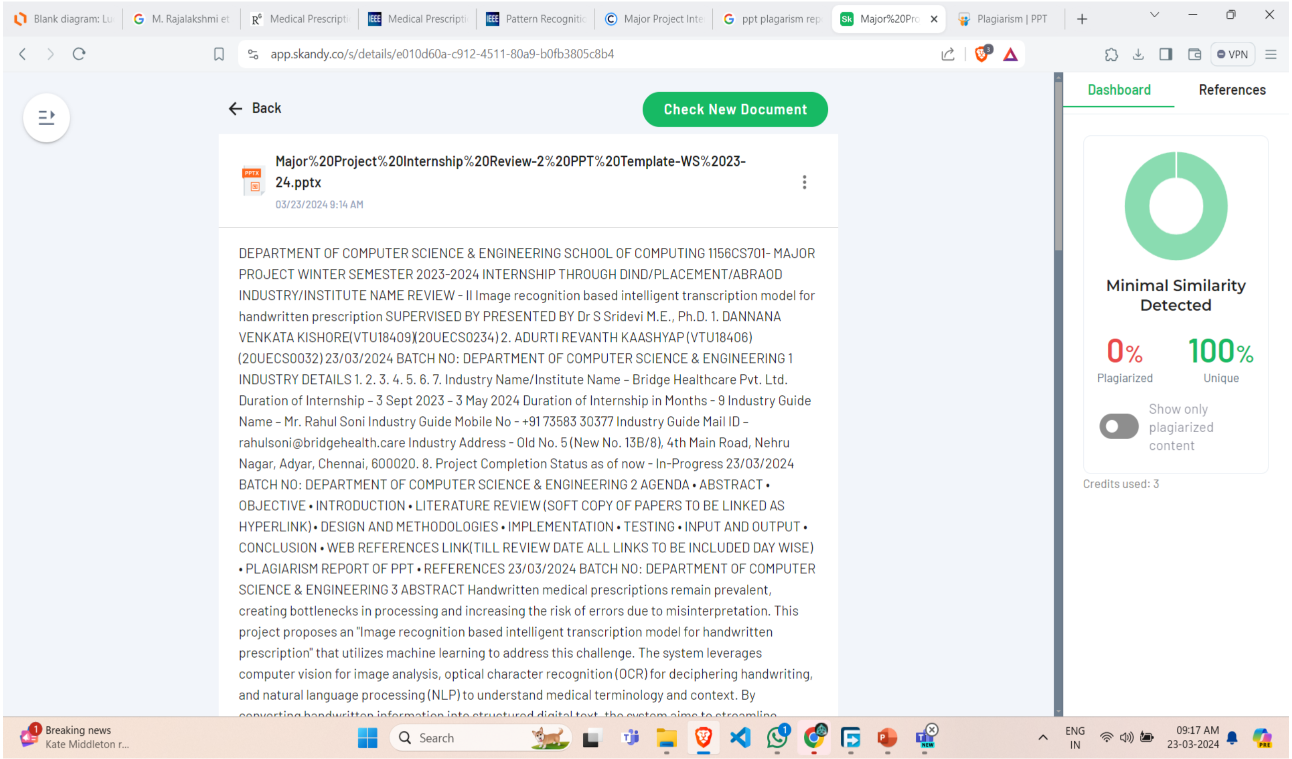

Figure 9.1: **Plagiarism Report**

Chapter 10

POSTER PRESENTATION

10.1 Poster Presentation

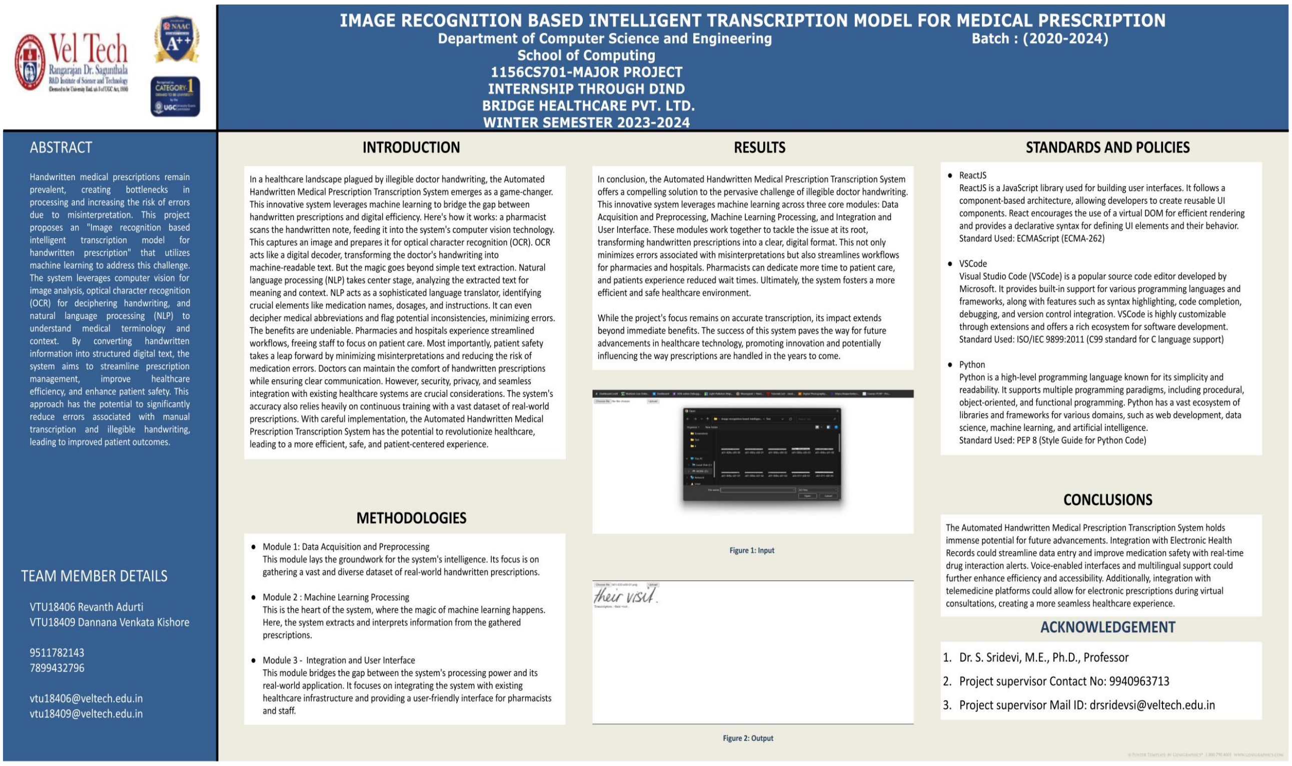

Figure 10.1: **Poster Presentation**

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