ENHANCING HEALTHCARE ACCESS: INNOVATIONS IN AI-DRIVEN MEDICAL INFORMATION SERVICES

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CONTENTS

ARTICLES

mint

ICMR study finds anomalies in prescriptions at major central run hospitals

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While prescribing, doctors are supposed to adhere to guidelines of by the World Health Organization and the Union health ministry. But nearly 10% of prescriptions showed "unacceptable deviations," from the guidelines, and 45% departed from normal treatment standards, found the study, which was conducted as part of the ICMR's Rational Use of Medicines (ICMR-RUM) task force project.

"Inappropriate prescribing is still a problem and worldwide over 50% of the medications may be prescribed or dispensed inappropriately and 50% of the patients may be non-compliant to their medication. Inappropriate prescriptions can lead to an increase in adverse drug reactions, hospitalization and increase in cost of treatment. To resolve this problem, we need to inculcate rational prescribing amongst medical student right from the undergraduate days and reinforce these principles during their further professional development," the study noted.

ARTICLES

Orissa HC directs doctors to write post-mortem reports, prescriptions in capital letters or in legible handwriting

Badly written medico-legal documents are affecting judicial process as it is very difficult to read those and come to a definite conclusion: HC

January 08, 2024 02:50 am | Updated 02:50 am IST - BHUBANESWAR

"The tendency of writing in such zig zag handwriting, which cannot be read by any common man or by judicial officers, has become a fashion among the doctors of the State. Substantial number of doctors in the State resort to such handwriting, which cannot be read by any ordinary person. In such view of the matter, the Chief Secretary of the State is directed to issue a circular to all the medical centres, private clinics and medical colleges and hospitals, directing them to write in proper handwriting or in a typed form when they are prescribing medicines or writing some medico-legal reports," he said in his order.

ARTICLES

Pak J Med Sci. 2024 Jan-Feb; 40(3Part-II): 257–258.
doi: 10.12669/pjms.40.3.9084
PMCID: PMC10862436
PMID: 38356836

Centralized healthcare database for ensuring better healthcare: Are we lagging behind?

Turkey has significantly improved its health care system under the Health Transformation Program launched by the ministry of health in 2003. The major component of this was to achieve e-health. They created a centralized health care system “saglik.net” whose objectives were to ensure standardization of healthcare data, creating and maintaining the health record of their population, data analysis, expedite the flow of information and saving resources ultimately increasing overall efficiency of the healthcare system. One of the component of this program is family medicine information system that integrated all public hospitals. They are maintaining their central database through the National Health Information System (NHIS). Ministry of Health Turkiye in collaboration with European countries is working on the Smart Open Services for European Patients (epSOS) to provide interoperability platform for sharing healthcare data. The consortium of the epSOS project composes of 48 partners form 23 European countries.[8]

India is working efficiently to maintain CHD. A recent example is an online centralized database management system for a newborn sickle cell program (NBSP), which is dedicated to a highly prevalent disease in India. More than 20 million sickle cell affected individuals reside in the country. This database is expected to help in eradication of sickle cell disease from India by the year 2047.[9]

DOCTOR'S POINT OF VIEW

In today's rapidly evolving healthcare landscape, it's imperative to leverage cutting-edge technology to enhance patient care. From the perspective of a doctor, the following services are essential for an efficient and patient-centric chatbot platform:

1.**Prescription Recommendation**: Provide accurate medication suggestions based on patient symptoms and medical history.

2.**Latest Medicine News:** Keep patients informed about the newest advancements and treatments in the medical field.

3.**Image Recognition:** Analyze medical images for diagnosis and treatment planning.

4. **QR Prescription:** Simplify prescription retrieval for patients through QR code technology.

5. **Text Generation for Health Query:** Generate informative responses to patient health queries in real-time.

6. **OCR Handwriting Recognition:** Convert handwritten prescriptions or notes into digital text for easy access and understanding.

7. **Digital Prescription:** Issue prescriptions digitally for convenient access and storage.

8. **Online Appointment Reservation:** Allow patients to schedule appointments seamlessly through the chatbot platform.

9. **Online Report Management:** Enable patients to securely store and manage their medical reports online.

By integrating these services into a chatbot platform, doctors can streamline patient interactions, improve accessibility to healthcare services, and ultimately enhance patient outcomes.

CASE STUDY

Prescription Recommendation & Digital Prescription: Imagine a scenario where a patient, John, visits his doctor for a consultation. Using the MedTech app, the doctor seamlessly generates a digital prescription tailored to John's needs, considering his medical history and current condition.

Latest Medicine News & Text Generation for Health Query: John, curious about his prescribed medication, accesses the app to stay updated with the latest medicine news. He also inputs his queries regarding potential side effects, and the app generates detailed, easy-to-understand responses, empowering him with knowledge.

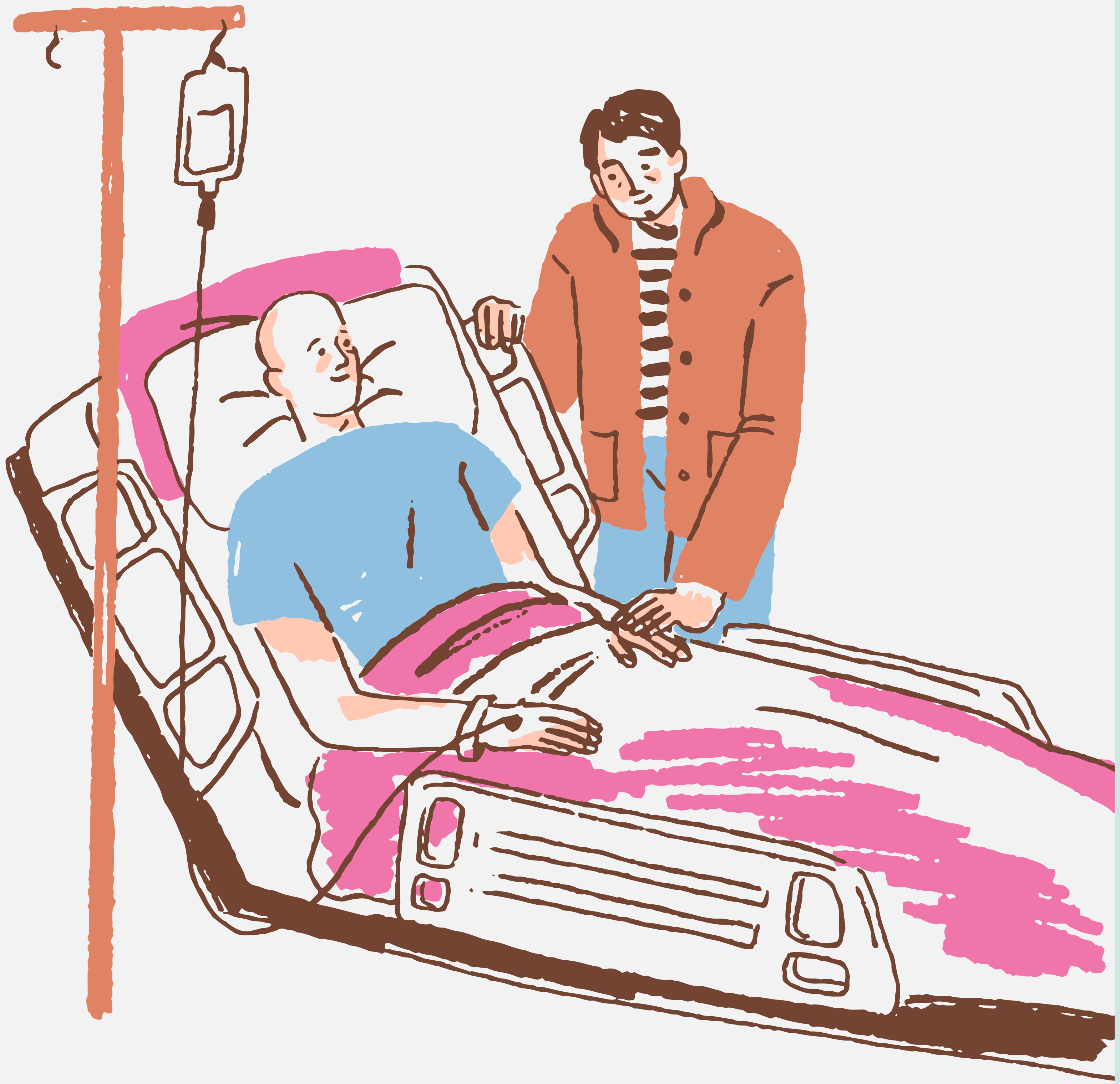
Image Recognition & OCR Handwriting Recognition: For patients with complex prescriptions or handwritten notes, the app employs image recognition and OCR handwriting recognition technologies. John simply uploads an image of his prescription, and the app accurately transcribes it into digital text for easy access and understanding.

QR Prescription & Online Appointment Reservation: Utilizing QR code technology, John conveniently retrieves his prescription details from the app whenever needed. Additionally, he schedules his follow-up appointments seamlessly through the app's online reservation system, eliminating the hassle of long waiting times.

Examination Seriousness: In critical situations, the app identifies the seriousness of examinations based on medical data, prioritizing urgent cases and facilitating prompt medical attention.

PROBLEM STATEMENT

1. Predicting Patient Condition Severity: Develop a system to assess the seriousness of a patient's condition by asking targeted questions and using the responses to predict the severity level, aiding in prioritizing patient care effectively.
2. Disease Recognition from Images: Implement image recognition technology to identify diseases like Alzheimer's, lung cancer, and breast cancer from medical images, enabling early detection and intervention.
3. Text Generation for Health Queries: Create a text generation model capable of addressing common health queries from users, providing accurate and timely responses.
4. Handwriting Recognition for Prescriptions: Implement handwriting recognition to decipher prescriptions accurately, aiding patients in identifying prescribed medications.
5. Digitizing Prescriptions with QR Codes: Transform paper prescriptions into digital format using QR codes to reduce errors and enable easy access for pharmacists, enhancing prescription management and patient safety.
6. Centralized Database for Patient Records: Establish a centralized database containing comprehensive patient history, reports, and prescriptions to support healthcare professionals in understanding patient issues and making informed decisions efficiently.



SCOPE OF THE PROJECT

1. Develop algorithms to predict the severity of patient conditions based on specific questions, aiding in efficient examination prioritization and treatment planning.
2. Implement a real-time medical news feed to keep users and hospital management updated with relevant healthcare information for informed decision-making.
3. Utilize advanced image recognition to identify diseases like Alzheimer's, lung cancer, breast cancer, and more from medical images, enabling early diagnosis and treatment.
4. Deploy a text generation model to address common health queries, providing accurate and contextual responses to users.
5. Analyze blood report documents using AI techniques to extract meaningful insights for healthcare professionals, aiding in diagnosis and treatment decisions.
6. Implement handwriting recognition technology to simplify medication identification from prescriptions, enhancing patient safety and convenience.
7. Digitize entire prescriptions to reduce paper usage and minimize prescription errors, integrating QR code technology for secure prescription access and medication dispensing.
8. Develop a centralized database to store and manage patient history, reports, and prescriptions, providing healthcare providers with a comprehensive understanding of patient issues for data-driven decision-making.

Objective

Optimize Prescription Management:

Implement handwriting recognition to facilitate easy identification of prescribed medications for patients and digitize entire prescriptions to reduce paper use, enhance accuracy, and mitigate malpractices.

Improve Information Accessibility:

Develop a comprehensive system that provides hospital staff and patients with the latest medical news, disease recognition capabilities through image inputs, and automated text generation for addressing common health queries.

Enable Seamless Data Analysis:

Leverage AI for analyzing blood report documents, summarizing findings, and storing data centrally in a secure database for comprehensive patient history access and informed decision-making by healthcare professionals.

Enhance Patient Care Delivery:

Utilize predictive modeling and AI-driven assessments to accurately gauge the seriousness of patient conditions, enabling timely and prioritized examination and treatment.

Enhance Communication:

Integrate automatic speech recognition and speech-to-speech translation features to improve communication between hospital staff and patients, ensuring accessibility and understanding across diverse language barriers.

SERVICES PROVIDED BY OUR CHATBOT

1. Prescription recommendation
2. Risk Prediction
3. Latest medicine news
4. Image recognition
5. QR prescription
6. Text generation for health query
7. OCR handwriting recognition
8. Digital prescription
9. Online appointment reservation
10. Online report management
11. Centralised Medical Record

LITERATURE SURVEY

Title	Year	Author	Inference	Gaps
Gemini: A Family of Highly Capable Multimodal Models	2023	Gemini Team, Google	• Multimodal Supremacy • Potential for Transformation • The Power of Scale	• Dataset Details • Beyond Human Benchmarks • Computational Cost
The survey: Text generation models in deep learning	2020	Touseef Iqbal , Shaima Qureshi	• Deep Learning Excellence • Evolution in NLP Advancements in Deep Generative Modeling • The Journey of Text Generation Models • Exploring DL Approaches	• Lack of theoretical foundation • Interpretability • Data and resource requirements • Overreliance on training data

LITERATURE SURVEY

Title	Year	Author	Inference	Gaps
A Hybrid Approach Handwritten Character Recognition for Mizo using Artificial Neural Network	2018	J. Hussain and Vanlalruata	**Hybrid approach** with neural networks. **Hybrid segmentation** merges blobs. **Hybrid feature extraction** improves accuracy. **BPNN** achieves 98% accuracy.	**feature extraction** algorithm **Online, cursive recognition** **Text-to-speech**
BmQGen: Biomedical Query Generator for Knowledge Discovery	2015	Feichen Shen, Hongfang Liu, Sunghwan Sohn, David W Larson, Yugyung Lee	Converts text to RDF/OWL. Clusters data based on semantics. Generates cross-domain queries. Case study on surgical reports.	Improve information extraction. Enhance annotation quality. Enhance performance, scalability. Test on other domains.

Title	Year	Author	Inference	Gaps
Detection of Alzheimer's Disease with Shape Analysis of MRI Images	2018	Hiroki Fuse, Kota Oishi, Norihide Maikusa, Tadanori Fukami	• Brain shape for classification. • P-type Fourier descriptor. • Outperforms volume ratio. • Shape may be more useful.	• Analyze complex shapes. • Longitudinal analysis needed. • Interpret shape features. • Larger dataset required
Chest X-Ray Analysis of Tuberculosis by Deep Learning with Segmentation and Augmentation	2018	Sergii Stirenko*, Yuriy Kochura, Oleg Alienin, Oleksandr Rokovyi, and Yuri Gordienko	• CXR analysis with deep learning. • Efficient lung segmentation. • Lossless and lossy data augmentation. • Improvement in CADx.	• Small dataset limitations. • Variability in image quality. • Influence of external regions. • Need for further validation.
Disease Risk Prediction by Using Convolutional Neural Network	2018	Sayali Ambekar,Rashmi Phalnikar	• Data analysis in healthcare. • Heart disease prediction. • CNN-UDRP algorithm.	• Missing data handling. • Accuracy improvement needed. • Literature review lacks depth.

Title	Year	Author	Inference	Gaps
Handwritten Optical Character Recognition (OCR): A Comprehensive Systematic Literature Review (SLR)	2020	JAMSHED MEMON , MAIRA SAMI , RIZWAN AHMED KHAN , AND MUEEN UDDIN	1. Deep learning (CNN) utilized in OCR. 2. Script-specific techniques employed. 3. Scarcity of datasets for non-mainstream languages. 4. Need for commercialized, real-time OCR solutions.	Limited research on other languages need for more datasets potential accuracy improvement
Handwritten Text Recognition Using Deep Learning Techniques	2020	L.Navya, MD.Farhan Ali, K.Pavan Sai K.Shyam, Alabazar Ramesh	1. HTR using deep learning gains attention. 2. OCR and HCR enable paperless environment. 3. Modules and components of HTR system. 4. Improving accuracy with deep learning and techniques like image enhancement.	1. Methodology description lacking. 2. Limited discussion on system limitations. 3. Insufficient results analysis and comparison. 4. Lack of validation on real-world datasets.

Title	Year	Author	Inference	Gaps
Implementing Digital Signature for the Secure Electronic Prescription Using QR-Code Based on Android Smartphone	2016	Mohamad Ali Sadikin, Septia Ulfa Sunaringtyas	1. Digital signature implementation. 2. Proposal of RSA algorithm. 3. Aim for secure application. 4. Testing methodologies employed.	1. Insufficient method details. 2. Lack of discussion on challenges. 3. Absence of empirical evidence. 4. Ethical and legal concerns overlooked.
Learning models for writing better doctor prescriptions	2019	Tingting Xu, Ioannis Ch. Paschalidis	1. Data-driven optimization for Type 2 diabetes prescriptions. 2. Potential to enhance prescription policies for other diseases. 3. Combines regression and classification for policy optimization. 4. Improves prescription efficacy through data-driven strategies.	1. Reliance on EHRs raises data privacy concerns. 2. Limited regression model comparison for treatment prediction. 3. Challenges with multinomial logistic regression for policy learning. 4. Lack of analysis on risks of modifying prescription policies.

Title	Year	Author	Inference	Gaps
Semi-Supervised Natural Language Processing Approach for Fine-Grained Classification of Medical Reports	2019	Neil Deshmukh Moravian Academy Bethlehem	1. Semi-supervised NLP for fine-grained medical report classification. 2. Uses unsupervised language model for document encodings. 3. Trained on clinical reports, classifiers on labeled datasets. 4. Achieves high AUCs (0.98, 0.95, 0.99) for occlusion, stroke, hemorrhage.	1. Lacks details on dataset limitations and biases. 2. Fails to address ethical implications of patient data use. 3. No comparison with existing methods or state-of-the-art. 4. Does not address model interpretability for medical trust.
Handwritten Character Recognition in English: A Survey	2015	Monica Patel1, Shital P. Thakkar	1. Review of Handwritten Character Recognition (HCR) in English language. 2. Discusses HCR system stages: pre-processing, segmentation, feature extraction, classification. 3. Examines methods: holistic, segmentation-based, recognition-based segmentation with strengths/weaknesses. 4. Emphasizes feature extraction, classification for accurate recognition in HCR.	1. No 100% accuracy achieved; indicates ongoing limitations/challenges. 2. Limited to English language; excludes other language character recognition. 3. Lack of dataset details affects result generalizability. 4. Missing comparative analysis of classifiers, features; method limitations not discussed.

Title	Year	Author	Inference	Gaps
Quick Response Code: Medication Prescription	2020	Nurul Fatina Yusni, Noreha Che Sidik, Nur Farah Hanani Mohd Zaim Shamsul Jamel Elias, Siti Khairul Niza Sukri, Zanariah Idrus,	1. Introduces Medication Prescription QR Code for efficient medicine information retrieval. 2. Implemented at Universiti Teknologi MARA, Kedah, Malaysia. 3. Positive impact on users: efficient info access, reduced paper use. 4. Users find MPQRC easy, time-saving, preferred over traditional methods.	1. Small sample size (30 respondents) limits representativeness. 2. No comparison with other medication information access methods. 3. Limited scope to one case study, lacks generalizability. 4. Short-term maintenance; lacks long-term evaluation for sustainability.

LITERATURE OUTCOME

1. Handwritten Character Recognition (HCR) and Optical Character Recognition (OCR)
    - Hussain and Vanlalruata (2018) introduced a hybrid approach for handwritten character recognition in Mizo using artificial neural networks, highlighting the importance of combining methodologies for accurate HCR.
    - Memon et al. (2020) conducted a systematic literature review on handwritten OCR systems, emphasizing advancements in preprocessing, feature extraction, and classification techniques.
2. Disease Risk Prediction and Diagnosis
    - Ambekar and Phalnikar (2018) demonstrated the application of convolutional neural networks (CNNs) for predicting disease risks, showing the potential of deep learning in medical diagnostics.
    - Stirenko and Kochura (2018) applied deep learning with segmentation and augmentation techniques for tuberculosis diagnosis using chest X-rays, showcasing the effectiveness of automated image analysis in healthcare.
    - Fuse et al. (2018) explored MRI-based shape analysis for detecting Alzheimer's disease, demonstrating the integration of imaging and shape recognition for early diagnosis.

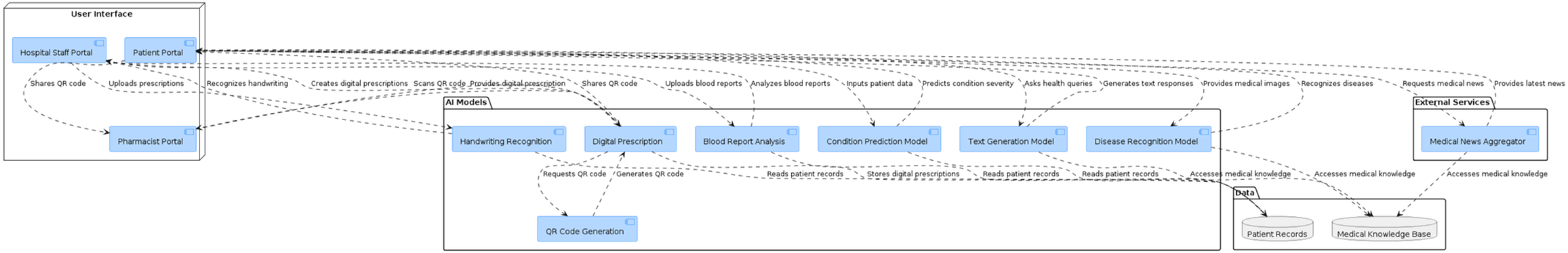
enabling efficient and error-free prescription management.

- Sadikin and Sunaringtyas (2016) developed a secure electronic prescription system with digital signatures and QR codes, improving data security in healthcare transactions.

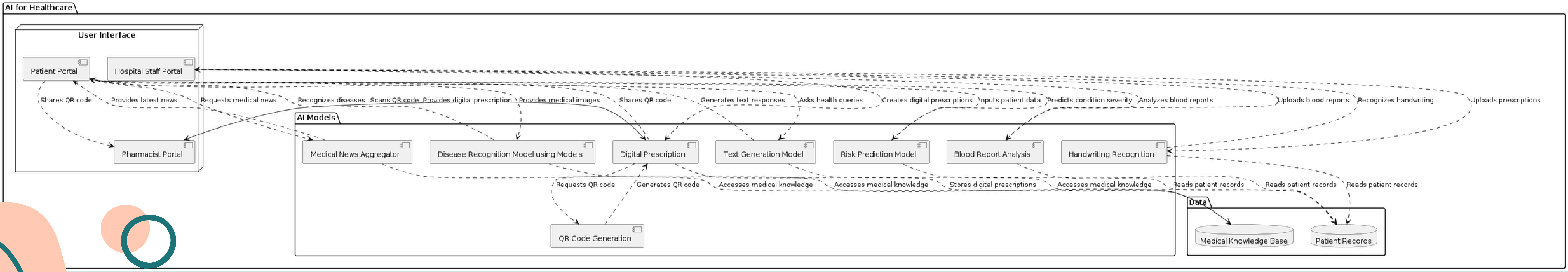
LITERATURE OUTCOME

3. Natural Language Processing in Healthcare
   - Deshmukh (2019) proposed a semi-supervised NLP approach for classifying medical reports, providing insights into fine-grained analysis and information retrieval in the healthcare domain.
   - Shen et al. (2015) presented a biomedical query generator (BmQGen), aiding knowledge discovery through precise query formulation in biomedical contexts.
4. Multimodal and Multilingual Models
   - The Gemini Team (2024) and Meta (2024) introduced advanced multimodal and multilingual models (e.g., Gemini and SeamlessM4T) that facilitate cross-lingual understanding and integration of text, image, and other modalities for diverse applications.
5. Document and Layout Analysis
   - Yiheng Xu et al. (2019) proposed LayoutLM, a pre-trained model for document image understanding that combines text and layout features, enhancing OCR and document analysis.
6. QR-Code Based Applications in Healthcare
   - Yusni et al. (2020) implemented a QR-code-based system for medication prescriptions, enabling efficient and error-free prescription management.
   - Sadikin and Sunaringtyas (2016) developed a secure electronic prescription system with digital signatures and QR codes, improving data security in healthcare transactions.

FLOWCHART



SYSTEM DESIGN



IMPLEMENTATION

PRESCRIPTION RECOMMENDATION

FLOWCHART

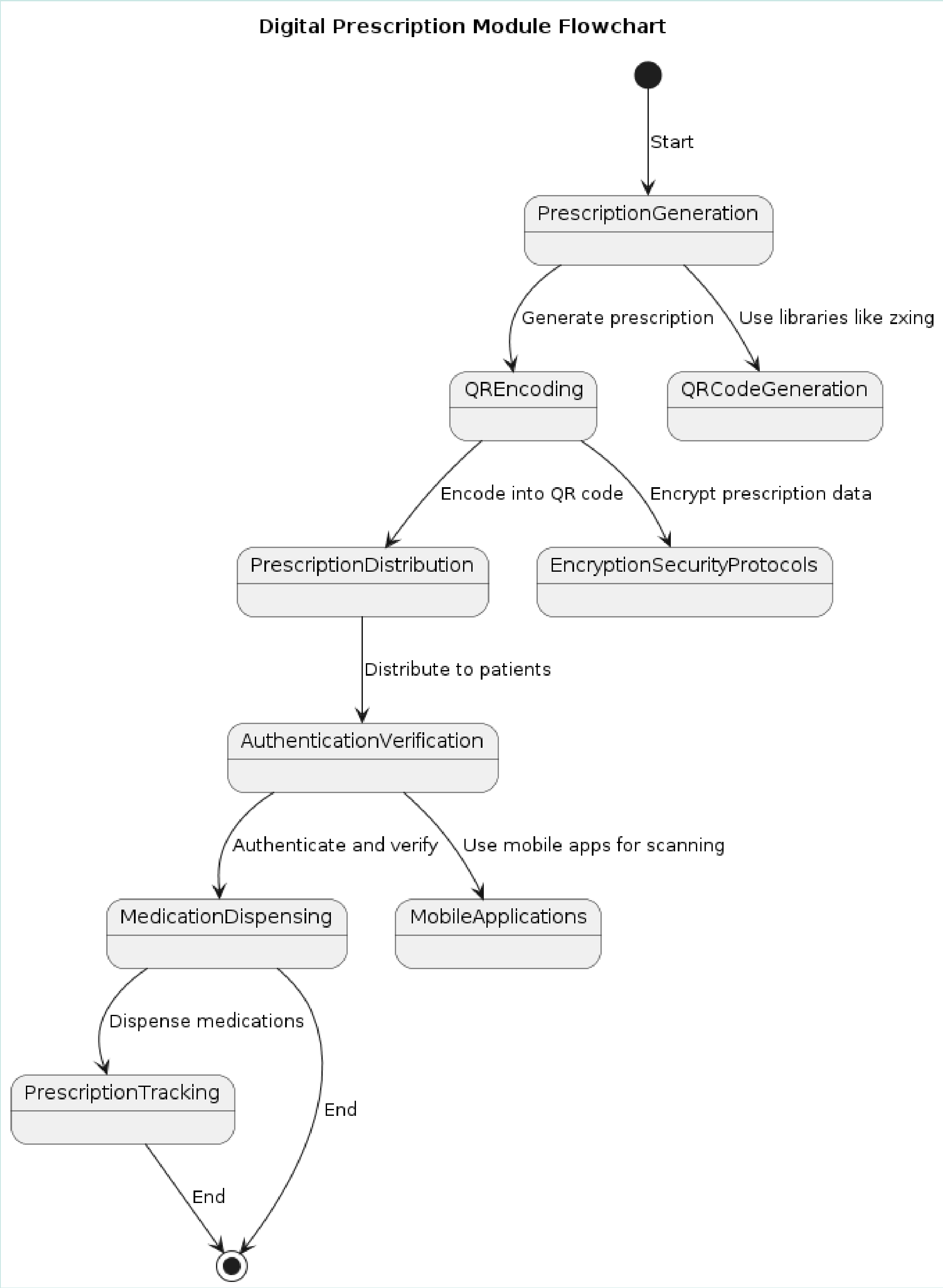
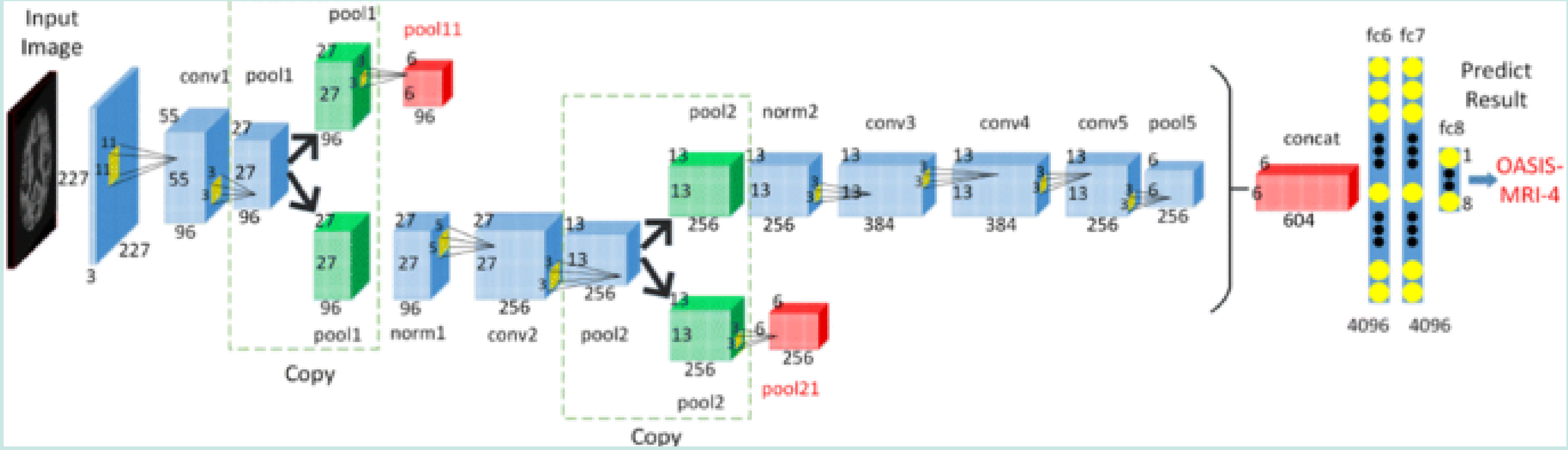


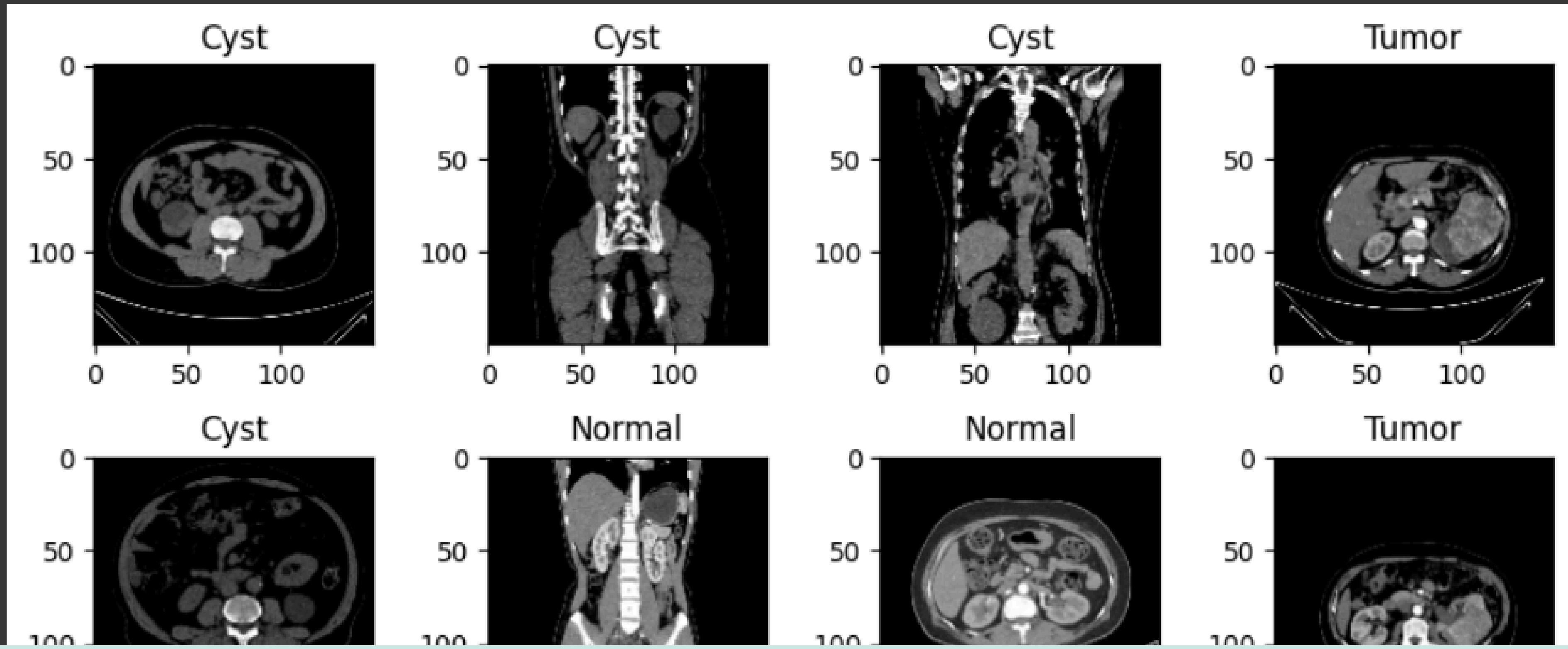
IMAGE RECOGNITION

FLOWCHART

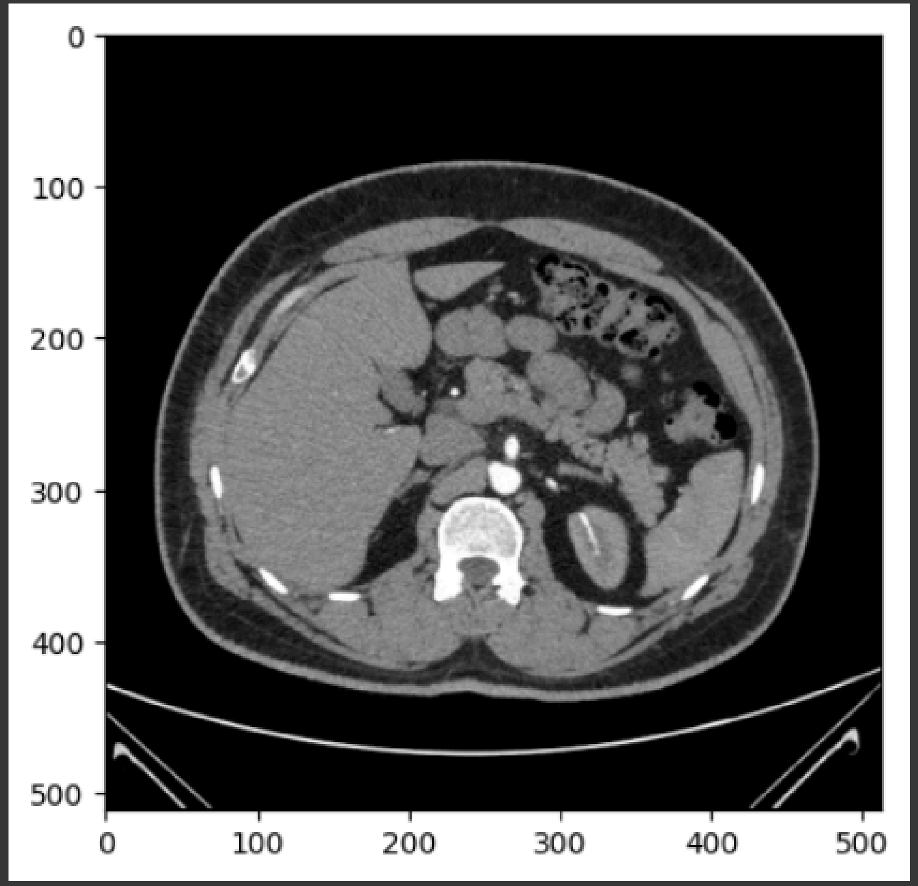


IMPLEMENTATION

```python
data_iterator = train.as_numpy_iterator()
batch = data_iterator.next()
fig, ax = plt.subplots(nrows=4, ncols=4, figsize=(10, 10))
for i in range(4):
    for j in range(4):
        index = i * 4 + j
        ax[i, j].imshow(batch[0][index].astype(int))
        ax[i, j].set_title(label_to_class_name[batch[1][index]])
plt.subplots_adjust(wspace=0.4, hspace=0.4)
plt.show()
```




```python
resize = np.expand_dims(resize, 0)  # Expand dimensions once outside the loop
resize = resize / 255  # Normalize once outside the loop

yhat = loaded_model.predict(resize)
max_index = np.argmax(yhat)
label_to_class_name[max_index]
```



```
1/1 [==============================] - 1s 772ms/step
'Normal'
```

QR PRESCRIPTION

FLOWCHART

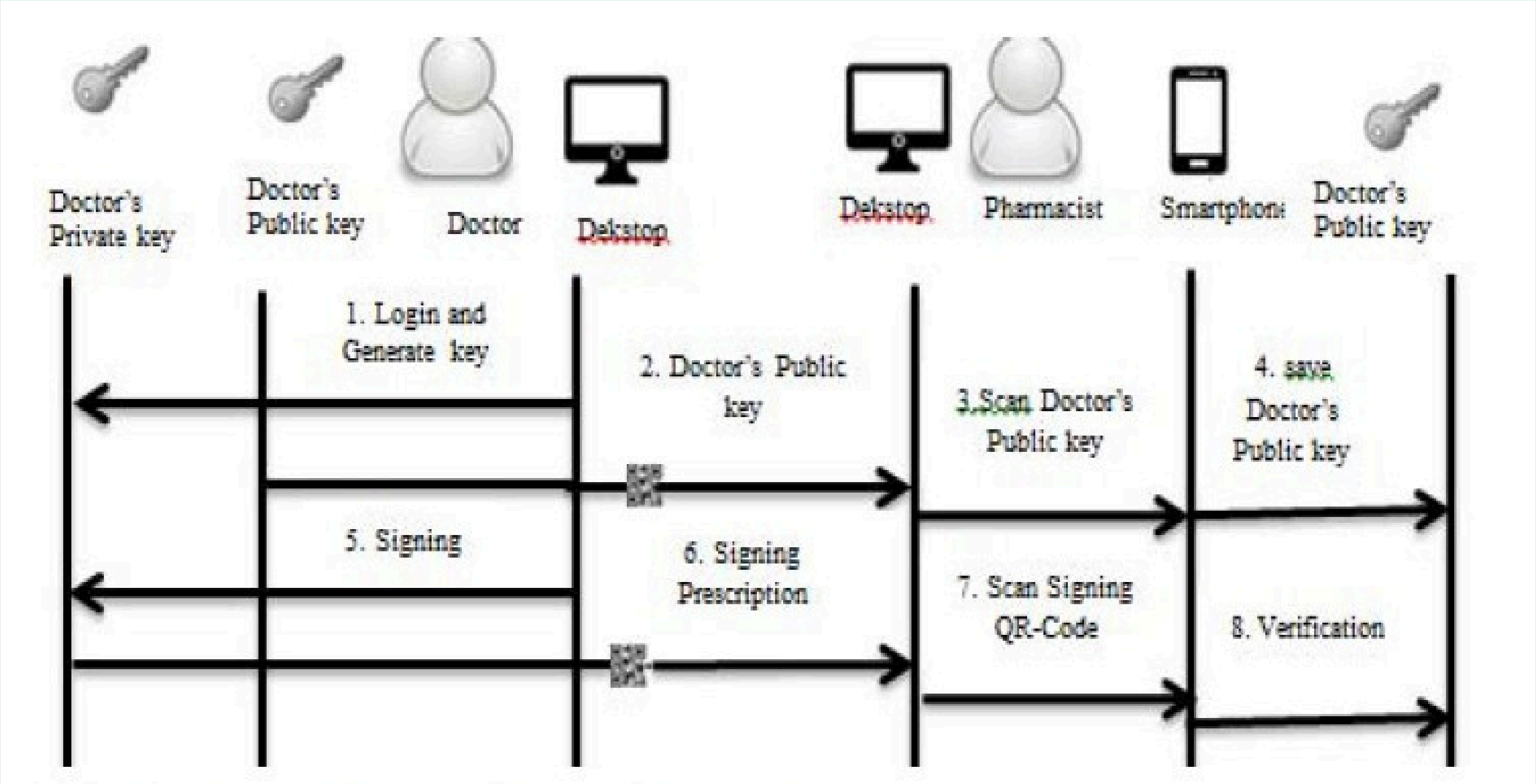


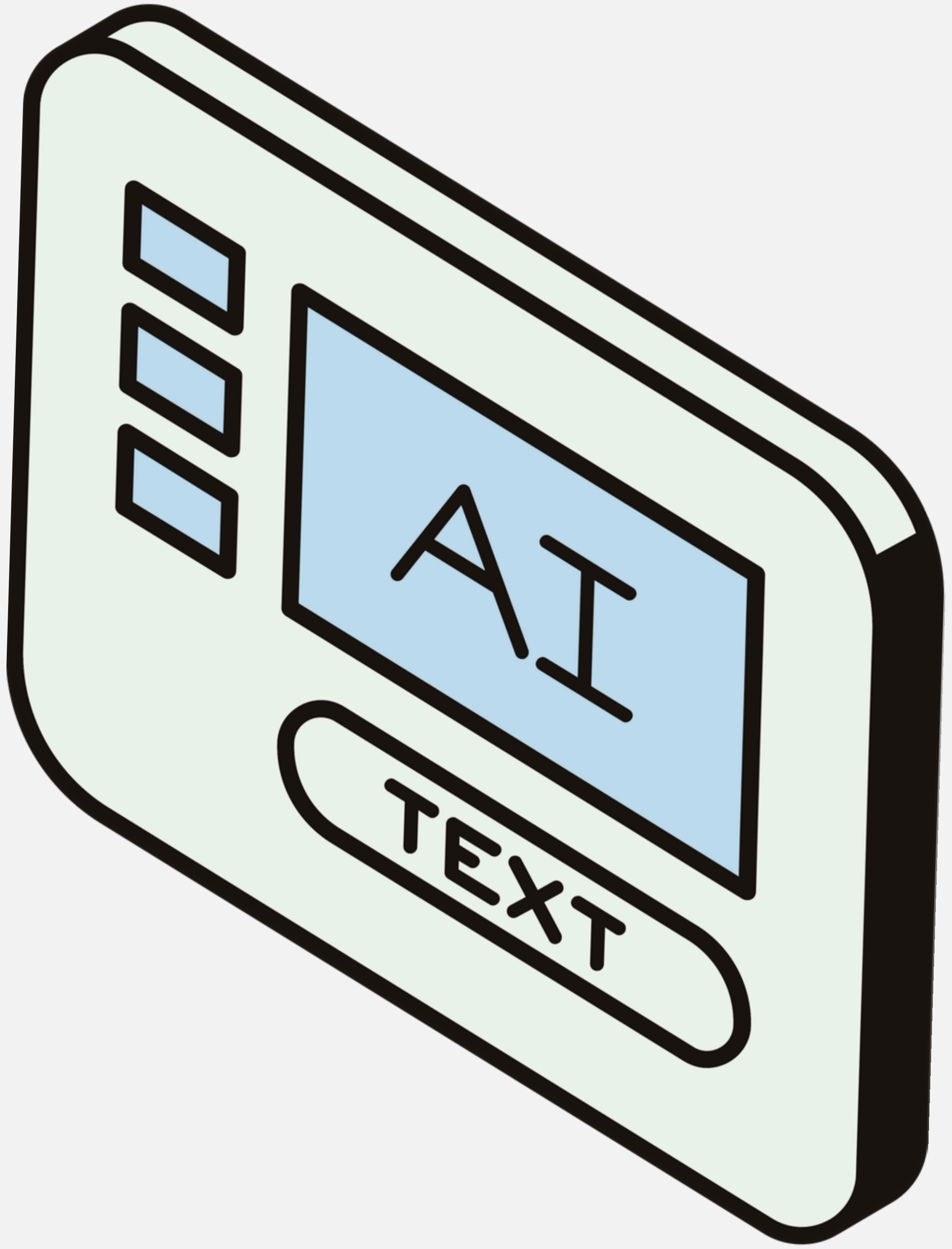
Fig. 2. Secure electronic prescription scheme

QR PRESCRIPTION

```python
import qrcode
from PIL import Image
from flask import Flask, send_file
import io
import datetime
import os
import threading

app = Flask(__name__)

# Generate PDF (using fpdf2) - This is similar to the previous example
from fpdf import FPDF

class PDF(FPDF):
    def header(self):
        self.set_font('Arial', 'B', 12)
        self.cell(0, 10, 'Medical Prescription', align='C', ln=1)

    def footer(self):
        self.set_y(-15)
        self.set_font('Arial', 'I', 8)
        self.cell(0, 10, f'Page {self.page_no()}', 0, 0, 'C')

    def add_prescription(self, patient_name, doctor_name, medicines):
        self.set_font('Arial', '', 12)
        self.cell(0, 10, f'Patient Name: {patient_name}', ln=1)
        self.cell(0, 10, f'Doctor: {doctor_name}', ln=1)
```

prescription_qr.png

TEXT GENERATION FOR HEALTH QUERY



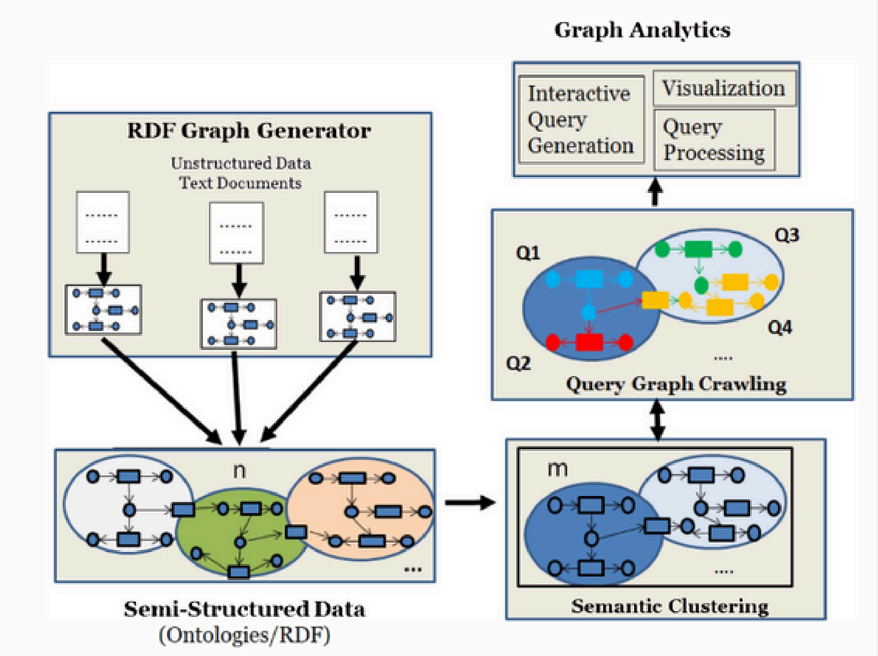


Fig 1: The BmQGen Framework

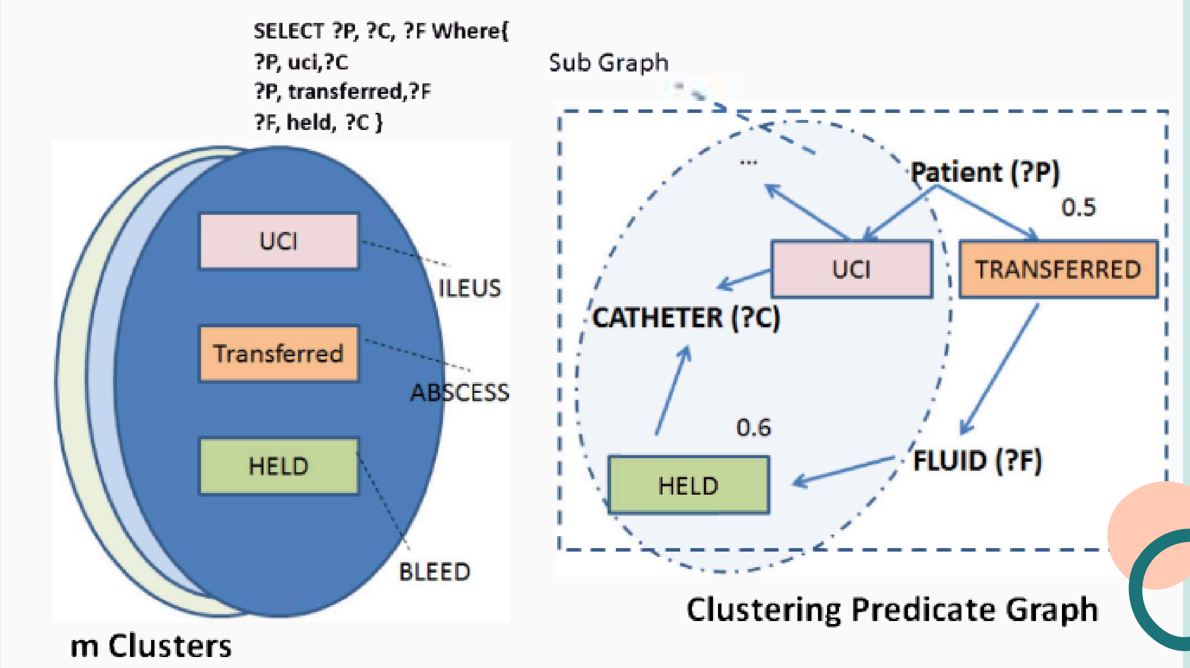
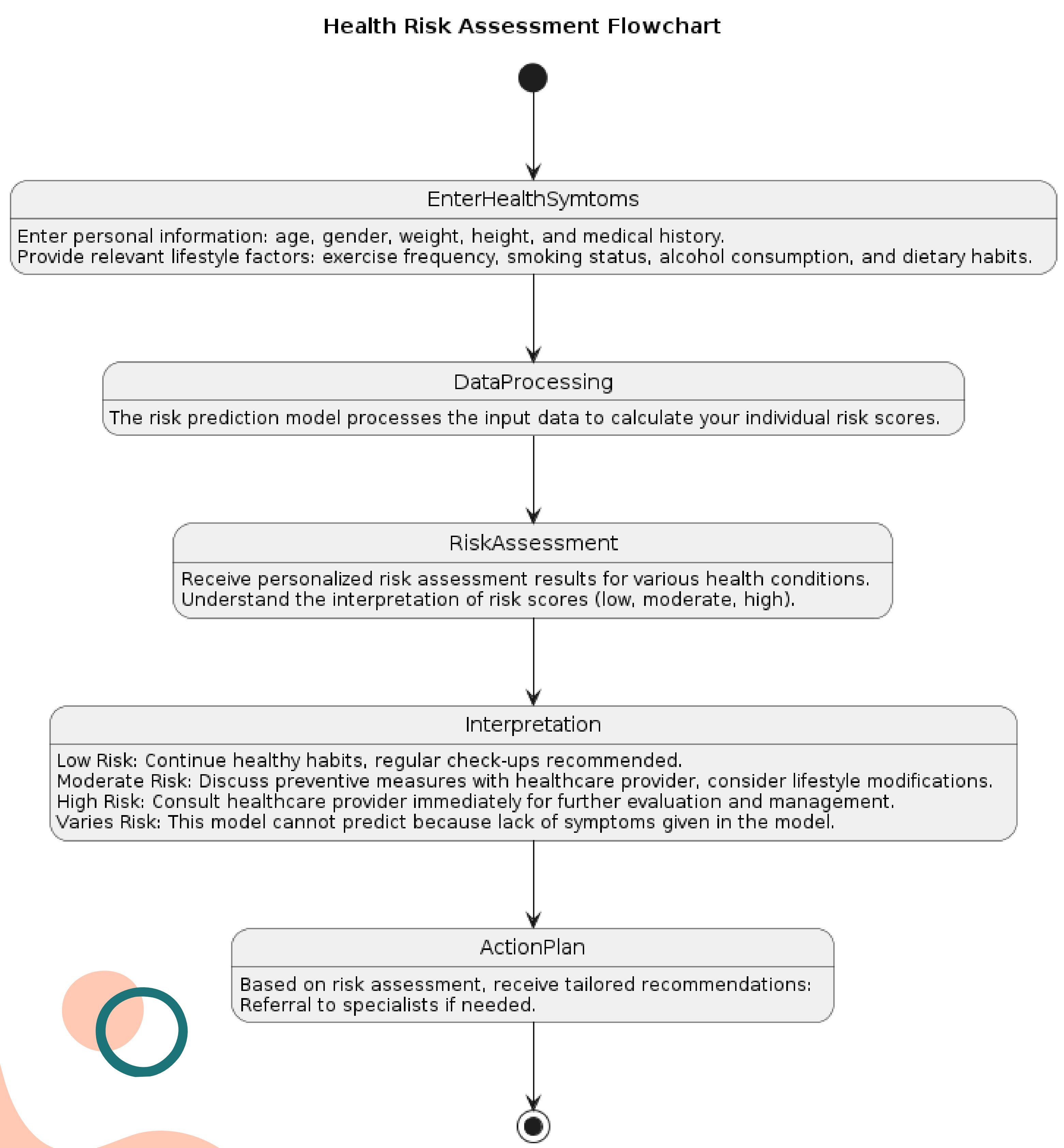


Fig3: Clustering Predicate Graph for Query Generation

RISK PREDICTION

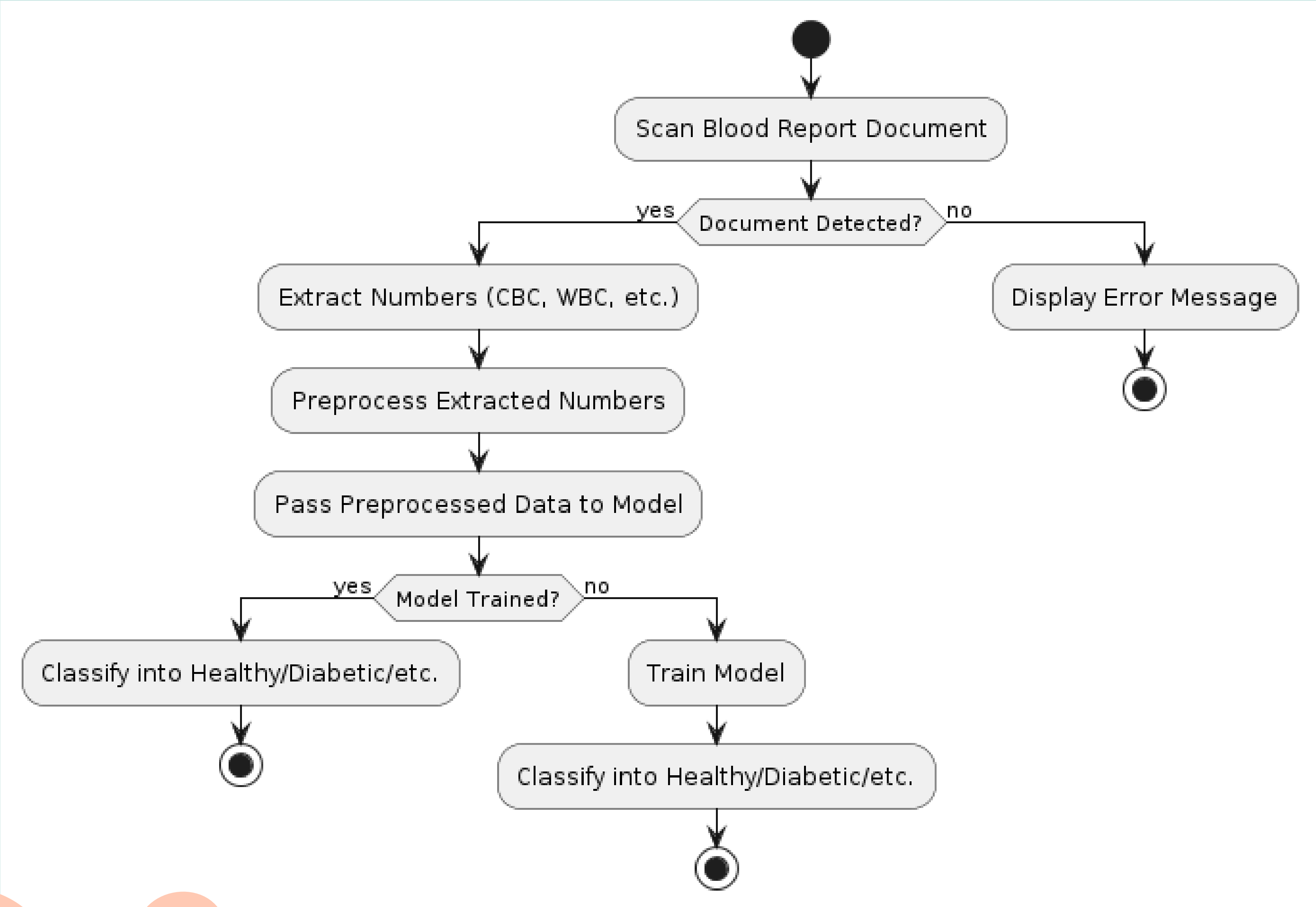


RISK PREDICTION

```
# Function to get user input for symptoms
def get_user_input(symptoms_columns):
    symptoms_input = input("Please enter your symptoms (comma-separated): ")
    print("Symptoms input:", symptoms_input)
    user_symptoms = {symptom: 0 for symptom in symptoms_columns}
    for symptom in symptoms_input.split(','):
        if symptom.strip() in symptoms_columns:
            user_symptoms[symptom.strip()] = 1
    return user_symptoms

# Get user input for symptoms
user_symptoms = get_user_input(symptom_columns)

# Convert user input to DataFrame
user_data = pd.DataFrame(user_symptoms, index=[0])

# Predict the risk level using the trained model
risk_level = model.predict(user_data)
print("Predicted risk level:", risk_level[0])
```

```
Symptoms input: chest pain,shortness of breath,nausea,vomiting,lightheadedness,sweating
Predicted risk level: high
```

DOCUMENT ANALYSER FOR BLOOD REPORT

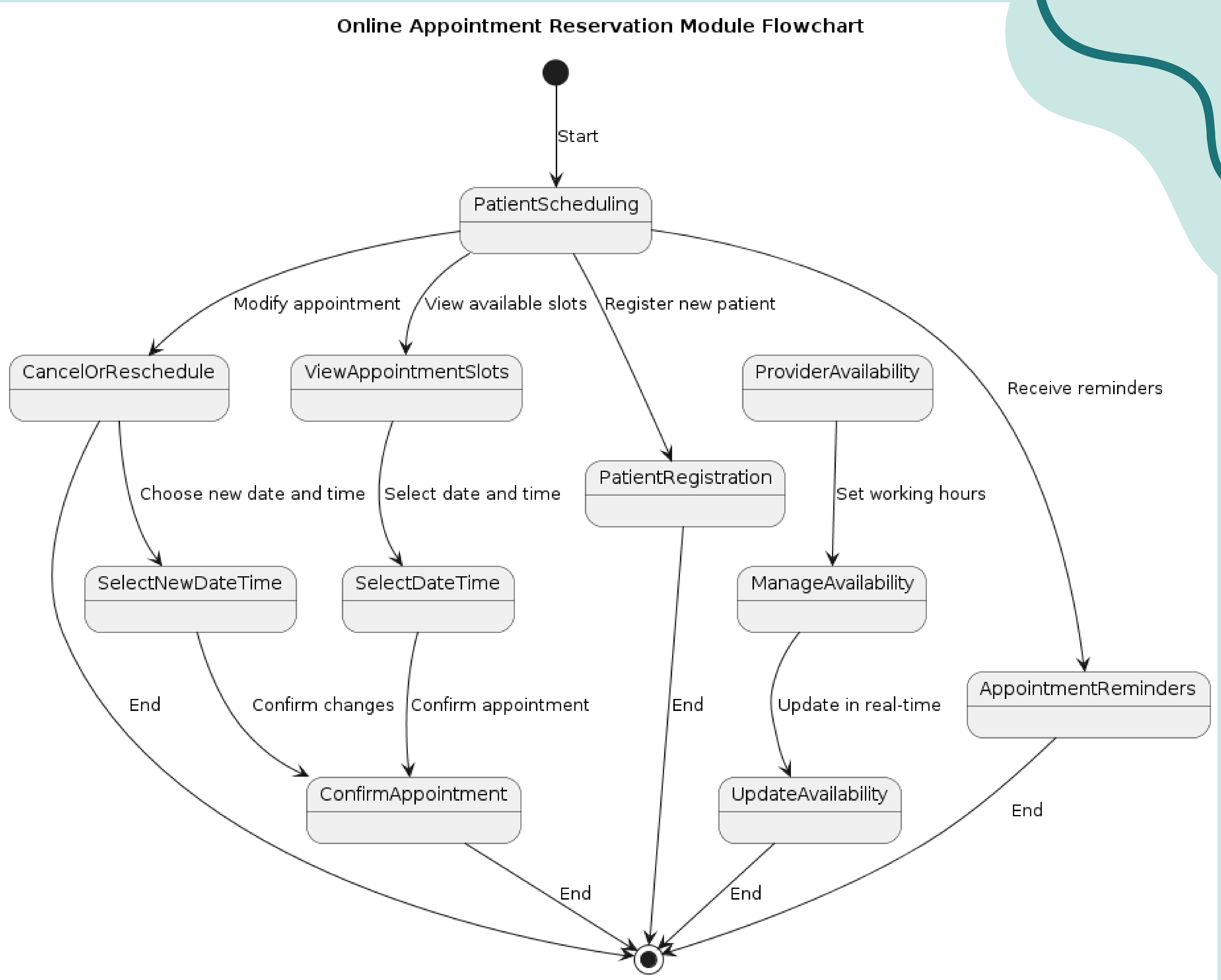


DOCUMENT ANALYSER FOR BLOOD REPORT

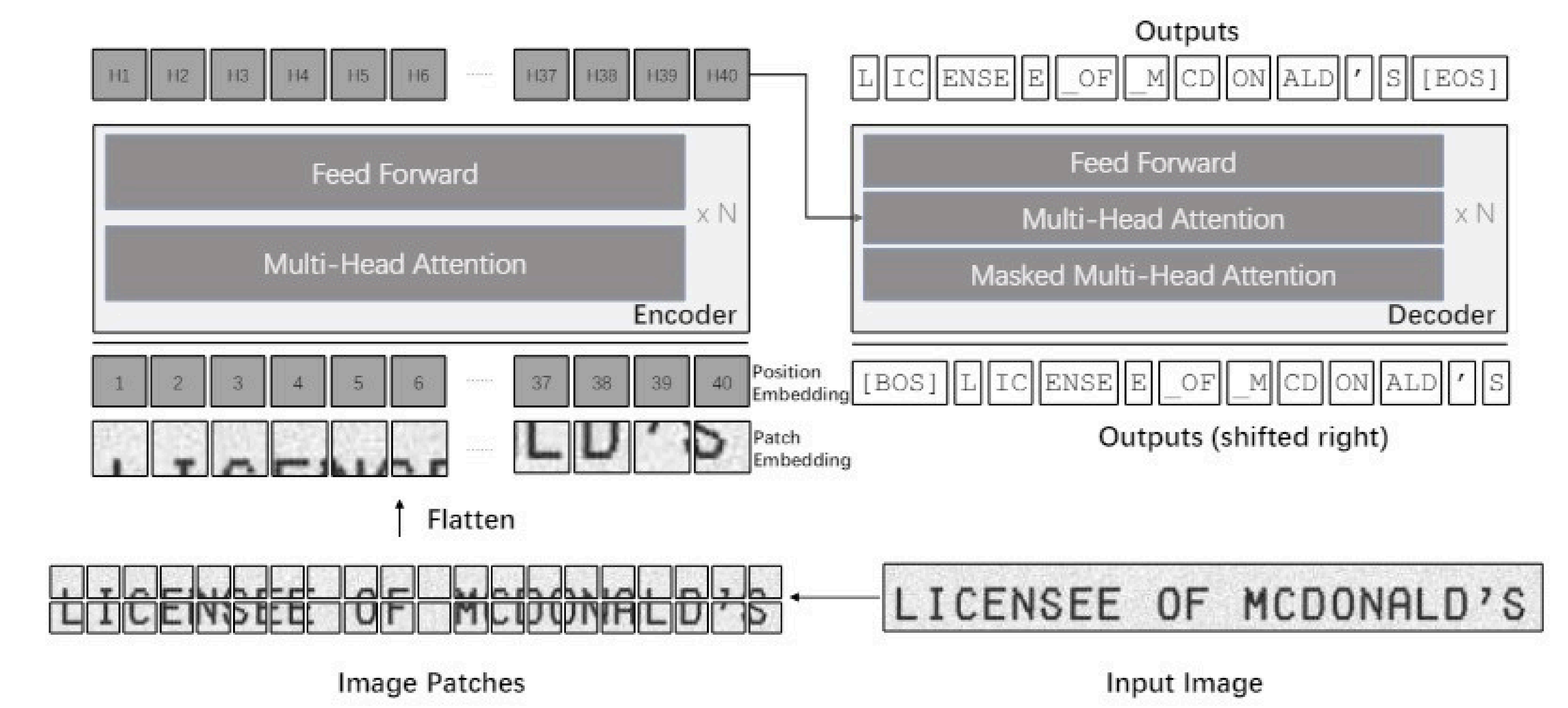
```python
# Example values for blood report parameters
glucose = 0.1
cholesterol = 0.1
hemoglobin = 0.23
platelets = 0.45
white_blood_cells = 0.56
red_blood_cells = 0.78
hematocrit = 0.23
mean_corpuscular_volume = 0.12
mean_corpuscular_hemoglobin = 0.56
mean_corpuscular_hemoglobin_concentration = 0.56
insulin = 0.67
bmi = 0.78
systolic_blood_pressure = 0.24
diastolic_blood_pressure = 0.51
triglycerides = 0.67
hba1c = 0.1
ldl_cholesterol = 0.1
hdl_cholesterol = 0.1
alt = 0.1
ast = 0.1
heart_rate = 0.1
creatinine = 0.1
troponin = 0.1
c_reactive_protein = 0.678

# Predict disease
prediction = predict_disease(glucose, cholesterol, hemoglobin, platelets, white_blood_cells,
                                red_blood_cells, hematocrit, mean_corpuscular_volume,
                                mean_corpuscular_hemoglobin, mean_corpuscular_hemoglobin_concentration,
                                insulin, bmi, systolic_blood_pressure, diastolic_blood_pressure,
                                triglycerides, hba1c, ldl_cholesterol, hdl_cholesterol,
                                alt, ast, heart_rate, creatinine, troponin, c_reactive_protein)

print("Predicted Disease:", prediction)
```

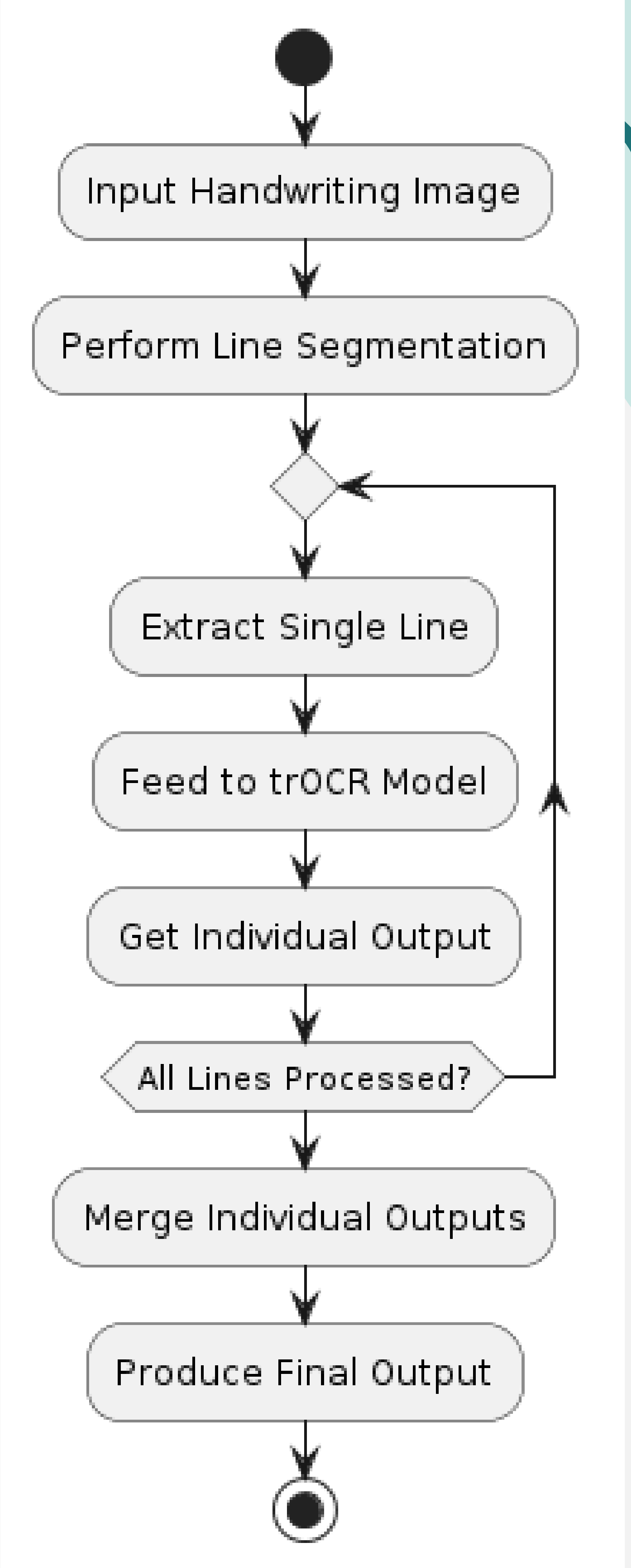
```
Predicted Disease: Healthy
```

ONLINE APPOINTMENT RESERVATION



OCR HANDWRITING RECOGNITION

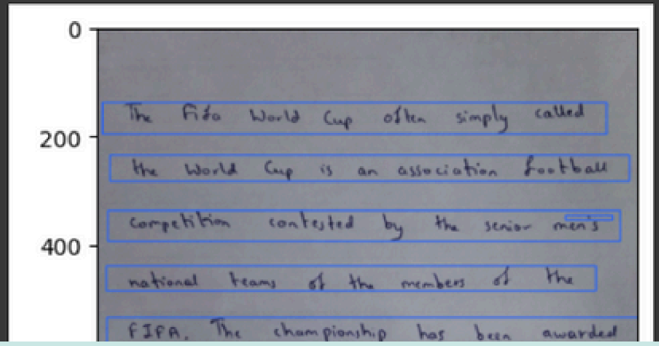




OCR HANDWRITING RECOGNITION

Line segmentation

```
img2 = img.copy()

for ctr in sorted_contours_lines:

    x,y,w,h = cv2.boundingRect(ctr)
    cv2.rectangle(img2, (x,y), (x+w, y+h), (40, 100, 250), 2)

plt.imshow(img2);
```



For array of lines

```
# List to store the generated text for each line
generated_lines = []

for i, line in enumerate(lines_list):
    # Crop each line and convert it to an image
    line_image = Image.fromarray(img[line[1]:line[3], line[0]:line[2]])

    # Process the image using the TrOCR model
    pixel_values = processor(images=line_image, return_tensors="pt").pixel_values
    generated_ids = model.generate(pixel_values)
    generated_text = processor.batch_decode(generated_ids, skip_special_tokens=True)[0]

    # Add the generated text to the list
    generated_lines.append(generated_text)

# Print the list of generated lines
print(generated_lines)
```

```
['The Fida World Cup often simply called', 'the World Cup is an association football', "competition contested by the senior men's", '0 0', 'national teams of the members of the', 'FIFA. The championship has
```

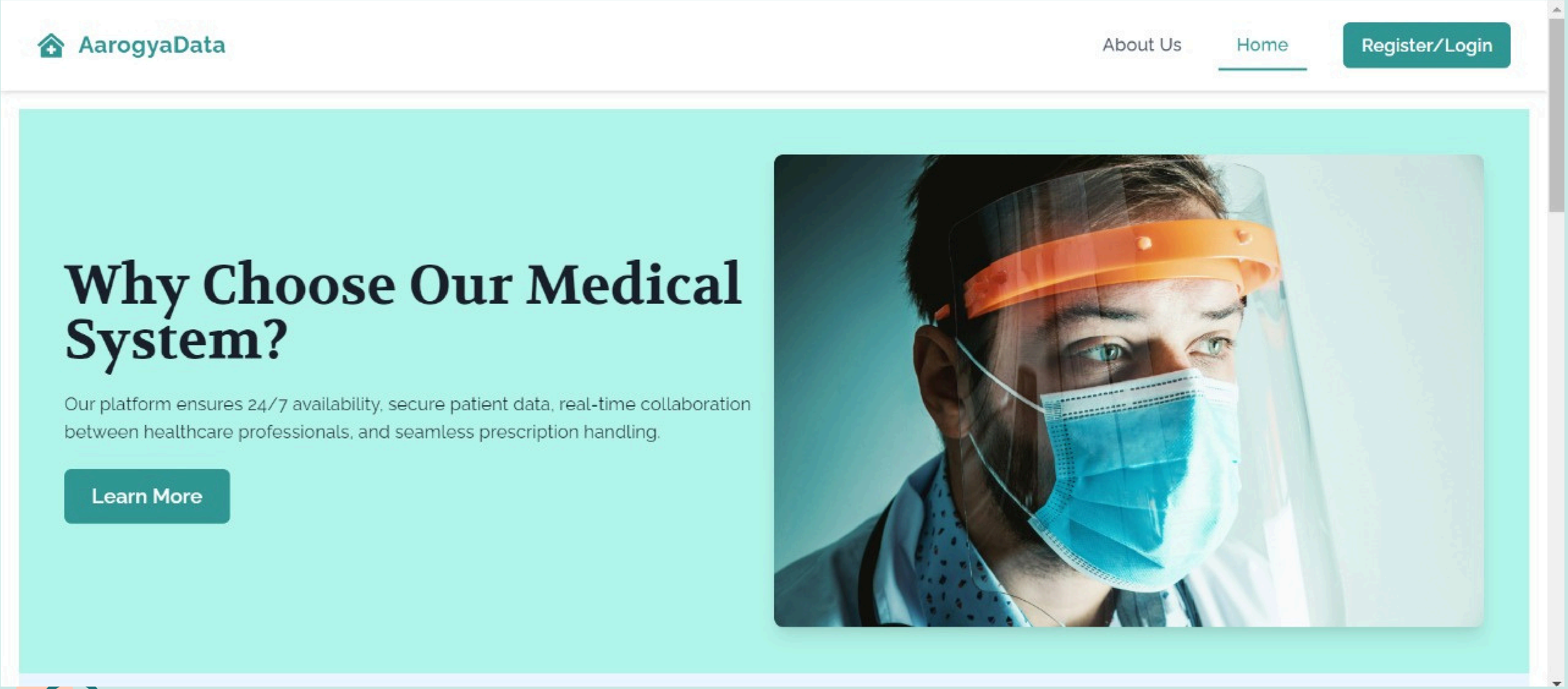
PERFORMANCE METRICS

Model	Performance Metrics
Kidney Stone Detection Model	
Brain Tumor Model	
Alzheimer Model	

Model	Performance Metrics
Skin Cancer	

IMPLEMENTATION DETAILS

HOME PAGE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Our platform ensures 24/7 availability, secure patient data, real-time collaboration between healthcare professionals, and seamless prescription handling.
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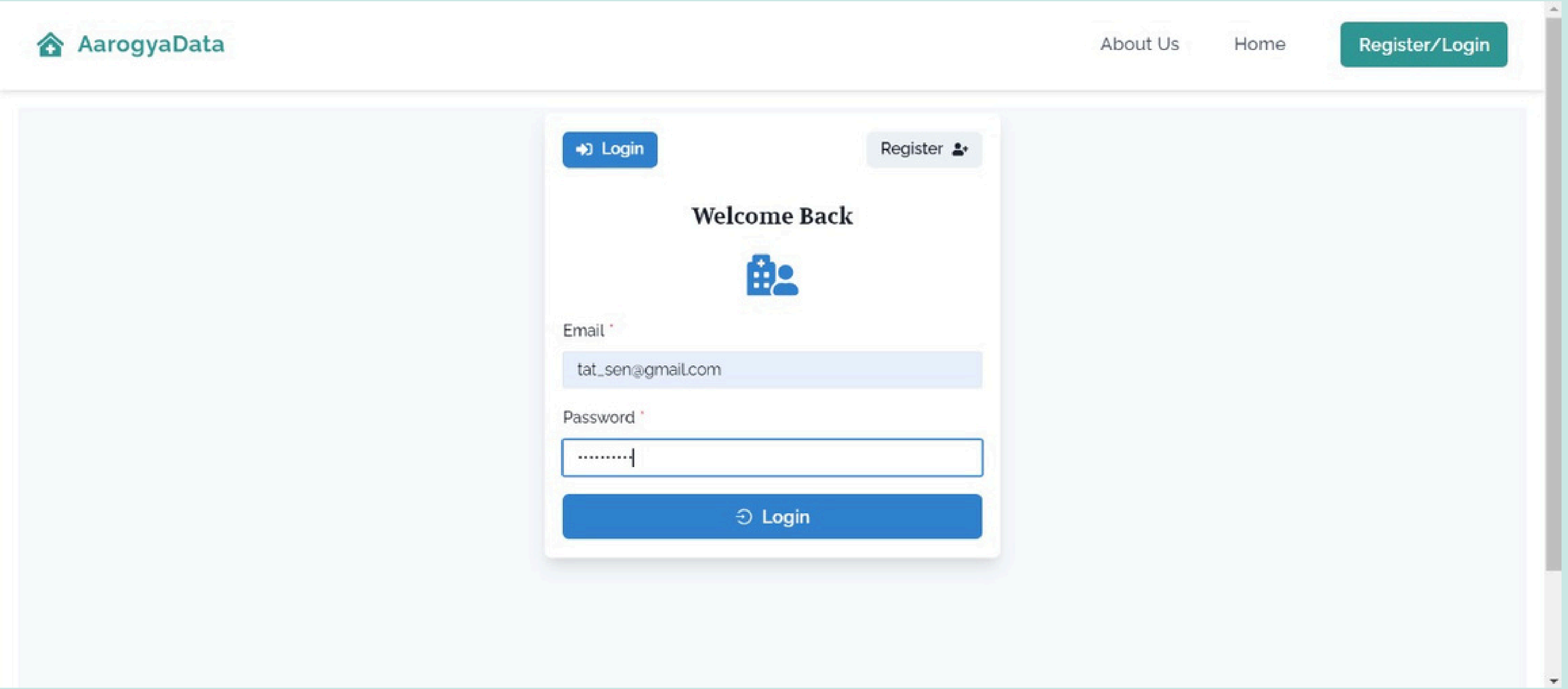
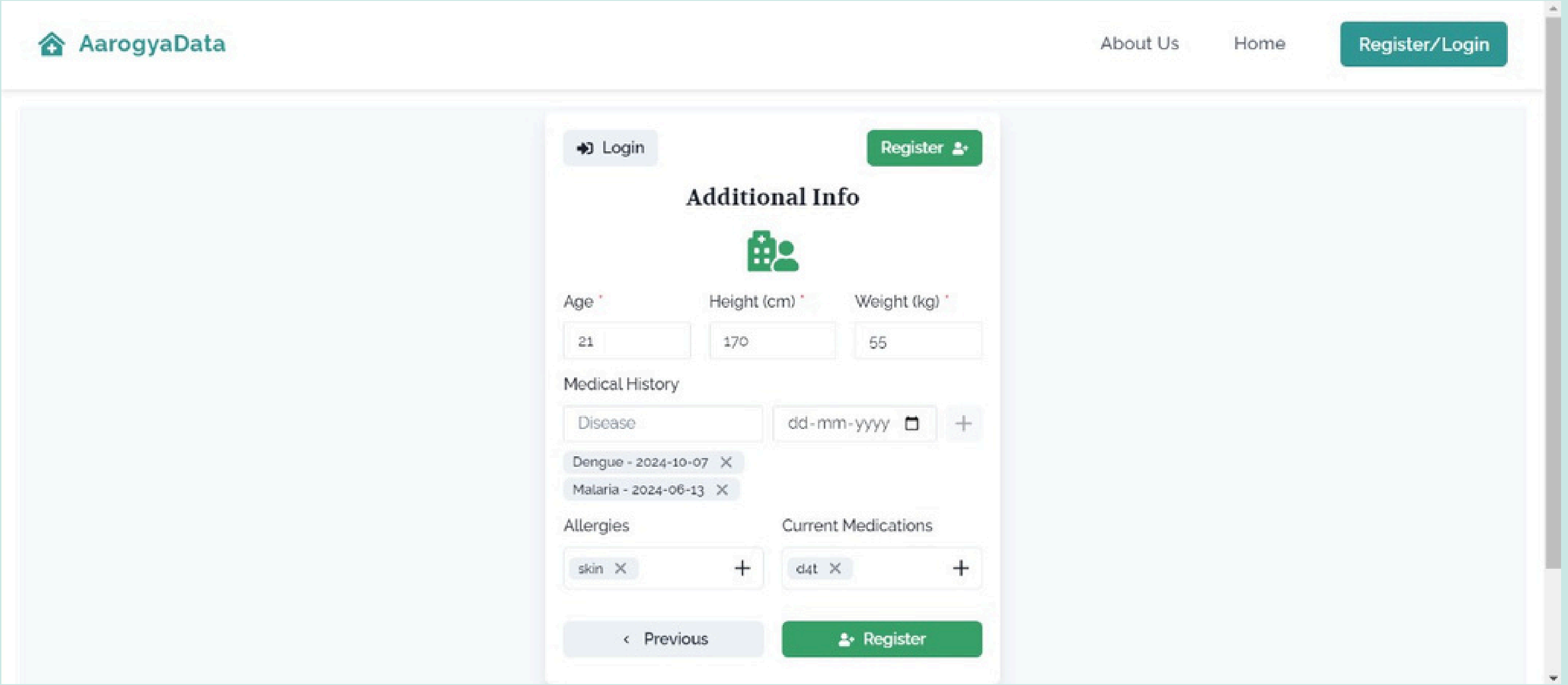
LOGIN AND REGISTRATION

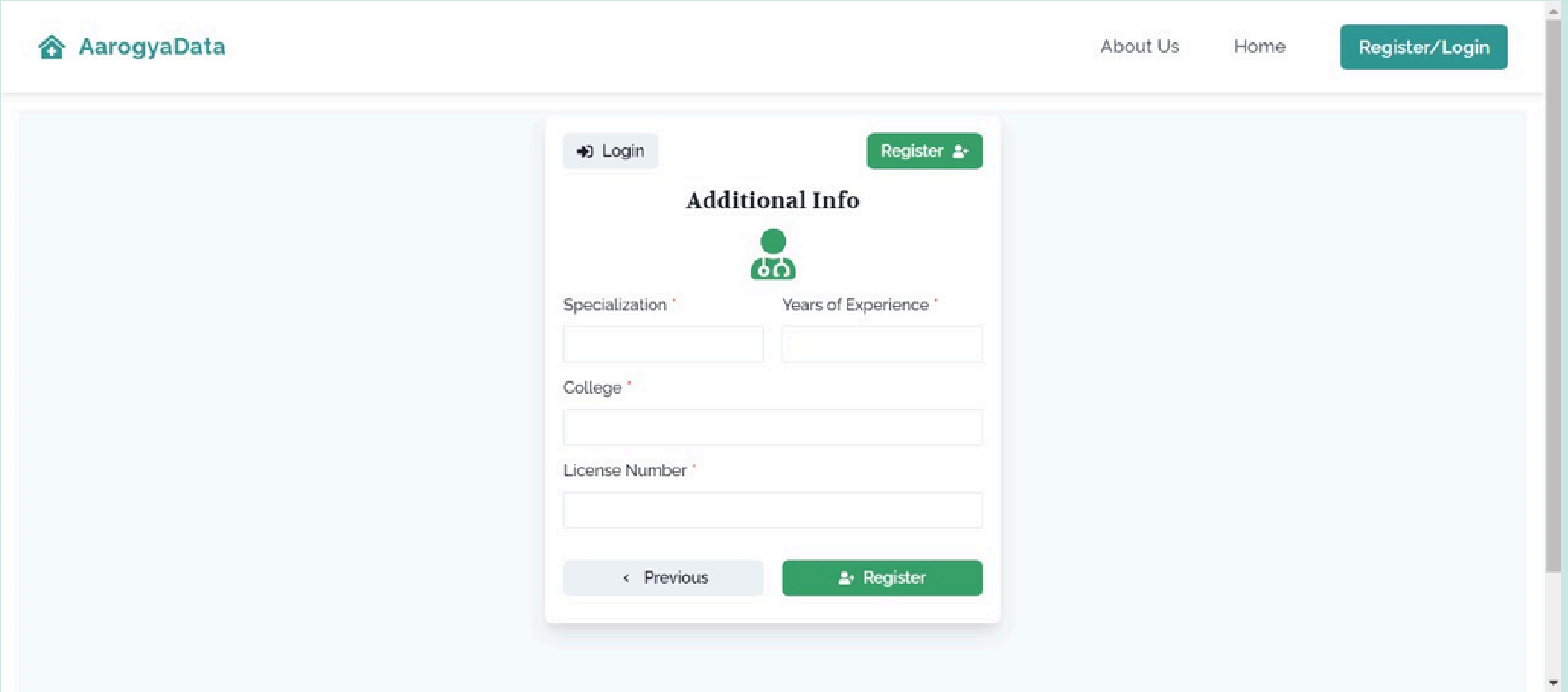


PATIENT LOGIN PAGE

PATIENT REGISTRATION PAGE

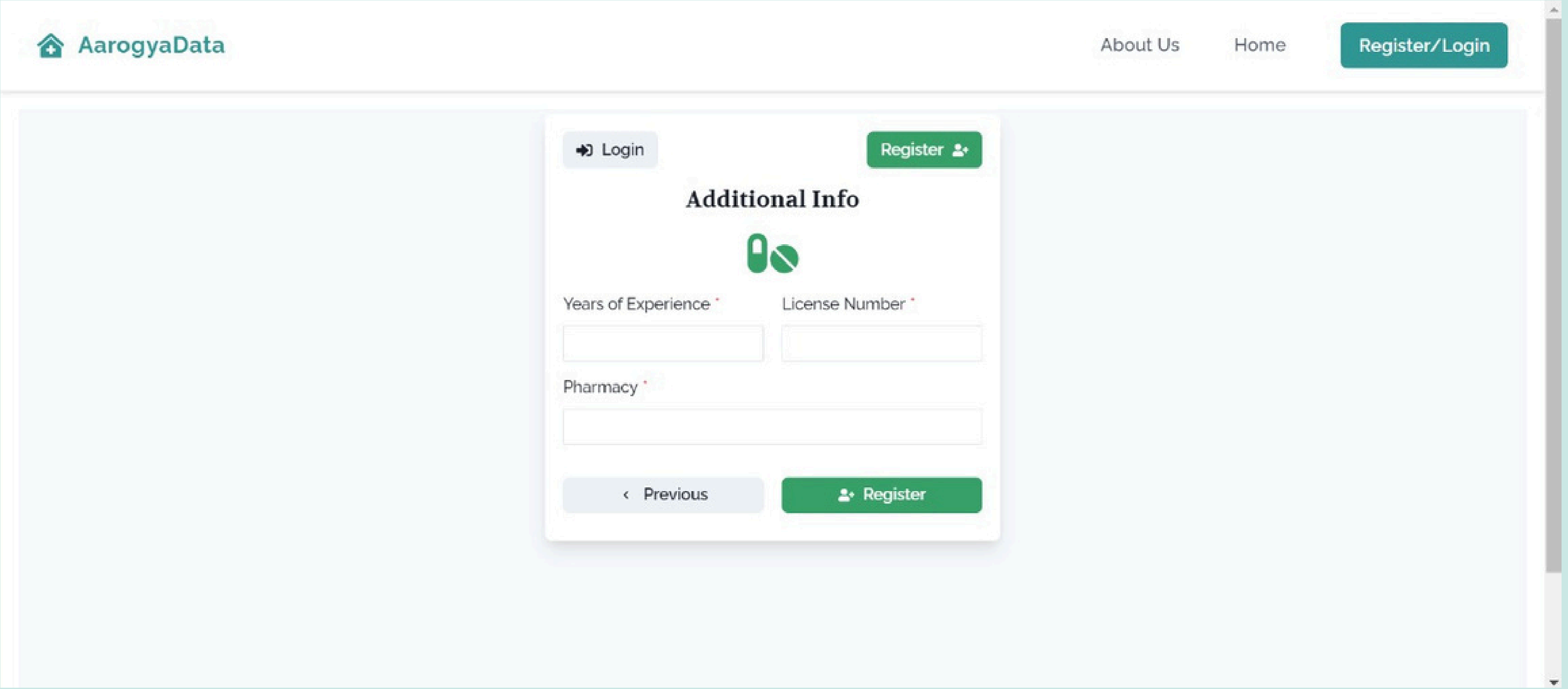


LOGIN AND REGISTRATION

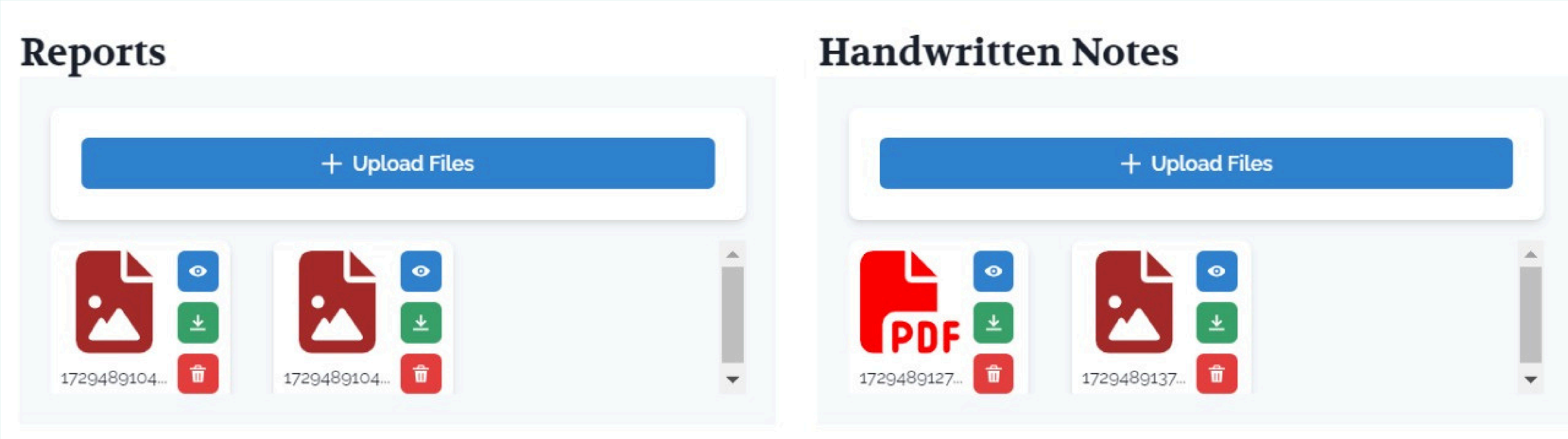


DOCTOR LOGIN PAGE

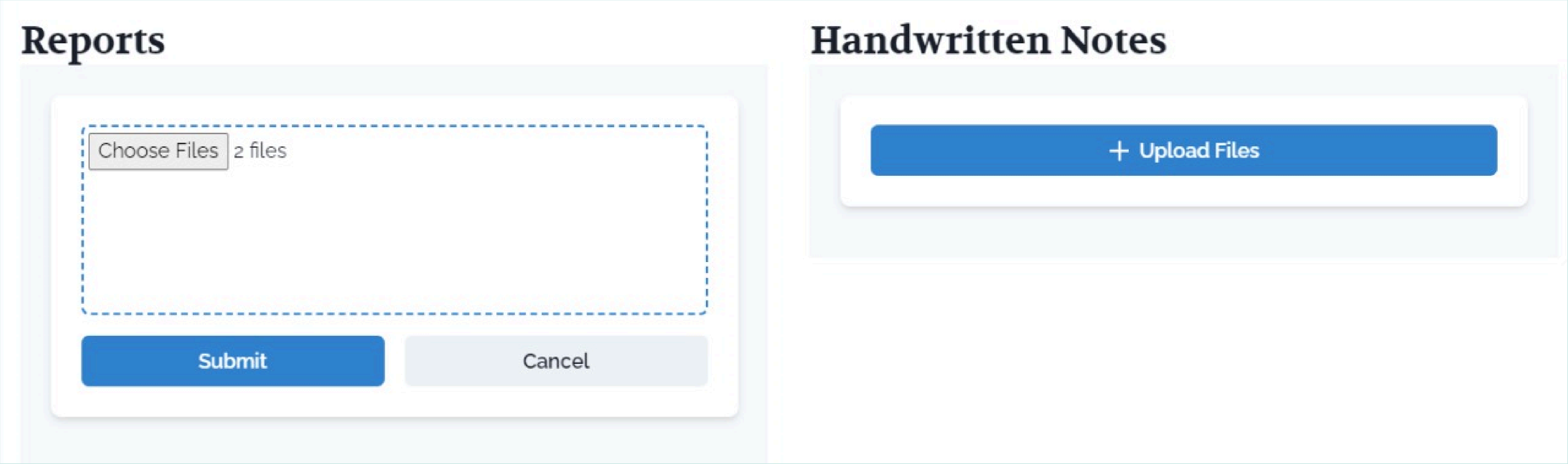
PHARMACIST LOGIN PAGE



FEATURES



REPORT ANALYSER AND HANDWRITTEN PRESCRIPTION CONVERTER

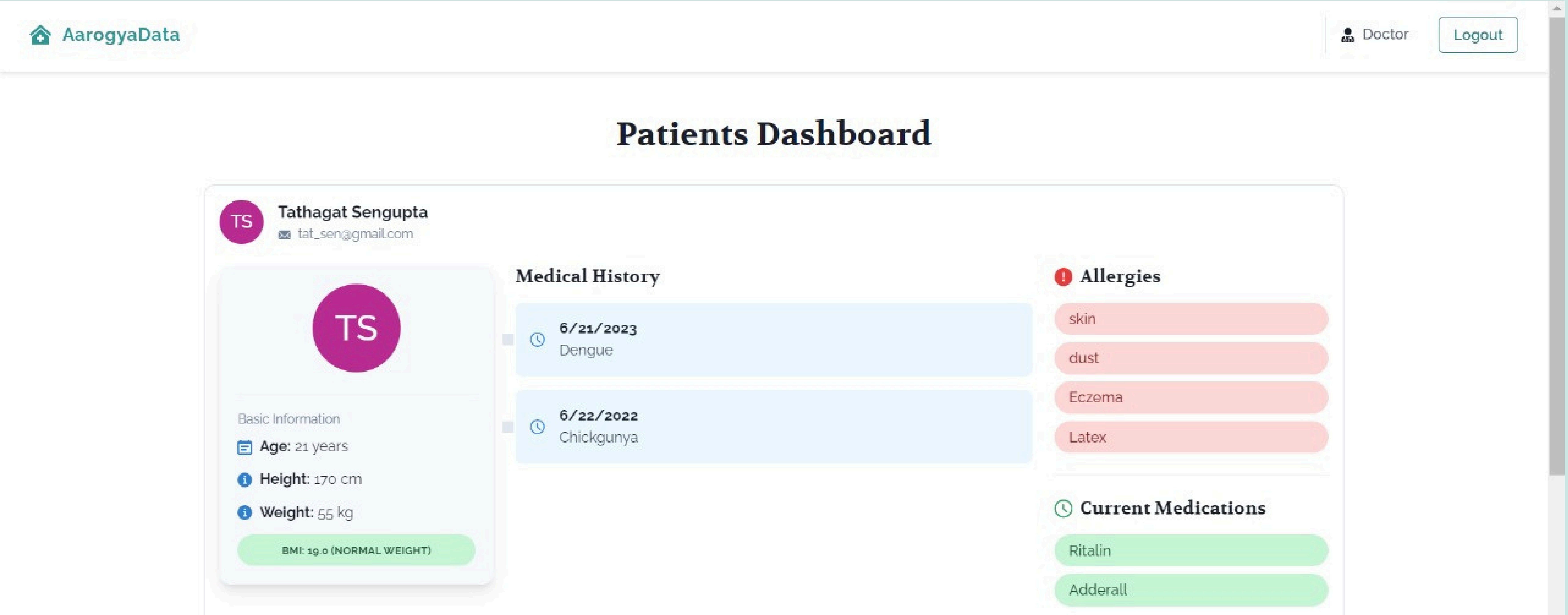


SAMPLE REPORT

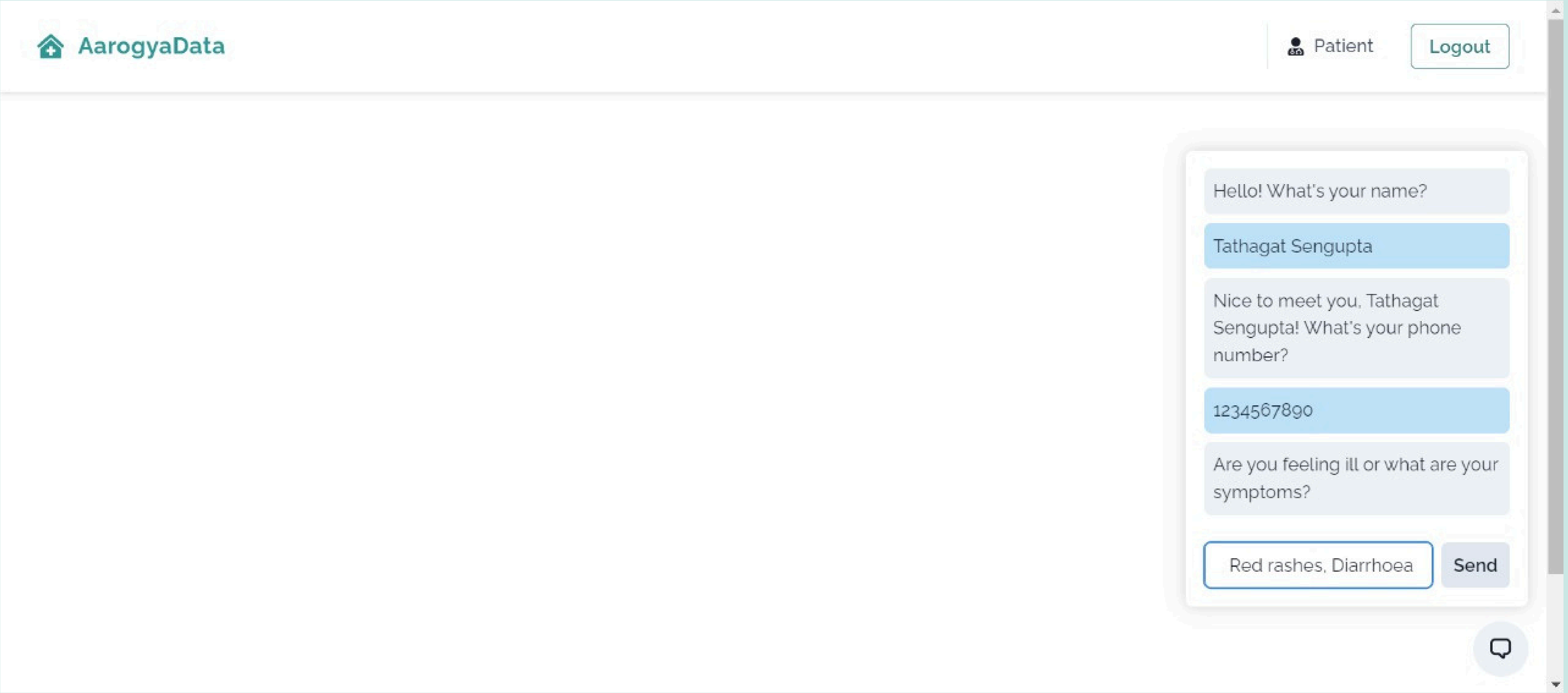
Table 1. Patients' blood test results from day of illness 3, 5, 6, 7, 8, 9, and 10. Numbers highlighted in red are outside the normal range. Normal range for each result is listed in italics below each blood test in the first column.

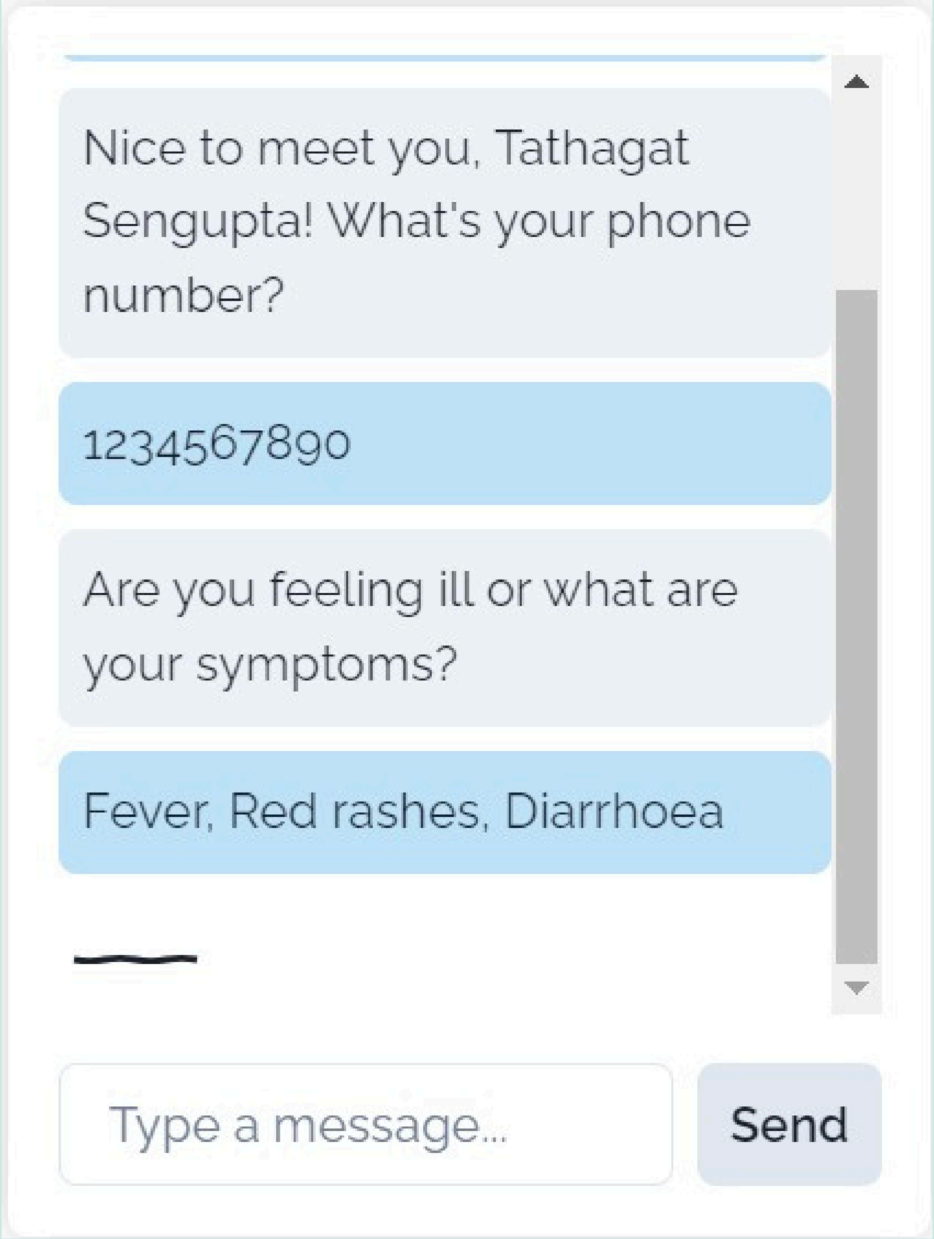
	DOI 3	DOI 5	DOI 6	DOI 7	DOI 8	DOI 9	DOI 10
WBC ($\times 10^3$/uL) Nl 4.0–12.0	7.2	9.8	**12.3**	**13.7**	**13.8**		**14.0**
Hemoglobin (g/dL) Nl 11.5–14.5	12.4	11.8	**10.7**	**10**	**10.7**		11.6
Platelet Count ($\times 10^3$/uL) Nl 150–450	190	**110**	**98**	164	238		**481**
Sodium (meq/L) Nl 135–145	137	**129**	**129**	136	135	137	136
AST (iU/L) Nl 23–58	54	**104**	**97**	**88**	**76**	57	56
ALT (iU/L) Nl 10–28	18	**46**	**39**	**34**	**34**	**32**	**34**
Albumin (g/dL) Nl 3.8–5.4	4.6	3.8	**3.3**	**3.2**	**3.2**	**3.2**	**3.5**
ESR (mm) Nl 0–10	**28**	**37**	**49**				
CRP (mg/dL) Nl 0–1.0	**16.1**	**42.7**	**40.3**	**18.2**		**4.5**	**3.1**
Ferritin (ng/mL) Nl 10–60	**98.5**	**528**	**524**	**472**		**271**	**234**
Troponin I (ng/mL) Nl 0.012–0.034	$<$0.012	**0.043**	**0.022**	**0.021**	$<$0.012		
NT-Pro-BNP (pg/mL) Nl $<$ 300	117	**15,600**	**18,400**	**11,200**	**6810**		**1250**
PT (s) Nl 12.4–14.6	**16.9**	**14.7**	**14.8**	13.9	13.6		13.4
D-dimer (ug/mL) Nl $<$ 0.5	Unable to determine	**4.17**	**5.60**	**4.66**	**4.84**		**3.74**
Fibrinogen (mg/dL) Nl 200–400	Unable to determine	**657**	**623**	**415**	335		270
PCR NAAT for SARS-Cov-2 (rapid Abbott)	Negative	Negative			Negative	Negative	
PCR NAAT for ORF1ab and S gene from SARS-	Negative	Negative			Negative	**Positive**	

PATIENT DASHBOARD

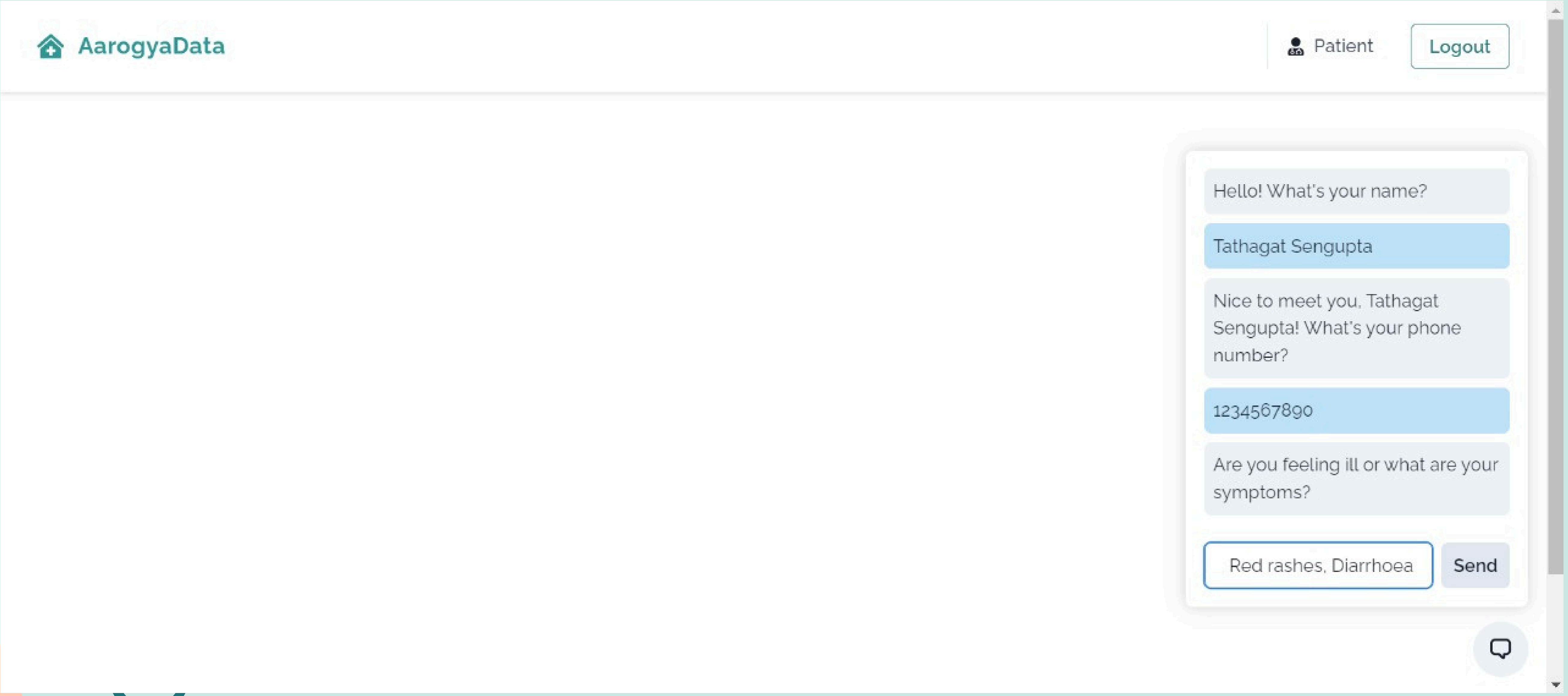


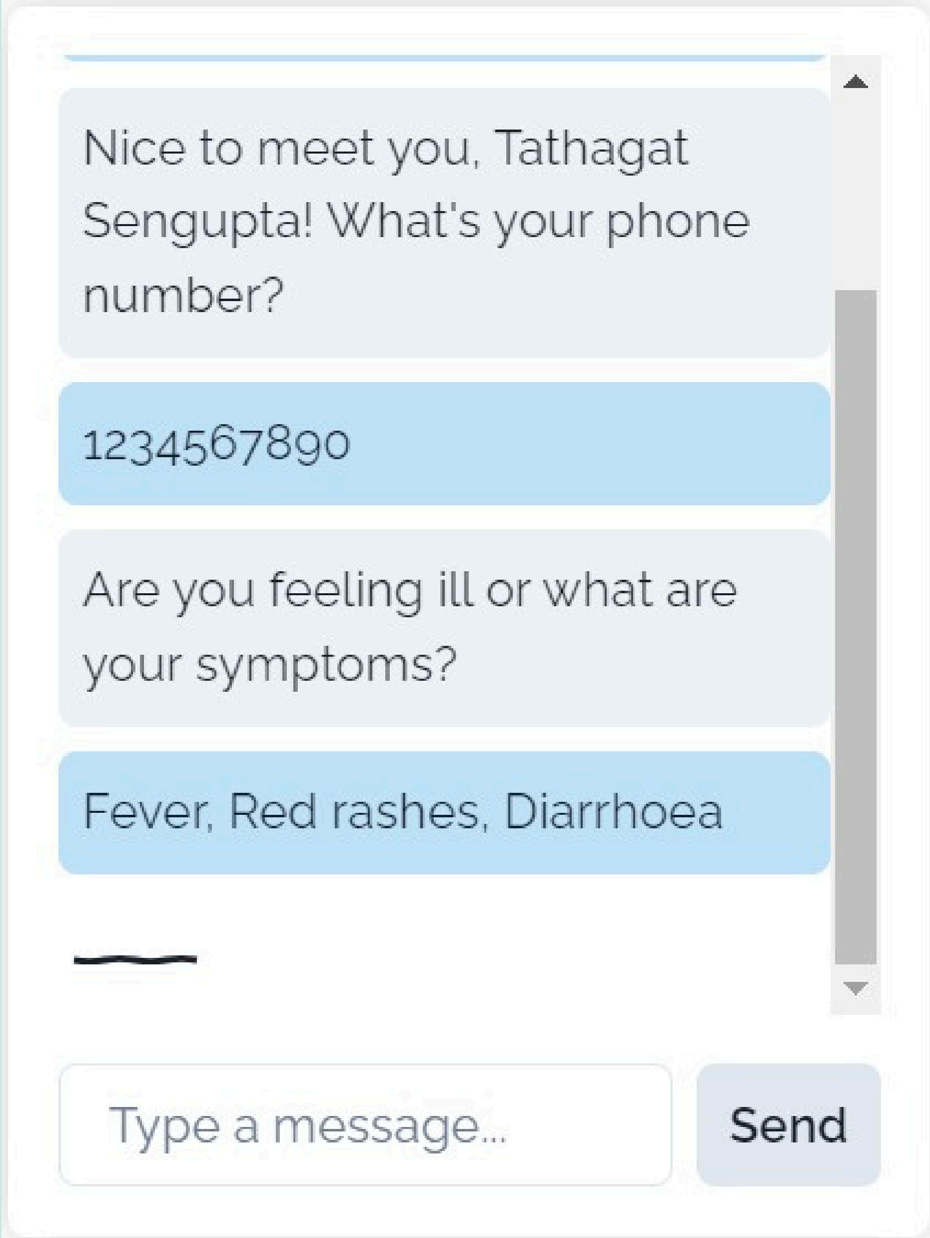
PERSONAL AI CHATBOT



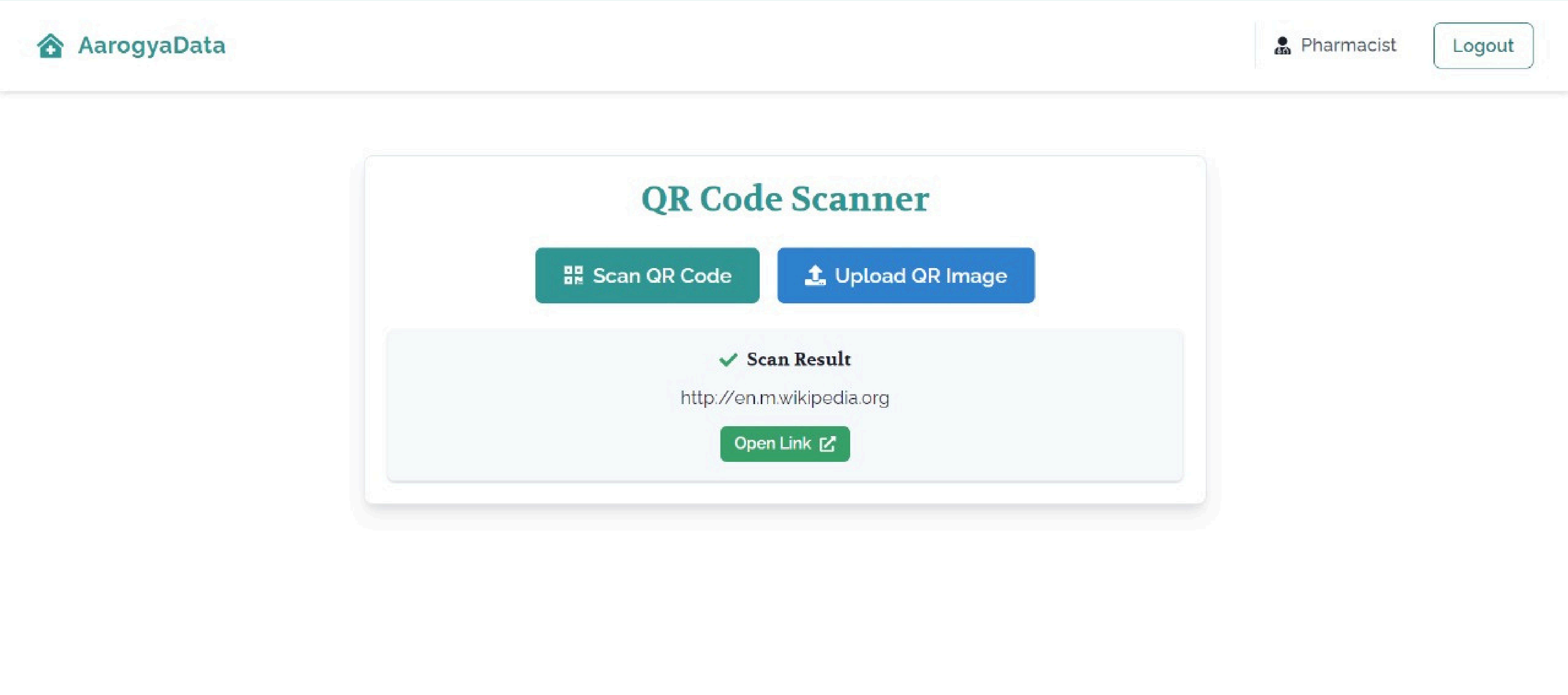


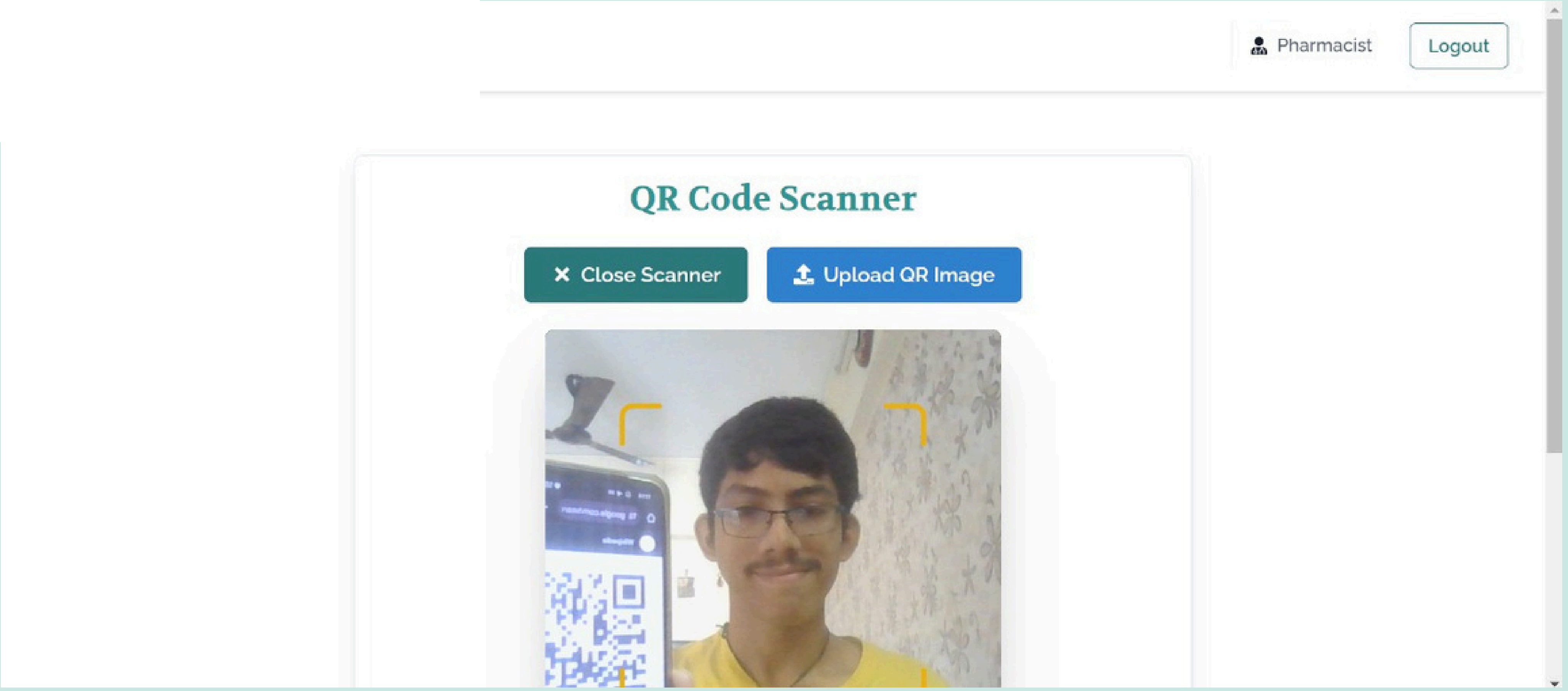
PERSONAL AI CHATBOT





QR CODE SCANNER





Thank You