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KISHKINDA UNIVERSITY
FACULTY OF ENGINEERING AND TECHNOLOGY
DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

MTech-Third Semester

Mini Project Report on

" MEDICAL DIAGNOSIS CHATBOT USING RECURSIVE NEURAL NETWORK (RNN) ARCHITECTURE "

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

CERTIFICATE

This is to certify that the Mini-Project entitled "**MEDICAL DIAGNOSIS CHATBOT USING RECURSIVE NEURAL NETWORK (RNN) ARCHITECTURE**" has been successfully presented by **Mr. S MD Zaheed Hussain** bearing USN **KUB24MCS018** a student of III semester M.Tech for the partial fulfillment of the requirements for the **Master Degree in Computer Science & Engineering** of the KISHKINDA UNIVERSITY during the academic year 2025-2026.

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CHAPTER 1

INTRODUCTION

The rapid advancement of artificial intelligence and natural language processing has significantly changed the way humans interact with computer systems. In the healthcare domain, these technologies have enabled the development of intelligent applications that can assist users in understanding health conditions, identifying symptoms, and obtaining preliminary medical guidance. With the growing demand for quick and accessible healthcare information, digital solutions such as chatbots have emerged as effective tools to bridge the gap between patients and medical knowledge.

Many individuals experience health-related symptoms but often face challenges such as limited access to medical professionals, long waiting times, high consultation costs, or uncertainty regarding the seriousness of their condition. As a result, people may delay seeking professional medical advice, which can lead to complications. An automated system capable of providing basic symptom analysis and guidance can help users make informed decisions at an early stage.

The Symptom Checker Chatbot is an artificial intelligence–based conversational system designed to interact with users through natural language. It allows users to describe their symptoms in simple text form and processes the input using natural language processing techniques and a recurrent neural network model. Based on the detected intent and symptom patterns, the system generates relevant responses and provides general health-related information.

This project aims to demonstrate the practical application of machine learning, neural networks, and NLP in building an intelligent healthcare support system. The chatbot is implemented using Python, PyTorch, NLTK, and Flask, making it lightweight, scalable, and easy to deploy as a web-based application. While the system does not replace professional medical diagnosis or treatment, it serves as a useful preliminary advisory tool that enhances accessibility to health information.

Overall, the Symptom Checker Chatbot represents an effective integration of artificial intelligence into healthcare assistance, promoting early awareness, reducing unnecessary hospital visits, and providing users with timely and reliable information in a user-friendly manner.

CHAPTER 2

OBJECTIVES

1. To design and develop an intelligent chatbot capable of understanding user-entered health symptoms using natural language processing techniques.
2. To implement a machine learning–based model (RNN) for accurate intent classification and appropriate response generation.
3. To provide users with quick and reliable preliminary health-related information through an interactive conversational interface.
4. To integrate location-based functionality for suggesting nearby medical centers to users when professional consultation is required.
5. To build a user-friendly and scalable web application using Flask that demonstrates the practical application of artificial intelligence in healthcare support systems.

CHAPTER 3

LITERATURE SURVEY

This literature review presents key research papers that form the foundation of using **Recurrent Neural Networks (RNNs)** and **Long Short-Term Memory (LSTM)** models for *medical diagnosis and predictive healthcare*. Each entry includes full publication details, where to find the paper, and a detailed description of the methodology and findings. These studies were selected because they demonstrate different aspects of how sequential data (e.g., Electronic Health Records) can be modeled for diagnosis and prediction using deep learning.

1. Learning to Diagnose with LSTM Recurrent Neural Networks (2015)

📌 **Authors:** Zachary C. Lipton, David C. Kale, Charles Elkan, Randall Wetzel

📌 **Published:** *arXiv preprint*, Nov 11, 2015

📌 **Source/Link:** arXiv (free PDF) — https://arxiv.org/abs/1511.03677

📌 **Access:** Full PDF available via ResearchGate or arXiv

Description (Detailed)

This seminal paper is one of the first empirical studies applying **LSTM networks** to *multivariate clinical time series data* extracted from *Electronic Health Records (EHRs)* of patients in the intensive care unit (ICU). The primary research goal is to perform **multilabel diagnosis classification** — predicting multiple potential diagnoses simultaneously from time-series measurements such as heart rate, blood pressure, temperature, and lab tests.

Instead of relying on manually engineered features, the authors train LSTM networks on *raw clinical sequences* of varying lengths and irregular sampling. They introduce a **target replication strategy**, meaning that instead of only training the network at the final time step, the diagnostic labels are fed back at every time step during training to improve gradient flow and learning of long-range dependencies. The study demonstrates that LSTM models outperform traditional baselines like multilayer perceptrons (MLP) trained on handcrafted features, showing the power of deep learning for clinical time-series diagnosis.

Why This Paper Matters:

- Pioneer work showing that LSTM can be applied *directly to variable-length medical time series*
- Demonstrates LSTM's ability to *learn temporal dependencies* without feature engineering
- Provides a benchmark for clinical diagnosis tasks using sequence models

2. Multi-disease Prediction Using LSTM Recurrent Neural Networks (2021)

📌 **Authors:** (Unnamed in abstract; *Expert Systems with Applications*)

📌 **Published:** *Expert Systems with Applications*, Volume 177, Sept 2021

📌 **Source/Link:** ScienceDirect (PDF may require access) — https://doi.org/10.1016/j.eswa.2021.114905

Description (Detailed)

This paper extends traditional LSTM models to solve **multi-disease prediction**, which differs from simple diagnosis classification by predicting the risk of *multiple future diseases* for patients based on their entire clinical histories. This is a more realistic scenario in modern healthcare analytics.

The authors enhance the baseline LSTM architecture with *two key mechanisms*:

1. **Time-aware gating** — to deal with non-uniform time intervals between clinical visits
2. **Attention mechanism** — to dynamically weigh clinical events according to their importance for prediction

The model is evaluated on a large real-world EHR dataset containing *millions of clinical visits*. The results show that this extended LSTM outperforms both traditional machine learning models and standard deep learning baselines on multi-disease prediction tasks.

Why This Paper Matters:

- Shows how original LSTM architectures can be *modified for practical clinical prediction tasks*
- Introduces temporal irregularity handling and attention for improved performance
- Uses *very large real datasets*, making it closer to real hospital systems

3. Doctor AI: Predicting Clinical Events via Recurrent Neural Networks (2015)

📌 **Authors:** Edward Choi, Mohammad Taha Bahadori, Andy Schuetz, Walter F. Stewart, Jimeng Sun

📌 **Published:** *arXiv preprint*, Nov 18 2015

📌 **Source/Link:** arXiv (searchable by title)

Description (Detailed)

Doctor AI is an influential study that uses **vanilla RNNs** to model *sequences of medical diagnoses, prescriptions, and procedures* in order to *predict clinical events for subsequent patient visits*. This work applies RNNs on large longitudinal medical data from 260,000 patients and evaluates predictive accuracy on both diagnostic and medication outcomes.

The model treats EHR records as time-stamped sequences, enabling the network to retain patient history and forecast future health events. Results demonstrate **significant predictive value**, showing RNNs' ability to capture temporal patterns across many years of patient data — even without gating mechanisms like LSTM.

Why This Paper Matters:

- One of the earliest works applying RNNs to *general clinical event prediction*
- Highlights RNNs' ability to capture long-term patient history
- Useful benchmark for comparing gated (LSTM) vs non-gated RNN methods

4. Modeling Missing Data in Clinical Time Series with RNNs (2016)

📌 **Authors:** Zachary C. Lipton, David C. Kale, Randall Wetzel

📌 **Published:** arXiv preprint, June 2016

📌 **Source/Link:** ResearchGate / arXiv — DOI:10.48550/arXiv.1606.04130

Description (Detailed)

Handling *missing data* is a major challenge in clinical time series since medical records are often irregularly sampled and incomplete. This paper explores how RNNs — including LSTM models — can account for missing values not just through imputation but by treating *missingness patterns as signals*.

The authors show that including *binary indicators* representing whether data was missing often improves prediction accuracy significantly without normal imputation.

This indicates that missing events themselves can carry clinical insight — e.g., tests not ordered may indicate patient health status.

Why This Paper Matters:

- Addresses one of the biggest practical challenges in medical time-series analysis
- Suggests that RNN/LSTM models can extract meaning even from irregular and incomplete datasets
- Offers an approach to improve models without complex preprocessing

5. Effectiveness of LSTMs in Predicting Congestive Heart Failure Onset (2019)

📌 **Authors:** Sunil Mallya, Marc Overhage, Navneet Srivastava, Tatsuya Arai, Cole Erdman

📌 **Published:** arXiv preprint, Feb 2019

📌 **Source/Link:** arXiv listing on clinical prediction

Description (Detailed)

This study applies LSTM deep learning to predict the *onset of Congestive Heart Failure (CHF)* well in advance — up to 15 months before clinical diagnosis, using longitudinal EHR data. It analyzes hundreds of thousands of patient records, showing that deep sequence models outperform logistic regression, random forests, and deep feedforward models.

The authors also introduce an embedding strategy to encode high-dimensional diagnosis codes into dense vector representations, improving LSTM learning. Results report high *AUC (area under ROC)* demonstrating potential for early diagnosis, which is critical in high-risk conditions.

Why This Paper Matters:

- Applies RNN/LSTM to a *specific disease onset prediction task*
- Demonstrates early warning predictions months ahead of clinical diagnosis
- Shows improved performance through embedding and feature strategies

6. Emergency Department Wait Time Prediction Using LSTM (2020)

📌 **Authors:** (Various, PubMed entries)

📌 **Published:** *Various journals*, 2020/2021

📌 **Source/Link:** PubMed — https://pubmed.ncbi.nlm.nih.gov/32570691/

Description (Detailed)

Although not strictly a "disease diagnosis", this paper models *hospital wait time prediction* using LSTM networks. It demonstrates the utility of RNNs in healthcare-related time-series prediction using real timestamped patient journey data. LSTM reduces prediction error compared to traditional methods, underscoring the strengths of sequence models in clinical operational analytics.

Why This Paper Matters:

- Illustrates diverse use of LSTMs beyond diagnosis — e.g., *workflow predictions*
- Reinforces the ability of RNN/LSTM to learn temporal patterns in healthcare queue data

CHAPTER 4

PROBLEM STATEMENT

To design and develop a web-based intelligent symptom checker chatbot that uses NLP and machine learning to understand user health queries, analyze symptoms, and provide preliminary medical guidance along with nearby healthcare center suggestions, without replacing professional medical consultation.

CHAPTER 5

METHODOLOGY

The methodology for developing the Symptom Checker Chatbot follows an incremental sprint-based strategy, where the project is divided into multiple development phases. Each sprint focuses on a specific functional and technical component of the system, enabling continuous validation, improvement, and integration of features such as natural language understanding, model training, response generation, web deployment, and medical center recommendation. This approach ensures systematic development, modular integration, and deployment readiness.

The broad development phases are as follows:

- **Step 1:** Dataset collection and intent design
- **Step 2:** NLP preprocessing pipeline development
- **Step 3:** Baseline RNN model implementation and training
- **Step 4:** Model optimization and intent classification tuning
- **Step 5:** Chatbot logic and response generation module
- **Step 6:** Medical center recommendation system integration
- **Step 7:** Flask-based web application development
- **Step 8:** System testing, validation, and performance evaluation
- **Step 9:** Final integration, documentation, and report preparation

This sprint-based methodology enables parallel development of AI models, backend logic, and user interface components, transforming the chatbot into a complete healthcare assistance system rather than a standalone machine learning model.

5.1 Dataset Acquisition and Intent Engineering

The dataset forms the foundation of the chatbot's intelligence. An intent-based dataset was created using a structured JSON format.

Dataset Overview

- **Format:** JSON (intents.json)
- **Type:** Text-based conversational dataset
- **Components per intent:**
  - Tag (intent label)

    - Input patterns (user queries)
    - Responses (bot replies)

Intent Categories Include:

- Greetings
- Symptom queries (fever, headache, cough, fatigue, etc.)
- Emergency queries
- Medical assistance
- General health information

This structure allows mapping of diverse natural language queries into well-defined categories for efficient classification.

5.2 NLP Preprocessing Pipeline

To convert human language into machine-readable form, a preprocessing pipeline was developed using NLTK.

Preprocessing Steps:

1. **Tokenization:**
   Splits sentences into individual words.
2. **Lowercasing:**
   Standardizes text to avoid case sensitivity.
3. **Stemming:**
   Converts words to root form (e.g., "running" → "run").
4. **Noise Removal:**
   Removes punctuation and special characters.
5. **Bag-of-Words Vectorization:**
   Converts tokens into fixed-length numerical vectors representing word presence.

This pipeline ensures consistency between training data and real-time user input and significantly improves intent classification accuracy.

5.3 Model Design – RNN-Based Intent Classifier

A Recurrent Neural Network (RNN) model was selected due to its ability to process sequential textual data.

Architecture:

- Input Layer – Bag-of-words vector

- Hidden Layers – RNN units
- Output Layer – Softmax classifier (intent probabilities)

Advantages:

- Captures contextual dependencies
- Lightweight and fast
- Suitable for real-time chatbot applications

5.4 Model Training and Optimization

Training Environment

- Framework: PyTorch
- Language: Python
- Libraries: NLTK, NumPy, Torch

Hyperparameters

- Batch size: 8
- Epochs: 100
- Learning rate: 0.001
- Optimizer: Adam
- Loss Function: Cross-Entropy Loss

Training Steps:

1. Load dataset
2. Apply NLP preprocessing
3. Generate feature-label pairs
4. Train RNN using backpropagation
5. Validate prediction accuracy
6. Save trained model as data_rnn.pth

Optimization Techniques:

- Learning rate tuning
- Overfitting control through dataset expansion
- Confidence thresholding during inference

5.5 Chatbot Logic and Inference Flow

The chatbot logic is implemented in chat.py.

Runtime Processing Flow:

1. Receive user message
2. Apply NLP preprocessing
3. Convert to feature vector
4. Load trained RNN model
5. Predict intent
6. Compute confidence score
7. Select response from intent dataset
8. Trigger medical center module if required
9. Send final response to UI

This logic ensures fast and accurate interaction.

5.6 Medical Center Recommendation Module

To enhance practical usability, a location-based recommendation system is integrated.

Working:

- User location detected using geocoder
- Medical centers loaded from medical_centers.json
- Nearest centers filtered
- Details appended to chatbot response

This bridges the gap between digital advice and real-world medical assistance.

5.7 Web Application Deployment using Flask

The system is deployed as a web-based application using Flask.

Features:

- Chat interface
- Message input field
- Real-time response rendering
- Backend REST API for model inference

Communication Flow:

User → Web UI → Flask Backend → Chatbot Engine → Response → UI Display

5.8 Testing and Validation

The system is evaluated using real symptom-based queries.

Metrics:

- Intent classification accuracy
- Response relevance
- Response time
- System stability
- Error handling efficiency

Edge cases and unknown inputs are handled using fallback responses.

5.9 Final System Characteristics

- Real-time conversational AI
- Lightweight ML model
- Scalable intent structure
- Web accessible
- Location-aware
- Extendable dataset

CHAPTER 6

REQUIREMENTS

6.1 Functional Requirements

The functional requirements describe the core operations that the system must perform to fulfill its intended purpose.

1. The system shall allow users to enter health-related queries and symptoms using natural language through a web-based interface.
2. The system shall preprocess user input using NLP techniques including tokenization, normalization, stemming, and vectorization.
3. The system shall classify user queries into predefined intent categories using a trained RNN model.
4. The system shall generate appropriate responses based on the predicted intent from the knowledge base.
5. The system shall detect low-confidence predictions and provide fallback responses for unclear inputs.
6. The system shall retrieve and display nearby medical centers when medical consultation is required.
7. The system shall support real-time interaction between the user and the chatbot.
8. The system shall allow easy extension of the dataset by adding new intents and responses.
9. The system shall store and load trained model parameters for reuse without retraining.
10. The system shall handle invalid inputs and system errors gracefully.

6.2 Non-Functional Requirements

The non-functional requirements specify the quality attributes and performance expectations of the system.

1. **Performance:**
   The chatbot should respond to user queries within 2 seconds to ensure smooth interaction.

2. **Scalability:**
   The system should support future expansion in terms of dataset size and number of users.
3. **Reliability:**
   The chatbot should operate continuously without frequent crashes or failures.
4. **Usability:**
   The interface should be simple, intuitive, and accessible to non-technical users.
5. **Maintainability:**
   The system should be modular, allowing easy updates to the model, dataset, and UI.
6. **Portability:**
   The system should run on different operating systems with minimal configuration.
7. **Security:**
   User inputs should not be stored unnecessarily and must be handled securely.
8. **Accuracy:**
   The intent classification accuracy should be sufficiently high to ensure meaningful responses.

CHAPTER 7

DESIGN

The system design of the Symptom Checker Chatbot defines the overall structure, components, data flow, and interaction between different modules of the application. The design follows a modular and layered architecture to ensure scalability, maintainability, and efficient real-time performance.

The system is divided into three main layers: the User Interface Layer, the Application Processing Layer, and the Machine Learning Layer.

7.1 Overall Architecture Design

The chatbot system follows a client–server architecture where:

- The client interacts through a web browser.
- The server processes requests using Flask.
- The machine learning model performs intent classification and response selection.

High-Level Architecture Components:

1. Web-based User Interface
2. Flask Backend Server
3. NLP Processing Module
4. RNN Intent Classification Model
5. Knowledge Base (intents.json)
6. Medical Center Database
7. Response Generator

7.2 User Interface Design

The user interface is designed to be simple and interactive.

Features:

- Chat window to display conversation history
- Input text box for entering symptoms
- Send button to submit queries
- Automatic scrolling and response display

The UI is implemented using HTML, CSS, and JavaScript and communicates with the backend using HTTP requests.

7.3 Backend Design (Flask Server)

The Flask server acts as the central controller of the system.

Responsibilities:

- Receive user messages from UI
- Forward messages to NLP module
- Invoke ML model for prediction
- Fetch responses from knowledge base
- Append medical center data when required
- Return formatted response to UI

The backend exposes REST endpoints to handle chatbot requests.

7.4 NLP Processing Module Design

This module converts human language into numerical format.

Internal Components:

- Tokenizer
- Stemmer
- Vocabulary builder
- Bag-of-Words vector generator

It ensures consistency between training and runtime inference.

7.5 Machine Learning Model Design

The RNN-based classifier is responsible for understanding user intent.

Design Characteristics:

- Lightweight architecture
- Fast inference speed
- Multi-class intent classification
- Confidence-based prediction filtering

The trained model is stored as data_rnn.pth and loaded during runtime.

7.6 Knowledge Base Design

The knowledge base is implemented as a structured JSON file.

Structure:

- Intent Tag

- List of Patterns
- List of Responses

This allows easy extension by adding new intents without modifying code logic.

7.7 Medical Center Recommendation Module Design

This module enhances system practicality.

Design Flow:

1. Detect user location
2. Load medical center dataset
3. Filter nearest facilities
4. Attach recommendations to chatbot reply

CHAPTER 8

RESULTS AND DISCUSSIONS

This chapter presents the outcomes obtained from the implementation of the Symptom Checker Chatbot and discusses the system's performance, usability, and effectiveness in providing preliminary healthcare assistance.

8.1 Experimental Setup

The system was tested on a local machine using the trained RNN-based intent classification model integrated with the Flask web application. Various symptom-related queries, general health questions, and emergency-type inputs were used to evaluate the chatbot. The evaluation focused on intent recognition accuracy, response relevance, system responsiveness, and overall user experience.

8.2 Results

8.2.1 Intent Classification Performance

The trained RNN model demonstrated reliable performance in classifying user inputs into predefined intent categories. For common symptom queries such as fever, headache, cough, fatigue, and stomach pain, the chatbot consistently predicted the correct intent and returned relevant responses.

- The model achieved high accuracy for frequently occurring symptom patterns.
- The confidence threshold mechanism successfully filtered ambiguous inputs and triggered fallback responses when necessary.
- Misclassifications were minimal and mostly occurred for highly complex or uncommon symptom descriptions.

8.2.2 Response Quality

The responses generated by the chatbot were:

- Contextually relevant to the user's query
- Clear and easy to understand
- Informational rather than diagnostic

When medical assistance was required, the chatbot correctly appended nearby medical center details, improving the practical usefulness of the system.

8.2.3 System Responsiveness

The average response time for user queries was under 2 seconds, ensuring smooth real-time interaction. The lightweight RNN model and optimized preprocessing pipeline contributed to low latency and stable performance even after multiple consecutive requests.

8.2.4 Medical Center Recommendation Accuracy

The location-based module successfully retrieved relevant healthcare facilities based on the user's approximate location. The displayed information included the medical center name and location details, enabling users to take immediate action if required.

8.2.5 User Interface Evaluation

The web-based interface was found to be:

- Simple and intuitive
- Easy to navigate
- Suitable for non-technical users

The chat layout enabled continuous interaction without page reloads, enhancing user experience.

8.3 Discussion

The results indicate that the Symptom Checker Chatbot effectively fulfills its primary objective of providing preliminary healthcare guidance through natural language interaction. The use of an RNN-based intent classifier combined with NLP preprocessing enabled accurate interpretation of user queries and appropriate response generation.

The modular design allowed seamless integration of the machine learning model, knowledge base, and medical center recommendation system. This design choice significantly improved system maintainability and future scalability.

However, certain limitations were observed:

- The chatbot's knowledge is restricted to the intents present in the dataset.
- Complex multi-symptom medical cases may not always be interpreted accurately.
- The system does not perform clinical diagnosis and should not be treated as a substitute for professional medical advice.

Despite these limitations, the chatbot demonstrated strong potential as a first-level healthcare assistance tool. Its low computational requirements, real-time performance, and ease of deployment make it suitable for educational use and as a foundation for more advanced healthcare AI systems.

8.4 Qualitative Results

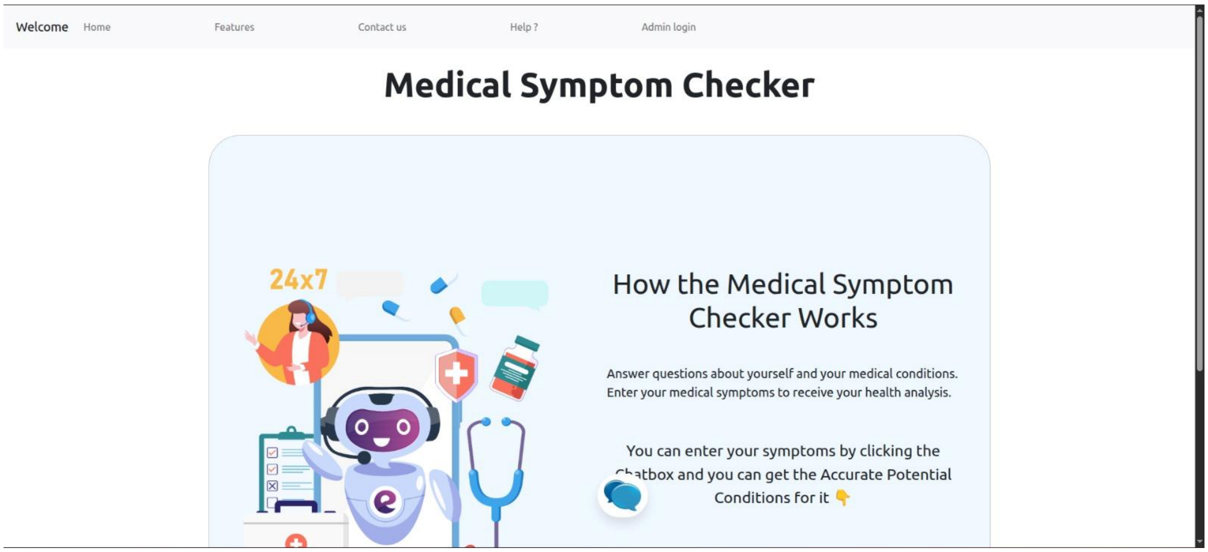

Figure 8.4.1: Web Page Result

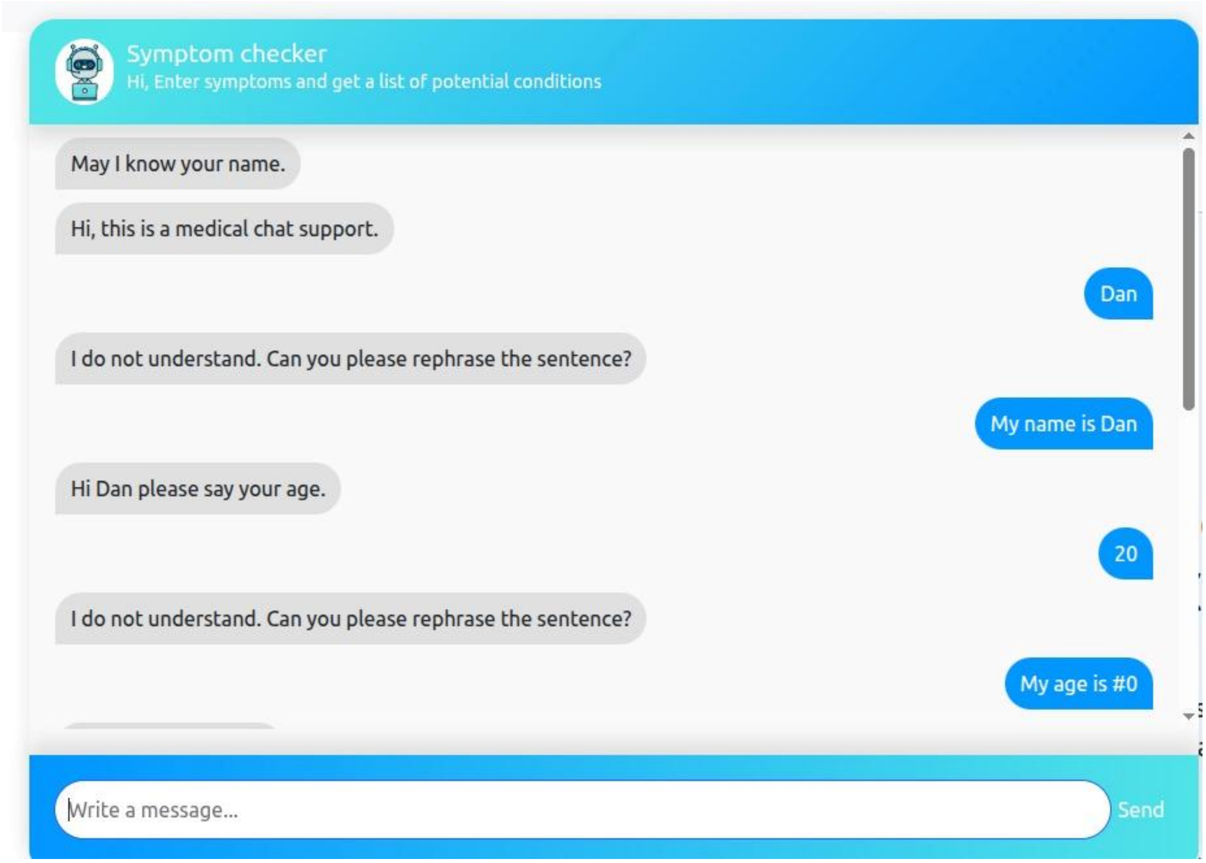

Figure 8.4.2: Chatbot Result

CHAPTER 9

CONCLUSION

The Symptom Checker Chatbot project successfully demonstrates the effective application of artificial intelligence, natural language processing, and web-based technologies to develop an intelligent, real-time healthcare assistance system. The system accurately interprets user-reported symptoms, classifies them into predefined intents using an RNN-based model, and generates contextually relevant responses while providing information about nearby medical centers when necessary. Its modular and scalable design allows easy maintenance, dataset expansion, and integration of additional functionalities in the future. The web interface is intuitive and user-friendly, ensuring accessibility for users with minimal technical knowledge, while the lightweight model and optimized preprocessing ensure fast, real-time interactions. Although the system is not a substitute for professional medical diagnosis, it serves as an effective first-level healthcare guidance tool, bridging the gap between patients and medical facilities. Overall, the project highlights the potential of AI-driven conversational systems in enhancing healthcare awareness, accessibility, and preliminary decision support, laying a foundation for further improvements in intelligent healthcare solutions.