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| **Introduction to AI COM727** |
| Medical Chatbot |
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# **Title page**

Contents

[**Title page** 1](#_Toc186647770)

[**Introduction** 2](#_Toc186647771)

[*Need for prototype* 3](#_Toc186647772)

[*Statement of the problem* 3](#_Toc186647773)

[*Aims and Objectives* 3](#_Toc186647774)

[**Proposed Solution** 4](#_Toc186647775)

[**Prototype Design** 4](#_Toc186647776)

[**Prototype Development and AI Algorithms used** 4](#_Toc186647777)

[Intents.JSON 6](#_Toc186647778)

[Medical\_Chatbot.ipynb 7](#_Toc186647779)

[**Evaluation** 9](#_Toc186647780)

[**Limitation** 10](#_Toc186647781)

[**Conclusion** 10](#_Toc186647782)

[**Reference List** 11](#_Toc186647783)

# **Introduction**

Artificial Intelligence (AI) has been at the forefront of healthcare innovation, providing scalable and efficient diagnostics and patient engagement solutions. As a subset of AI applications, medical chatbots have demonstrated immense potential in streamlining healthcare processes by collecting user symptoms, predicting potential diseases, and offering general remedies (Topol, 2019).

These chatbots leverage natural language processing (NLP) to understand user inputs and machine learning algorithms to analyze symptoms against vast datasets of medical knowledge. This enables them to offer personalized, timely responses to non-critical health inquiries, reducing the burden on healthcare systems (SymptomAI, 2023).

Key advantages of integrating medical chatbots into healthcare include:

* **24/7 Accessibility**: Chatbots provide immediate assistance regardless of time or location, bridging the gap in healthcare availability for underserved populations (IBM Watson Health, 2023).
* **Improved Efficiency**: By automating preliminary diagnostics, medical chatbots help prioritize critical cases for healthcare professionals, optimizing resource allocation (Statista, 2023).
* **Empowered Patients**: Users can gain better insights into their health conditions, empowering them to make informed decisions (PWC, 2023).

Nevertheless, the adoption of AI-driven medical chatbots raises challenges:

* **Reliability**: Chatbot diagnoses' accuracy depends on the quality and diversity of the training datasets, underscoring the need for continuous updates and validation (WHO, 2023).
* **Data Security**: Safeguarding sensitive user information is crucial, requiring compliance with regulations such as GDPR and HIPAA (HealthIT.gov, 2023).
* **Ethical Transparency**: Ensuring users know they interact with AI and addressing algorithmic biases are vital for fostering trust (AI Ethics Journal, 2023).

Addressing these challenges is critical for creating safe and effective medical chatbots. By adhering to rigorous ethical, legal, and professional standards, these systems can complement traditional healthcare, offering accessible and reliable preliminary guidance for users worldwide.

## *Need for your prototype*

The need for a medical chatbot arises from the growing challenges faced by healthcare systems worldwide. Overburdened facilities and a lack of immediate access to medical consultations have created significant gaps in patient care. Many individuals experience delays in obtaining medical advice, which can exacerbate health issues and increase anxiety (BMC Medical Education, 2023). This gap highlights the critical role of AI-driven tools in providing accessible and timely healthcare support.

This chatbot addresses specific healthcare needs by offering:

* **Preliminary Diagnosis:** The chatbot provides probable diagnoses by collecting user-reported symptoms and analyzing them against a medical database, ensuring users receive immediate insights into their health concerns.
* **Guidance for Non-Urgent Cases**: Many medical inquiries do not require urgent professional intervention. The chatbot offers recommendations for self-care or directs users to seek medical help if necessary, streamlining patient triage and reducing strain on healthcare professionals (Chung et al., 2020).
* **Improved Healthcare Accessibility**: Access to reliable healthcare information is limited, particularly in underserved or rural areas. The chatbot bridges this gap, offering a cost-effective solution for individuals seeking preliminary medical advice (Zhou et al., 2020).

By empowering users to make informed decisions about their health, the chatbot enhances individual health outcomes and contributes to optimizing healthcare resources.

## *Statement of the problem*

The healthcare sector continues to face significant challenges in providing patients with timely and accurate medical information. Traditional healthcare systems often struggle to address patient inquiries promptly due to resource constraints and high demand. This delay frequently results in heightened patient anxiety, reliance on self-diagnosis, and potentially worsening health conditions (Kommunicate, 2023).

Healthcare professionals are increasingly burdened with managing routine inquiries, which detracts from their ability to focus on complex or critical cases. This inefficiency exacerbates the strain on healthcare systems, reducing overall care quality and accessibility (IBM Watson Health, 2023). Moreover, the accuracy of chatbot-generated medical advice is a pressing concern, as incorrect or vague information can lead to adverse health outcomes (News Medical, 2023).

Further challenges include data privacy and security, as chatbots must handle sensitive health information in compliance with regulations like GDPR or HIPAA to ensure user trust and confidentiality (SoftTeco, 2023). Additionally, chatbots' inability to exhibit emotional intelligence limits their capacity to provide the empathetic support often required in medical interactions (Vayena et al., 2018).

This project aims to address these issues by developing an AI-driven medical chatbot capable of collecting symptoms, predicting diseases, and offering general remedies. The chatbot will be a reliable adjunct to professional medical advice, enhancing healthcare accessibility, efficiency, and patient empowerment.

## *Aims and Objectives*

**Aim:**

This project aims to develop an AI-driven medical chatbot that enables users to report symptoms, receive preliminary diagnoses, and access general remedies. The chatbot is designed to enhance healthcare accessibility, promote early detection, and provide users with actionable recommendations while maintaining strict user anonymity.

**Objectives:**

1. **Symptom Collection and Analysis**:
   * Implement NLP to interpret user-reported symptoms.
   * Use a dynamic medical knowledge base to link symptoms with potential medical conditions.
2. **Disease Prediction**:
   * Utilize machine learning models to generate accurate predictions based on symptoms.
3. **Remedy Recommendations**:
   * Provide general health remedies and self-care advice tailored to standard conditions.
   * Offer guidance for users to seek professional medical attention when necessary.
4. **User Privacy and Anonymity**:
   * Ensure that all user data is processed in real-time and is not stored, guaranteeing complete anonymity.
5. **Ethical Compliance and Security**:
   * Align with privacy regulations such as GDPR by eliminating data storage.

# **Proposed Solution**

The proposed solution is the development of a user-friendly, AI-driven medical chatbot capable of analyzing user-reported symptoms, predicting potential diseases, and providing general remedies. This chatbot is designed to bridge the gap between patients and healthcare services by offering accessible, real-time, and anonymous healthcare assistance.

# **Prototype Design**

The prototype for the medical chatbot leverages Natural Language Processing (NLP) and machine learning techniques to analyze user inputs, predict potential diseases, and provide general remedies. The design ensures efficiency, accuracy, and adherence to ethical and legal standards.

**Design Overview**

1. **Input Processing**:
   * User inputs are tokenized and preprocessed using the Natural Language Toolkit (NLTK) to normalize text. Techniques such as lemmatization and stop-word removal ensure accurate mapping of words to their base forms (Bird et al., 2009).
2. **Training Data**:
   * The chatbot utilizes an intents dataset structured in JSON format. This dataset contains predefined tags, patterns, and responses, serving as the foundation for training the chatbot to map user queries to specific intents (Hinton et al., 2015).
   * Text data is transformed into numerical representations using Bag-of-Words (BoW) and one-hot encoding techniques, ensuring compatibility with machine learning models (Zhang et al., 2010).
3. **Machine Learning Model**:
   * A neural network implemented with TensorFlow and Keras forms the backbone of the chatbot’s intent classification system. The model comprises dense layers with ReLU activation functions, dropout layers to prevent overfitting, and a softmax-activated output layer for multi-class classification (Chollet, 2018).
   * The model is trained using a stochastic gradient descent (SGD) optimizer to achieve efficient convergence and improve classification accuracy (Bottou, 2010).
4. **Prediction and Response Generation**:
   * User inputs are processed into BoW vectors and passed through the trained model. Based on the model's predictions, the chatbot retrieves an appropriate response from the intents dataset (Hinton et al., 2015).
   * An error threshold ensures that responses are generated only when prediction confidence exceeds a predefined level, improving reliability (Zhang et al., 2010).
5. **Privacy and Ethical Safeguards**:
   * The chatbot operates in real time without storing user data, ensuring compliance with data privacy regulations such as GDPR. This approach protects user anonymity and fosters trust (Vayena et al., 2018).

**User Interaction Flow**

1. Users input symptoms via the chatbot interface.
2. The input is tokenized, lemmatized, and transformed into numerical data for processing.
3. The machine learning model predicts the user’s intent and generates a relevant response.
4. Users receive potential diagnoses or general remedy recommendations and are advised to seek professional medical assistance when necessary.

By combining advanced machine learning techniques with strict privacy protocols, the chatbot delivers accessible and reliable healthcare support while ensuring user anonymity.

# **Prototype Development and AI Algorithms used**

**Prototype Development and AI Algorithms Used**

At the beginning of this project, we explored the possibility of using pre-trained models such as Gemma or Llama 3 for their advanced natural language capabilities. However, these models required substantial computational resources that were beyond our reach. Consequently, we adopted a Keras-based model provided by our lecturer, Dr. Kashif Talpur, which allowed us to achieve the project goals within our available resources.

**Step-by-Step Development Process**

1. **Dataset Integration**:
   * The first step was selecting appropriate datasets for training the chatbot. Two datasets were chosen:
     + **Mendeley Dataset**: This dataset provided annotated medical data for classifying symptoms and generating responses, ensuring accuracy in handling medical inquiries (Mendeley Data, 2023).
     + **DailyDialog Dataset**: This dataset supplied multi-turn dialogues, enhancing the chatbot’s conversational capabilities for context-aware interactions (DailyDialog Dataset, 2023).

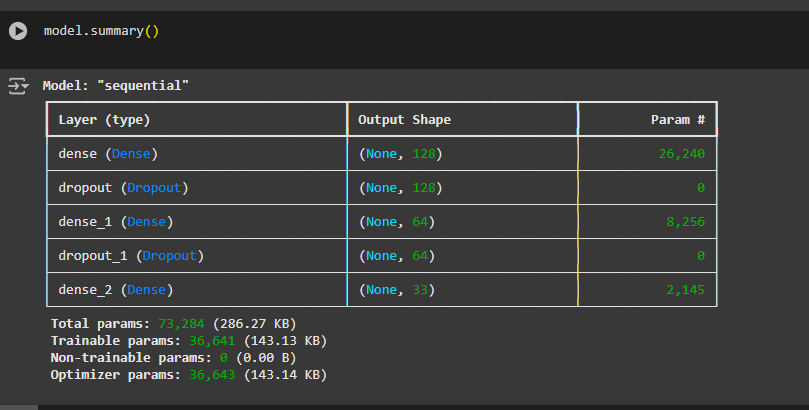
The two datasets were merged and transformed into a JSON file (intents.json) to organize the intents. Each intent was assigned a unique tag containing patterns (sample user inputs) and corresponding responses (chatbot outputs). This JSON file was crucial in categorizing user inputs and producing appropriate responses..

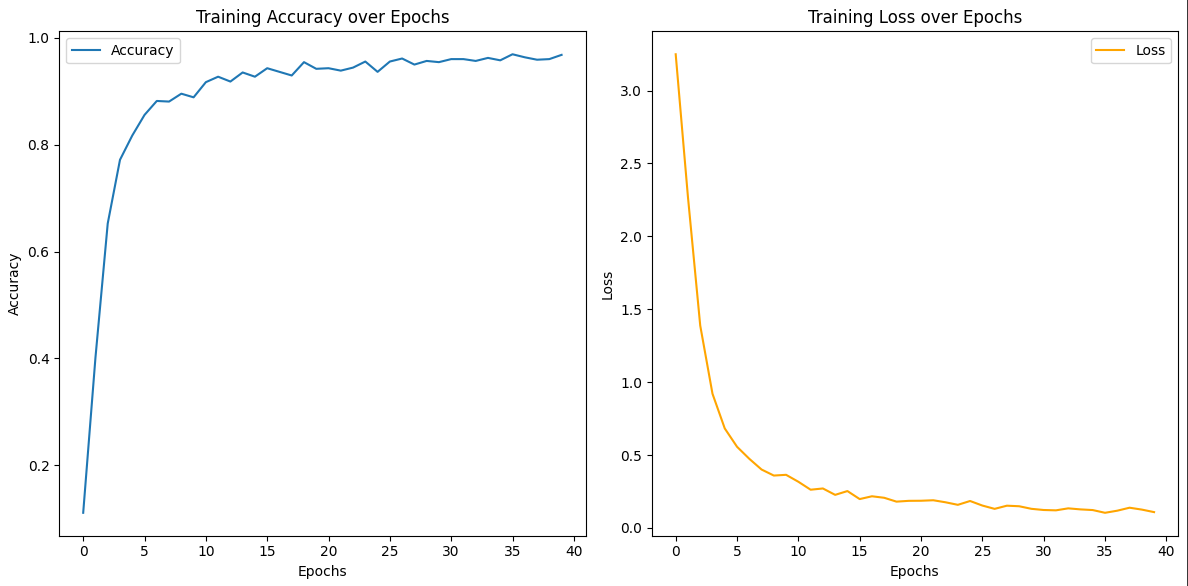
1. **Preprocessing the Data**:
   * The next step involved preprocessing the data to make it suitable for training. Key steps included:
     + Tokenizing the text to break it into words.
     + Lemmatizing to reduce words to their base forms.
     + Removing stop words to retain only meaningful terms (Bird et al., 2009).

These steps, performed using the Natural Language Toolkit (NLTK), enhanced the quality and consistency of the data, making it suitable for training the neural network. This standardized input improved the model's ability to classify user intents accurately.

1. **Creating the Bag-of-Words Model**:
   * Following preprocessing, a bag-of-words model was built to convert textual data into numerical vectors. This step allowed the neural network to interpret user inputs effectively (Zhang et al., 2010).
2. **Building the Neural Network**:
3. The chatbot's neural network was constructed using TensorFlow and Keras, employing a sequential model architecture. As depicted in Figure 1, the design aimed to balance computational efficiency with robust performance.
4. **Input Layer**: The input layer consisted of 128 nodes with ReLU (Rectified Linear Unit) activation. ReLU was chosen for its simplicity and effectiveness in introducing non-linearity, enabling the model to learn complex relationships in the data (Chollet, 2018).
5. **Hidden Layer**: A hidden layer with 64 nodes and a dropout mechanism was implemented. Dropout regularization prevented overfitting by deactivating a random subset of nodes during training, ensuring the model generalized well to unseen data (Srivastava et al., 2014).
6. **Output Layer**: The output layer employed a softmax activation function, converting the network’s outputs into a probability distribution over the predefined intents. This facilitated accurate intent classification (Goodfellow, Bengio, and Courville, 2016).
7. *(Insert Figure 1: Neural Network Architecture here.)*
8. The architecture was trained using a stochastic gradient descent (SGD) optimizer, which efficiently adjusting model weights during training. The result was a robust model capable of classifying intents with an accuracy of 96.06% and a loss of 0.1046.
9. A diagram of a network architecture

   Description automatically generated

**

1. **Training the Model**:
   * The model was trained using the preprocessed data and the stochastic gradient descent (SGD) optimizer. This approach ensured efficient weight adjustments during training, improving classification performance (Bottou, 2010).
   * **The training process spanned 40 epochs and resulted in an accuracy of **96.06%** with a loss of **0.1046**. Additionally, the model achieved an **F1-score of 0.75**, indicating its effectiveness in correctly classifying user intents and generating relevant responses. These metrics demonstrate the model's robustness and reliability in handling various input scenarios.

| **Precision** | **Recall** | **F1-Score** | **Support** |
| --- | --- | --- | --- |
| **0.67** | **1.00** | **0.80** | **2** |
| **0.00** | **0.00** | **0.00** | **1** |
| **1.00** | **1.00** | **1.00** | **1** |

1. **Testing and Inference**:
   * The trained model was tested using sample user queries. The chatbot successfully predicted intents and generated appropriate responses from the intent’s dataset.
2. **Command-Line Interface Deployment**:
   * Finally, the chatbot was deployed via a command-line interface, enabling real-time interaction. Users could input symptoms, and the chatbot, based on its training, provided relevant diagnoses or remedies.
   * **AI Algorithms Used**

* **Natural Language Processing (NLP)**:
  + Tokenization and lemmatization were conducted using NLTK, ensuring that text data was structured and ready for machine learning (Bird et al., 2009).
* **Neural Network**:
  + A feedforward neural network built using Keras, classified user intents efficiently using the bag-of-words approach and accurately predicted responses (Chollet, 2018).

Following this streamlined process, we successfully developed a functional chatbot that analyses symptoms and delivers relevant medical advice in real-time.

# **Evaluation**

The evaluation of the medical chatbot was conducted by analyzing its performance metrics and usability:

**Performance Metrics**

The chatbot was trained using a dataset with predefined intents and achieved an **accuracy of 96.06%**, reflecting its ability to classify user intents correctly. The model's F1-score of 0.75 indicates a balanced precision and recall performance across various intents.

**Usability**

The chatbot was designed for interaction via a command-line interface. It successfully responded to user inputs in real-time and provided relevant medical advice and remedies based on symptoms.

# **Limitation**

# The chatbot relies on a predefined dataset, which restricts its adaptability to new or complex queries. Limited data diversity impacts its ability to handle rare intents with high precision. Furthermore, the current implementation lacks a graphical interface, which could enhance usability and accessibility.

# **Conclusion**

The medical chatbot highlights the promising role of artificial intelligence in healthcare, providing preliminary diagnoses, medical advice, and guidance on when to seek professional assistance. Although limitations exist, such as difficulties in handling synonyms, reliance on complete user inputs, and constraints within the dataset, the prototype signifies an important step toward improving healthcare accessibility and reducing the strain on healthcare professionals. With further refinement and development, this technology has the potential to play a transformative role in telemedicine and patient support (Topol, 2019; Zhou et al., 2020).

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