# Symptom Checker Chatbot

Sakshi Rai<sup>1</sup>, Ujawal Rai<sup>2</sup>, Dr. Nitin Janwe<sup>3</sup>, Prof Sharda Dabhekar<sup>4</sup>

<sup>1,2</sup>Department of Computer Science and Engineering, Rajiv Gandhi College of Engineering Research And Technology, Chandrapur, India

<sup>3</sup>H.O.D, Department of Computer Science and Engineering, Rajiv Gandhi College of Engineering Research And Technology, Chandrapur, India

<sup>4</sup>Guide, Department of Computer Science and Engineering, Rajiv Gandhi College of Engineering Research And Technology, Chandrapur, India

Abstract: Our study introduces a chatbot for preliminary disease diagnosis, employing Flask, NLP, and machine learning techniques. Through Spacy's pretrained model, the chatbot extracts symptom keywords, which are vectorized using TF-IDF and fed into a Random Forest classifier. The chatbot provides users with accurate disease predictions, enriched with dynamically integrated disease descriptions and precautions. This fusion of NLP and machine learning demonstrates a scalable approach to healthcare technology.

Keyword Extraction: Spacy was used to tokenize the text and extract keywords, filtering out stop words and nonalphabetic tokens.

# 1.INTRODUCTION

The integration of technology into healthcare services has opened up new opportunities for enhancing patient care and accessibility. Our paper focuses on one such innovation: a symptom-checker chatbot designed to assist users in identifying potential diseases based on their reported symptoms. By harnessing the power of Flask, Spacy, and Scikit-learn, we have developed a robust and efficient tool for preliminary health assessment that does not rely on advanced AI techniques. This introduction provides an overview of our chatbot's development and implementation, emphasizing its significance in providing practical and scalable solutions for preliminary disease diagnosis and health information dissemination.

#### 2. METHODOLOGY

#### Data Collection

The dataset used for this project consists of symptoms and their associated diseases. The data was sourced from publicly available health datasets and compiled into a comprehensive CSV file. Additional datasets were used to gather detailed disease descriptions and precautionary measures, ensuring that the chatbot can provide well-rounded and informative responses.

# **Data Preprocessing**

Loading Data: The datasets were loaded using pandas for data manipulation and analysis.

Symptom Extraction: Columns starting with 'Symptom\_' were identified and extracted, with symptoms combined into a single text entry per disease case.

## Text Vectorization

A TF-IDF vectorizer from Scikit-learn was employed to transform the text data (symptoms) into numerical features. This method converts a collection of raw documents to a matrix of TF-IDF features, which are suitable for machine learning models.

#### **Model Training**

A Random Forest classifier was chosen due to its robustness and accuracy in handling classification tasks. The model was trained on the vectorized symptoms and corresponding disease labels from the dataset. The training process involved splitting the dataset into training and test sets, fitting the model, and validating its performance.

### **Chatbot Implementation**

The chatbot was implemented using Flask, a lightweight WSGI web application framework in Python. The web interface allows users to input their symptoms and interact with the chatbot.

#### **Handling Conversations** if len(predicted diseases) > 0: A conversation management system was implemented predicted disease = predicted diseases[0] to handle ongoing user interactions, ensuring that response = f"Based on your symptoms, it appears multiple symptoms can be gathered and processed that you may have {predicted disease}." effectively. # Add disease description to response if predicted disease in disease descriptions: 3. CODE response Description: {disease descriptions[predicted disease]}" from flask import Flask, render template, request, # Add disease precautions to response isonify if predicted disease in disease precautions: response += "\nPrecautions:" import pandas as pd import spacy precautions = sklearn.ensemble disease precautions[predicted disease] from import RandomForestClassifier for key, value in precautions.items(): response $+= f'' \cdot n - \{key\}: \{value\}''$ from sklearn.feature extraction.text import TfidfVectorizer else: app = Flask(name)response += "\nPrecautions: Precautions not available for this disease." # Load dataset from CSV file def load dataset(file path): df = pd.read csv(file path) response = "I couldn't find a matching disease for the provided symptoms." return df # Load disease descriptions from CSV file return response def load disease descriptions(file\_path): # Load dataset df = pd.read csv(file path)dataset = load dataset("dataset.csv") # Load disease descriptions df.set index('Disease')['Description'].to dict() disease descriptions # Load disease precautions from CSV file load disease descriptions("symptom description.csv def load disease precautions(file path): df = pd.read csv(file path)# Load disease precautions disease precautions df.set index('Disease').to dict(orient='index') load disease precautions("symptom precaution.csv" # Load English tokenizer, tagger, parser, and NER nlp = spacy.load("en core web sm") # Split dataset into symptoms and diseases # Define function to extract keywords from text symptoms columns = [col for col in dataset.columns def extract keywords(text): if col.startswith('Symptom')] doc = nlp(text)symptoms return [token.text.lower() for token in doc if not dataset[symptoms\_columns].apply(lambda x: token.is stop and token.is alpha] '.join(x.dropna()), axis=1) # Define function for chatbot conversation diseases = dataset['Disease'] def chat(user input, vectorizer, classifier, # Vectorize symptoms vectorizer = TfidfVectorizer() disease descriptions, disease precautions): symptoms = extract\_keywords(user\_input symptoms vectorized vectorizer.fit transform(symptoms) # Vectorize symptoms symptoms text = ''.join(symptoms) # Train classifier classifier = RandomForestClassifier() symptoms\_vectorized classifier.fit(symptoms vectorized, diseases) vectorizer.transform([symptoms text]) # Predict diseases based on symptoms # Flag to indicate whether conversation is ongoing predicted diseases ongoing conversation = False symptoms list = [] classifier.predict(symptoms vectorized)

```
# Define endpoint for symptom checker
@app.route('/symptom checker', methods=['POST'])
def symptom_checker():
  global ongoing conversation, symptoms list
   data = request.json
  user input = data['user input']
 if not ongoing conversation:
    ongoing conversation = True
    symptoms list.clear()
  if user input.lower() == 'done':
    if len(symptoms list) < 1:
       response = "Bot: Please provide at least one
symptom."
    elif len(symptoms list) < 2:
       response = "Bot: Please provide at least two
symptoms for accurate assessment."
    else:
       response =
                      chat('
                               '.join(symptoms list),
                               disease descriptions,
vectorizer,
                classifier,
disease precautions)
       ongoing conversation = False
       response += "\nBot: Do you want to restart the
conversation? (yes/no)"
  else:
symptoms list.append(user input.strip().lower())
    response = "Bot: Do you have any other
symptoms? If yes, please describe them. If no, type
'done'."
return jsonify({'response': response})
# Define route for serving the homepage
@app.route('/')
def home():
  return render template('index.html')
if name == ' main ':
  app.run(debug=True)
```

#### 4. RESULT

The chatbot underwent rigorous testing with various user inputs to evaluate its performance. It demonstrated high accuracy in predicting diseases and provided informative descriptions and precautions. User feedback indicated satisfaction with the chatbot's functionality and usability.

### **5.REFERENCE**

[1] Gupta, R., et al. (2023). "Advances in Natural Language Understanding: A Comprehensive

- Survey." ACM Computing Surveys, 56(3), 123-145.
- [2] Zhang, Y., Kim, M. (2022). "Multilingual Natural Language Processing: Challenges and Opportunities." Proceedings of the International Conference on Language Resources and Evaluation, 78-91.
- [3] Chen, L., et al. (2024). "Integration of Wearable Health Devices with Chatbot Systems: A Review." Journal of Medical Internet Research, 16(5), e11234.