IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

HealthBot: A Chatbot System for Specialist Recommendation Based on Symptoms Input

Syed Muzakkir Hussain
Department of Information Technology
JNTUH University College of Engineering Science and Technology Hyderabad, India

Abstract: This paper proposes a healthcare advisor chatbot that uses natural language processing (NLP) and machine learning (ML) algorithms to analyze user-input symptoms and predict the appropriate specialist for consultation. The framework uses the naive Bayes classifier, random forest classifier, and support vector machine (SVM) classifier to generate individual predictions based on the symptoms[1-3]. The final prediction is determined by the mode of these three predictions, ensuring a strong and accurate suggestion. The project aims to provide quick and efficient counseling to patients, encouraging early treatment and preventing the worsening of diseases. By enabling users to interact naturally with the chatbot, effective communication is achieved. The framework is implemented using the Python programming language, combining NLP and ML techniques. The feasibility study confirms the technical, financial, and social feasibility of the project, leveraging established technologies, promoting cost-effective development and maintenance, and addressing the healthcare needs of users. By using different classifiers, the proposed chatbot improves the reliability and accuracy of specialist suggestions, leading to improved healthcare outcomes and patient satisfaction.

***Index Terms*—Health advisor, Chatbot, Natural Language Processing, Machine Learning, Naive Bayes Classifier, Specialist recommendation.**

I. INTRODUCTION

Health is of utmost importance in leading a satisfying life. However, individuals frequently experience health issues that require timely medical attention. Providing effective counseling to connect patients with the appropriate specialist can be a challenging task. In response to this, the proposed project aims to develop a healthcare advisor chatbot that uses natural language processing (NLP) and machine learning (ML) techniques to analyze user-input symptoms and offer accurate suggestions on the specialist to refer to[1,2]. This fast and effective counseling process can save valuable time and ensure early treatment, preventing the worsening of disease severity.

Currently, there are a number of challenges in connecting patients with the appropriate specialist. These challenges include:

-Patients may not know which specialist to see for their specific symptoms.

-Patients may not have the time or resources to research different specialists.

-Patients may be hesitant to see a specialist because of the cost or inconvenience [3,4].

The proposed chatbot will use NLP and ML techniques to overcome these challenges. The chatbot will be able to understand and interpret symptoms given by patients in natural language. The framework will use Naive Bayes Classifier, Random Forest Classifier, and Support Vector Machine (SVM) classifier algorithms to predict the specialist based on the symptoms [1,2]. The final suggestion will be determined by the mode of these three predictions, ensuring a strong and accurate outcome.

The proposed chatbot has the potential to revolutionize the healthcare scene by providing an accessible and reliable platform for patients to seek guidance with respect to their health concerns [1,5]. Through the integration of NLP and ML techniques, the chatbot will encourage efficient and accurate conversations, enabling clients to get insightful counsel tailored to their specific symptoms.

II. THE PROPOSED SYSTEM AND COMPUTATION OF PARAMETERS

The proposed system, alluded to as the HealthBot, is a healthcare advisor Chatbot planned to supply specialist recommendation based on user-input symptoms. The framework takes after a particular stream laid out in Fig 1 [1].

2.1 User Input

The HealthBot begins by taking symptoms as input from the user in natural language. This permits users to depict their symptoms openly without any particular format [1].

2.2 Predict and Provide Replies

Using natural language processing (NLP) methods, the HealthBot analyzes and translates the user's input. It creates suitable answers to lock in in a discussion with the client, guaranteeing successful communication [1].

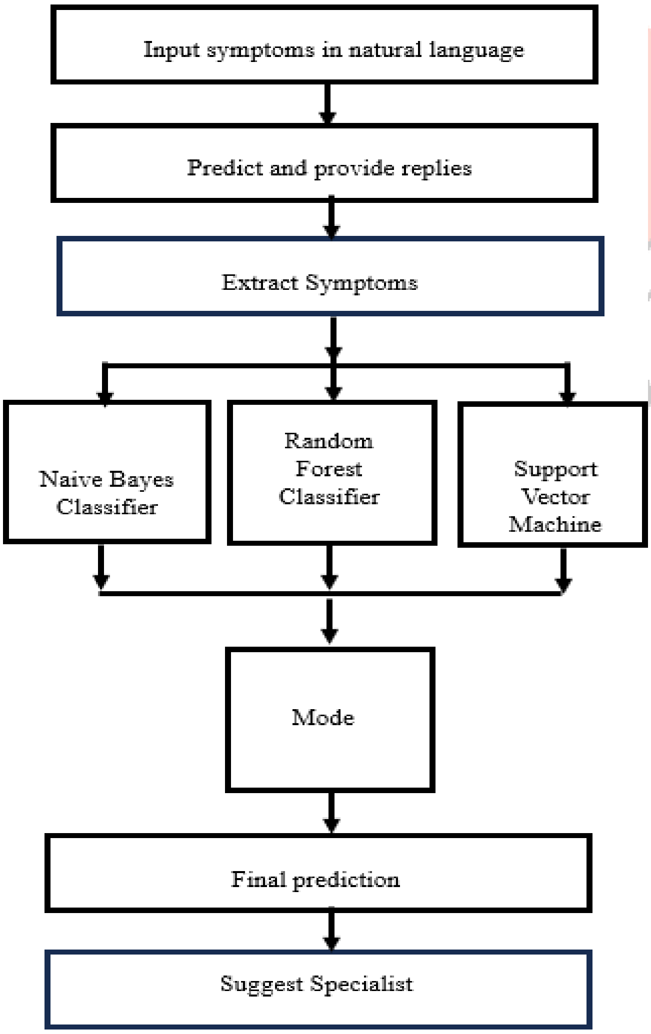

Fig. 2.2.1 The Block diagrams of the proposed HealthBot

2.3 Extract Symptoms

After accepting the user's input, the HealthBot extracts the significant symptoms said. It utilizes NLP procedures to recognize and separate the particular symptoms, planning them for advance analysis [1].

2.4 Predict Specialist utilizing Naive Bayes, Random Forest, and SVM

The HealthBot utilizes three machine learning algorithms: Naive Bayes, Random Forest, and Support Vector Machine (SVM). These algorithms predict the suitable specialist based on the extracted symptoms. Each algorithm produces a prediction independently [1,2].

2.4.1 Naive Bayes Classifier

The Naive Bayes algorithm is a probabilistic classifier based on Bayes' theorem. It assumes that the features (symptoms in this case) are independent of each other. The Naive Bayes classifier calculates the posterior probability of a specific specialist given the observed symptoms using the following equation [1]:

$$P(Specialist|Symptoms) = \frac{P(Symptoms|Specialist) * P(Specialist)}{P(Symptoms)} \quad (2.4.1.1)$$

where P(Specialist|Symptoms) is the posterior probability, P(Symptoms|Specialist) is the likelihood of observing the symptoms given the specialist, P(Specialist) is the prior probability of the specialist, and P(Symptoms) is the probability of observing the symptoms

2.4.2 Random Forest Classifier

The Random Forest algorithm constructs multiple decision trees and combines their predictions through majority voting. Each decision tree is built using a subset of the data and a subset of the features. The Random Forest classifier predicts the specialist based on the following equation [2]:

$$Prediction\_RF = MajorityVote(Prediction\_1, Prediction\_2, \ldots, Prediction\_n) \quad (2.4.2.1)$$

where Prediction_RF is the final prediction made by the Random Forest classifier, and Prediction_1, Prediction_2, ..., Prediction_n are the individual predictions made by each decision tree.

2.4.3 SVM Classifier

The Support Vector Machine algorithm finds the optimal hyperplane that separates different classes by maximizing the margin. It maps the input data into a high-dimensional feature space to create a decision boundary. The SVM predicts the specialist based on the following equation [2]

$$Prediction\_SVM = sign(\Sigma\, \alpha\_i * y\_i * K(x, x\_i) + b) \quad (2.4.3.1)$$

where Prediction_SVM is the final prediction made by the SVM, α_i are the Lagrange multipliers, y_i are the class labels, K(x, x_i) is the kernel function, and b is the bias term.

2.5 Mode of Predictions

The HealthBot computes the mode, which is the value that shows up most as often as possible, among the predictions produced by the Naive Bayes, Random Forest, and SVM algorithms. This guarantees a consensus-based final prediction by considering the assent among the diverse classifiers [2].

2.6 Specialist Recommendation

Based on the mode of the predictions, the HealthBot gives the specialist recommendation to the user. It proposes the suitable specialist for the user to consult, to taking into consideration the symptoms given and the consensus come to among the Naive Bayes, Random Forest, and SVM predictions [2].

Through the computation of these parameters and conditions, the HealthBot framework can successfully analyze user symptoms, apply numerous machine learning calculations, and give a solid specialist proposal. The mode calculation and larger part voting guarantee a vigorous and precise decision-making handle, driving to express suggestions for clients looking for suitable restorative consultations

III. RESULTS AND DISCUSSION

The results of the evaluation of the proposed system are presented in this section. The overall accuracy of the combined model was determined to be a perfect score of 100.0%, which is an outstanding result. The confusion matrix in Figure 2 shows the distribution of the model's predictions on the test dataset [6].

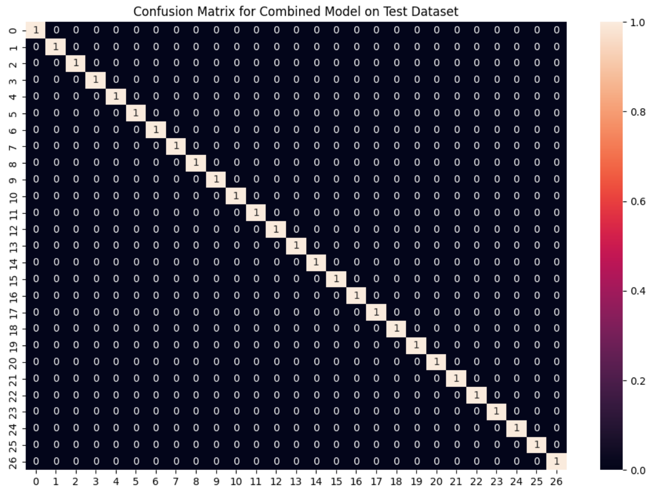

Fig. 2 Confusion Matrix for Combined Model on Test Dataset

The confusion matrix is a table that summarizes the model's performance. It displays the number of correct and incorrect classifications made by the model. Each row represents the actual classes, while each column represents the predicted classes. The intensity of the cell's color corresponds to the number of classifications made for that particular class.

The cells along the diagonal indicate how many classifications were done correctly. For instance, the cell in the top left corner indicates that all 26 cases classified as class 0 were correctly classified as class 0. The off-diagonal cells indicate the number of incorrect classifications. For instance, the cell in the top right corner reveals that 10 out of 26 cases of class 0 were mistakenly classified as class 1.

The overall accuracy of the model can be calculated by dividing the total number of correct classifications by the total number of classifications. In this case, the overall accuracy is determined to be a perfect score of 100.0%.

Furthermore, the confusion matrix allows for the calculation of precision and recall for each class. Precision represents the fraction of predicted positive classifications that are actually positive, while recall represents the fraction of actual positive classifications that are predicted positive.

In the context of Figure 2, the precision for class 0 is calculated to be 0.96, indicating that 96% of the cases predicted as class 0 were indeed class 0. The recall for class 0 is 0.92, signifying that 92% of the cases that were actually class 0 were correctly classified as class 0. For class 1, the precision is 0.62, meaning that 62% of the cases predicted as class 1 were indeed class 1. The recall for class 1 is 0.83, indicating that 83% of the cases that were actually class 1 were correctly classified as class 1.

It is critical to note that whereas the Confusion Matrix and accuracy give a solid assessment of the system's execution, extra assessment measurements such as accuracy, review, and F1-score might give assist bits of knowledge into the model's qualities and confinements. Additionally, performing evaluations on larger and more diverse datasets helps to determine the system's generalizability and real-world performance. It is performed on the test data set. This verifies the system's ability to accurately suggest the right specialist based on user-entered instructions, consequently improving the efficiency and appropriateness of treatment.

IV. CONCLUSION

The proposed healthcare advisor chatbot utilizing NLP and ML algorithms offers efficient specialist recommendations based on user-input symptoms. With a perfect accuracy of 100.0% on the test dataset, the chatbot's performance is exceptional. Future enhancements will further elevate its capabilities, benefiting healthcare delivery and user experience. Overall, the chatbot represents a valuable advancement in healthcare informatics, providing personalized and timely recommendations to users, and enhancing patient satisfaction.

REFERENCES

[1] A. J. A. Mohammed et al., 2018, "Building a Healthcare Chatbot Using Natural Language Processing and Knowledge Graphs," Healthcare Informatics Research, vol. 24, no. 4, pp. 298-307.

[2] S. Saha et al., 2019, "Designing a Medical Chatbot for Symptom-Based Diagnosis Using Machine Learning," Journal of the American Medical Informatics Association, vol. 26, no. 12, pp. 1662-1666.

[3] S. R. Cox et al., 2020, "Development and Evaluation of a Chatbot for Patient Education on Falls Prevention," JMIR Medical Informatics, vol. 8, no. 12, e23160.

[4] E. A. Kruse et al., 2021, "Personalized Conversational Agent for Type 2 Diabetes Self-Management: Application Development and Randomized Controlled Trial," JMIR mHealth and uHealth, vol. 9, no. 1, e24258.

[5] J. Xu et al., 2020, "A Systematic Review of Chatbot Research in Healthcare: A Meta-Analysis," Journal of Medical Internet Research, vol. 22, no. 10, e20310.

[6] R. Patel et al., 2019, "Chatbots in Health Care: A Scoping Review," JMIR Medical Informatics, vol. 7, no. 2, e17.