Chronic disease prediction chatbot using deep learning and machine learning algorithms

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ABSTRACT

Ever since the rise of human civilization, more and more diseases have been discovered with the rapid growth of medical knowledge. This sheer volume of information makes it hard for humans to memorize or even utilize it efficiently. Thus, machine learning emerged as a powerful tool for complex calculations by offering a solution to this challenge. This paper intends to use deep learning and machine learning algorithms to develop a predictive model that can recognize potential diseases based on symptoms. The model is then seamlessly integrated into a text-based disease prediction assistant chatbot that serves as a communication platform between the users and the system. The algorithms researched for the disease prediction models are k-nearest neighbours (KNN), support vector machines (SVM), random forest, and neural networks. After that, a chatbot application is created by integrating long short-term memory (LSTM), natural language toolkit (NLTK) libraries, and Telegram. As a result, the SVM models demonstrated excellent performance by achieving an accuracy of 92.24%, closely followed by random forest with 92.23%, KNN with 91.57%, and artificial neural network (ANN) with 91.52% accuracy. In short, this paper presents a potential solution for a more accurate disease prediction tool by implementing the best disease prediction model with the chatbot models together.

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1. INTRODUCTION

The world today has been on high alert for public health hazards due to the COVID-19 outbreak since the end of 2019. Worse still in July 2022, a second public health threat, Monkeypox, was declared a worldwide health epidemic while the COVID-19 pandemic is still raging. These successive public health threats have put immense strain on a population still recovering from the initial impact. However, these crises have also heightened public awareness regarding health issues, particularly the importance of early symptom detection for timely treatment [1], [2]. Yet, the vast number of diseases and their associated symptoms make it impractical for individuals to memorize them accurately. This creates a significant challenge in analyzing potential illnesses based on specific symptoms.

Fortunately, machine learning techniques offer a promising solution [3]-[5]. These techniques can accurately predict diseases based on black-and-white data. Machine learning comes at no cost and is less influenced by personal judgments. The machine learning model will act like the brain of a physician while the chatbot acts as the bridge to communicate with the patient [6]-[8]. A chatbot can be handy in collecting the necessary inputs and guiding the conversation in the right direction [9]-[12]. Therefore, by combining the disease prediction model with the chatbot, people can reach out for help from this disease prediction assistant to identify their possible conditions for free.

Some of the well-known machine learning techniques are decision tree, random forest, enseble learning, boosted trees, and so on [13], [14]. As decision tree can predict using a predefined classification tree that combines both numerical and categorical features, it can yield high average accuracies. Random forests, which is the evolution of decision trees, have the advantage of handling huge amounts of inputs and determining the importance of features [15]. The ensemble learning classifier is also a good choice for disease prediction. It used some simple but effective methods for dominant or weak classifiers while producing a well-balanced output. As such, it can solve the possible domination of single tree classifiers [16]. C4.5 is an extension of decision tree that can deal with the issue of incomplete data very well. Hence it fits perfectly for disease prediction since the patient records are impossible to be complete [17]. Additionally, the boosted trees can detect complicated data patterns. Yet, the performance of this algorithm depends a lot on the dataset [18]. If the data are noisy, then the model could begin to overfit by simulating the noise.

On the other hand, deep learning [19]-[21] is an artificial neural network-based (ANN) machine learning which can imitate the way humans gain certain types of knowledge by learning from large amounts of data. Deep learning does not require much human intervention to learn from its mistakes since it can gain knowledge itself by transferring data across layers of a neural network. Besides, deep learning is also able to execute feature extraction by itself without being expressly instructed to do so. Thus, deep learning is more capable when it comes to decision-making. However, there is a limitation to the usage of deep learning. Deep learning needs large and high-quality data to ensure its performance. But the problem now is that high-quality health information datasets are very hard to obtain. The reason for this happening is that health-related information is a type of personal privacy. It is supposed to be confidential and secured by the authorities. Therefore, there aren't many existing papers that implement deep learning methods in this field of disease prediction.

Some of the deep learning methods are forward chaining [22], longitudinal siamese neural-network (LSN) [23], convolutional neural network (CNN) [24], and multilayer perceptron (MLP) [25]. MLP is a feedforward ANN that translates the input to a nonlinear space before attempting to predict the related outputs. During the training phase, it will use the backpropagation algorithm to train the model. MLP can balance the perception by adding an identity input with weight b called Bias. MLP is famous for its slow but low-risk modeling. It is slow but always offers a steady investment return. Last but not least, the CNN is capable of both structured and unstructured data of a hospital to perform classification. However, CNN is mainly for image data processing. In most cases, CNN returns a high accuracy in image recognition problems and weight sharing [26], [27]. There are also some drawbacks in which CNN are lacking spatial invariance with respect to the input data and needs relatively larger training data compared to ANN and recurrent neural network (RNN).

From the review, we noticed the importance of having reliable solutions to overcome the healthcare staff shortage issue. Despite the significant potential of these methods to enhance disease prediction accuracy, their application and studies in chronic disease remain limited. The current landscape of chronic disease prediction has not been fully explored, leaving an opportunity to develop innovation. Therefore, this research aims to develop automated solutions using chatbot empowered by machine learning techniques. It is capable of predicting potential chronic diseases based on provided symptoms. This innovative approach allows individuals to seek help from the chatbot to identify potential problems. By leveraging cutting-edge technology, we can mitigate the downsides associated with relying solely on healthcare professionals, such as misjudgments, high costs, and outdated information [10], [28]-[30]. In brief, this paper presents a better solution to empower individuals with free, accurate chronic disease prediction through the implementation of a machine learning-powered chatbot.

2. METHOD

2.1. The architecture

The implementation of the chronic disease prediction chatbot revolves around two main categories: disease prediction models and chatbot models. The disease prediction models focus on utilizing machine learning algorithms to predict chronic diseases based on the user's symptoms. After completing literature review, support vector machines (SVM), ANN, random forest, and k-nearest neighbours (KNN) are chosen due to their proven effectiveness in handling different types of data and their suitability for classification tasks. SVM is known for its robustness in high-dimensional spaces and its ability to create a clear margin of separation between classes. ANN is selected for its resistance to overfitting capacity to model complex relationships and learn from large datasets. Random forest is chosen for its resistance to overfitting and high accuracy even when handling a large number of features. KNN is included for its intuitive approach, particularly in scenarios where the decision boundary is irregular or complex. The chatbot models focus on enhancing user interaction and engagement with the assistance of long short-term memory networks (LSTM). More details of implementations are shown in Figure 1.

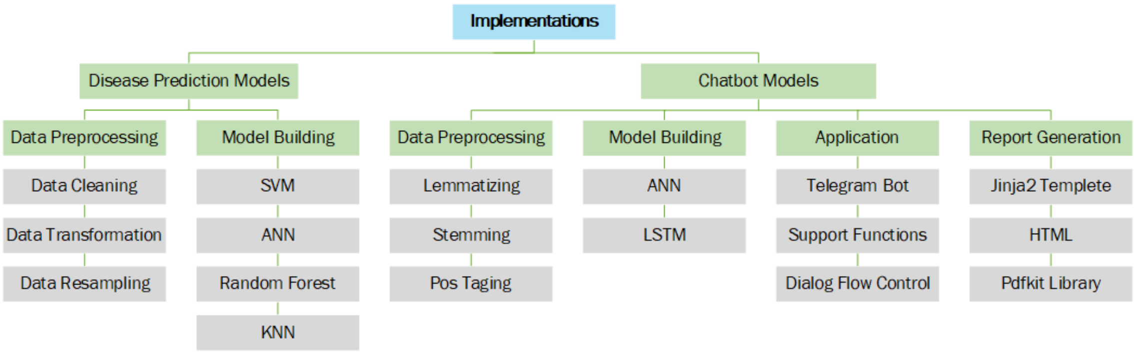

Figure 1. The drill-down implementations of chronic disease prediction chatbot

After data preprocessing, the dataset is split into training and testing sets with an 80:20 ratio using stratification to ensure that the class distribution is preserved. For the traditional machine learning algorithms, the models will undergo hyperparameter tuning. On the other hand, for ANN, different designs are experimented with to find the best construction and compilation. The minimal targeted testing accuracy is set to 85%. The process of training and testing the disease prediction models is depicted in Figure 2.

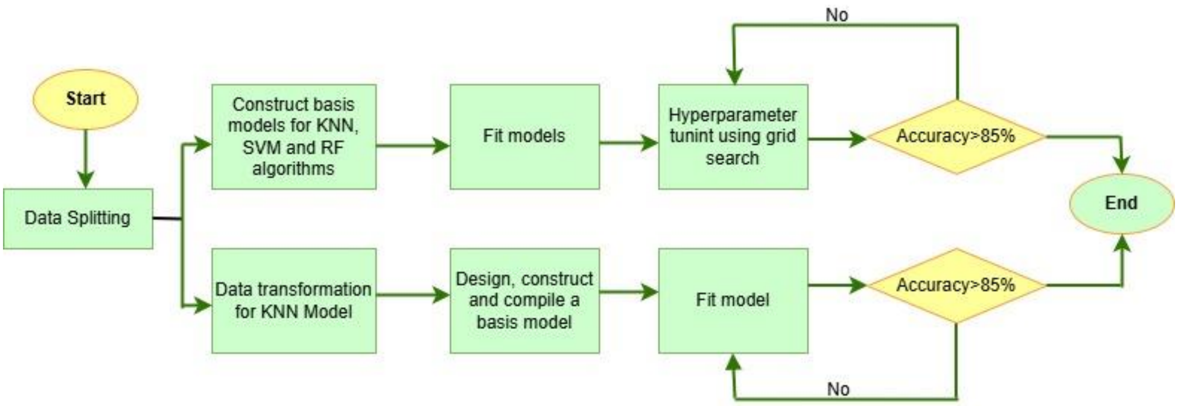

Figure 2. The flowchart of building the chronic disease prediction models

The best chronic disease prediction model will then be implemented into a chatbot application. The chatbot application operates through the Telegram platform for any individual who is seeking medical consultation. In Figure 3, the consultation begins when the user initiates a consultation with the chatbot through Telegram.

The user can input their symptoms or describe their medical condition while the chatbot's underlying system starts analyzing the user's message. Natural language toolkit (NLTK) processing techniques, such as tokenization and synonym identification, are employed to understand and process the user's input effectively. Next, the chatbot collects entities, which in this case refers to symptoms. It uses a combination of a preset symptoms list and an LSTM model to identify and extract the symptoms mentioned by the user in their message. This step ensures that the relevant symptoms are collected for further analysis.

In cases where the number of collected symptoms does not meet the predefined threshold, or if there is a need for additional information, the chatbot replies to the user's message. The reply may involve requesting more symptoms, seeking correlations between symptoms, or asking for confirmation on specific details. Based on the state of the diagram flow, the chatbot adjusts its response to engage the user effectively and gather the necessary information. If the number of collected symptoms exceeds a predefined threshold

(N) or if the user signals the end of symptom input, the chatbot proceeds to feed the collected symptoms into the disease prediction model built. Then, the results are then presented to the user, providing insights into potential diseases based on the symptoms provided.

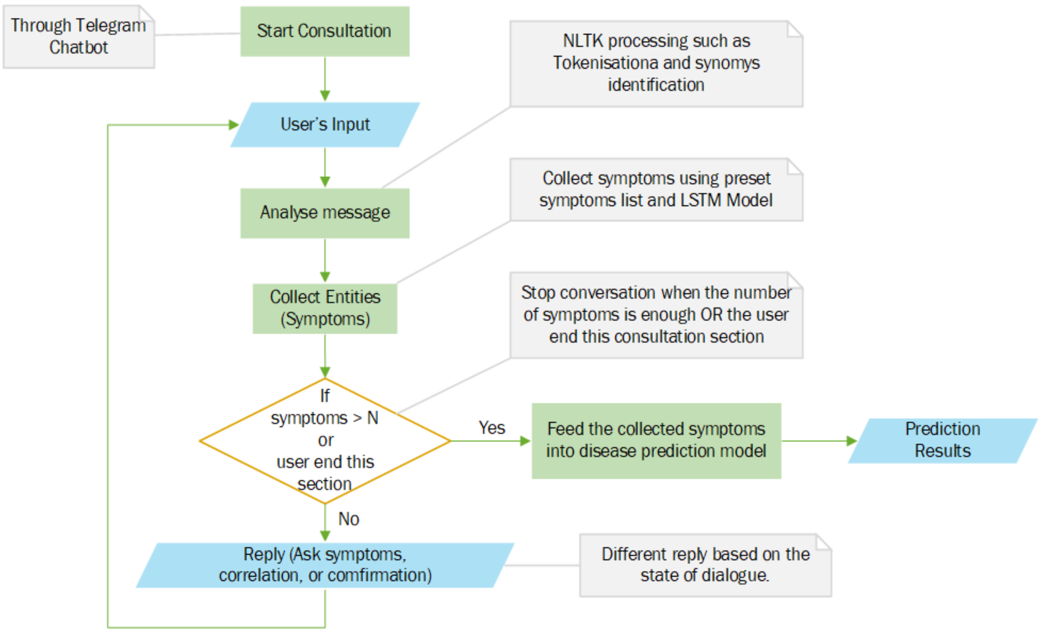

Figure 3. The design of chronic disease prediction chatbot application

2.2. The dataset and data processing

The datasets are obtained from Kaggle (as depicted in Table 1 and Figure 4). The dataset consists detailed disease-symptom relationship, but it is quite messy and require additional cleaning. As such, data cleaning is necessary to boost overall outcomes by guaranteeing the best information quality. The first step of the data cleaning process is to drop other non-disease/symptom columns such as the desc column, common tests and procedures desc column, and common tests and procedures column. However, it might be a bit tricky due to the misplaced symptoms columns' values in the wrong columns as depicted in Figure 5. Figure 6 shows the snapshot of the dataset after converting those non-disease/symptom values into NaN.

Table 1. Description of dataset used

Source	Name	No. of records	No. of diseases	Details	Notes
Kaggle	Kaggle.csv	796	796	Disease name, symptoms, explanation, treatment, symptoms by age.	Summary of disease-symptoms relationship. Used larger samples compared to other datasets. *(Very messy)*

	name	symptoms	Unnamed: 2	Unnamed: 3	Unnamed: 4	Unnamed: 5	Unnamed: 6
0	Panic disorder	[{"symptoms":"Anxiety and nervousness"}	{"symptoms":"88"}	{"symptoms":"Depression"}	{"symptoms":"55"}	{"symptoms":"Shortness of breath"}	{"symptoms":"40"}
1	Vocal cord polyp	[{"symptoms":"Hoarse voice"}	{"symptoms":"91"}	{"symptoms":"Sore throat"}	{"symptoms":"47"}	{"symptoms":"Difficulty speaking"}	{"symptoms":"27"}
2	Turner syndrome	[{"symptoms":"Groin mass"}	{"symptoms":"27"}	{"symptoms":"Leg pain"}	{"symptoms":"27"}	{"symptoms":"Hip pain"}	{"symptoms":"27"}
3	Cryptorchidism	[{"symptoms":"Symptoms of the scrotum and test...	{"symptoms":"50"}	{"symptoms":"Swelling of scrotum"}	{"symptoms":"16"}	{"symptoms":"Pain in testicles"}	{"symptoms":"9"}
4	Poisoning due to ethylene glycol	[{"symptoms":"Abusing alcohol"}	{"symptoms":"78"}	{"symptoms":"Fainting"}	{"symptoms":"64"}	{"symptoms":"Hostile behavior"}	{"symptoms":"45"}
...	...	...	...	...	...	...	...

Figure 4. Snippert of the dataset

Desc
lipid panel
{"symptoms":"Back mass or lump"}
Pituitary adenoma Pituitary adenomas are noncancerous tumors that occur in the pituitary gland. Pituitary adenomas are generally divided in
Uterine fibroids Also known as Fibroids
Idiopathic nonmenstrual bleeding Idiopathic nonmenstrual bleeding is encountered rarely on Symcat. We will add more content to this page if
Chalazion Also known as Meibomian Cyst and Tarsal Cyst A chalazion (/kəˈleɪziən/; plural chalazia /kəˈleɪziə/)
Ovarian torsion Also known as Ovary Torsion
Retinopathy due to high blood pressure Also known as Hypertensive Retinopathy Hypertensive retinopathy is damage to the retina and retina
Vaginal yeast infection Also known as Vaginal Candidiasis
Mastoiditis Mastoiditis is the result of an infection that extends to the air cells of the skull behind the ear. Specifically
Lung contusion Also known as Pulmonary Contusion A pulmonary contusion (or lung contusion) is a contusion (bruise) of the lung
Hypertrophic obstructive cardiomyopathy (HOCM) Also known as HCM
{"symptoms":"3"}

Figure 5. Example of misplaced symptoms columns' values in wrong columns

Unnamed: 19	Unnamed: 20	Unnamed: 21	Unnamed: 22	Unnamed: 23	Unnamed: 24	Desc	commonTestsAndProceduresDesc	commonTestsAndProcedures
NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Muscle cramps	NaN	NaN	7	Low back cramps or spasms	7	Back mass or lump	4	NaN
Nosebleed	20	Long menstrual periods	20	Muscle swelling	1	NaN	NaN	NaN
Vaginal discharge	8	Involuntary urination	8	Cramps and spasms	6	NaN	NaN	NaN
Frequent menstruation	17	Blood clots during menstrual periods	17	Sweating	17	NaN	NaN	NaN
...	...	...	...	...	...	...	...	...

Figure 6. Snapshot of dataset after data cleaning process

2.3. Data preprocessing

Next step is to clean values into a more human-readable. For example, the extra regexes such as {} and "" are removed. Figure 7(a) shows the snippet of the original format, while Figure 7(b) shows the new format after the cleaning process.

[{"symptoms":"Anxiety and nervousness"}	{"symptoms":"88"}	{"symptoms":"Depression"}	{"symptoms":"55"}

(a)

Anxiety and nervousness	88	Depression	55

(b)

Figure 7. The data cleaning process: (a) original format of symptoms columns and (b) new format of symptoms columns after cleaning

The third step is to fix the bugs that slipped through the net by manually scanning the Excel file using Google Sheets. Lastly, read the file into the Jupyter notebook again to perform some basic processes such as renaming the columns and removing duplicate rows. Figure 8 shows the snippet of the final output of the dataset after the cleaning process. The subsequent process is data transformation. The objective of data transformation is to label encode the cleaned dataset in the right ways. At the end of the data transformation, the columns will be changed to all the symptoms that appeared in this dataset while the rows will contain the diseases' names while the values in each cell will be either 0 or 1, as depicted in Figure 9.

The next process is data resampling. It is a set of statistical procedures utilizing data samples to increase accuracy and reduce uncertainty in the population. By evaluating the transformed dataset process, there are certain characteristics that should be noted. First is the imbalanced distribution of each disease.

Although the names of diseases are ambiguous, the long tail of the bar chart proves the imbalance and high variance in the number of records of each disease. For example, the largest number of records is “Lymphogranuloma venereum” with 100 records, while the lowest is “Open wound due to trauma” with 2 records. Therefore, upsampling for the disease with a low number of records is required to alter a signal in a way that increases the sample rate unnaturally. However, before performing upsampling, there are 11 diseases with a number of records under 20 that need to be eliminated to prevent overfitting during upsampling. After that, the dataset is fed into the synthetic minority oversampling technique (SMOTE) to perform an upsample of the records of diseases to 100.

	name	sym1	count1	sym2	count2	sym3	count3	sym4	count4	sym5	...
0	Panic disorder	Anxiety and nervousness	88	Depression	55	Shortness of breath	40.0	Depressive or psychotic symptoms	33.0	Sharp chest pain	...
1	Vocal cord polyp	Hoarse voice	91	Sore throat	47	Difficulty speaking	27.0	Cough	27.0	Nasal congestion	...
2	Turner syndrome	Groin mass	27	Leg pain	27	Hip pain	27.0	Suprapubic pain	27.0	Blood in stool	...
3	Cryptorchidism	Symptoms of the scrotum and testes	50	Swelling of scrotum	16	Pain in testicles	9.0	Flatulence	9.0	Pus draining from ear	...
4	Poisoning due to ethylene glycol	Abusing alcohol	78	Fainting	64	Hostile behavior	45.0	Drug abuse	45.0	Depressive or psychotic symptoms	...
...	...	...	...	...	...	...	...	...	...	...	...

Figure 8. Final output of data cleaning procedures

	name	Anxiety and nervousness	Depression	Shortness of breath	Depressive or psychotic symptoms	Sharp chest pain	Dizziness	Insomnia	Abnormal involuntary movements	Chest tightness	...	Stuttering or stammering	Problems with orgasm	Nose deformity
0	Panic disorder	1	1	1	1	1	1	1	1	1	...	0	0	0
1	Panic disorder	1	1	1	1	1	1	1	1	1	...	0	0	0
2	Panic disorder	1	1	1	1	1	1	1	1	1	...	0	0	0
3	Panic disorder	1	1	1	1	1	1	1	1	1	...	0	0	0
4	Panic disorder	1	1	1	1	1	1	1	1	1	...	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
52775	Open wound of the nose	0	0	0	0	0	0	0	0	0	...	0	0	0
52776	Open wound of the nose	0	0	0	0	0	0	0	0	0	...	0	0	0
52777	Open wound of the nose	0	0	0	0	0	0	0	0	0	...	0	0	0

Figure 9. Transformed data-whole dataset

2.4. Machine learning models

In the method, hyperparameter tuning for the KNN model was conducted using grid search and the elbow method to determine the optimal k-value, which was found to be 6. The Euclidean distance metric was selected due to its widespread use in KNN algorithms. Grid search was also employed for model training to identify the best combination of hyperparameters. The best combination in this scenario is to use a linear kernel with a C value of 10 and gamma of 1.

For SVM, grid search was applied across various kernel functions, including RBF, linear, polynomial, and sigmoid. Cross-validation was utilized to minimize error rates and ensure the selection of the most effective support vectors. Also, the one-to-rest approach was implemented to divide the multiclass problem into several binary classification tasks. The final combination of hyperparameters is using the linear kernel with C=10 and gamma=1.

Random forest uses the bagging technique to make predictions by aggregating the most voted results from these trees. Hyperparameters such as the number of trees, the number of features considered for splitting, and the maximum depth of the trees were tuned to optimize model performance. For the criterion, both Gini index and entropy were tested to determine the most effective attribute selection measure. After grid search, the Gini criterion is chosen with the combination of unlimited tree depth, 110 decision trees, and feature consideration limited to the square root of the total features.

The neural network was designed with two hidden layers of 16 and 64 units respectively. ReLU activation was used in the hidden layers while Softmax in the output layer with 374 units for multiclass classification. The model was compiled using categorical crossentropy for loss and stochastic gradient descent (SGD) for optimization. Hyperparameters were tuned with a batch size of 16 and training for up to 100 epochs, with early stopping employed to prevent overfitting. Cross-validation was implemented using validation data to monitor model performance.

On the other hand, the disease prediction chatbot is built using entity classification through LSTM networks. It was designed to overcome the limitations of traditional RNNs in capturing and retaining long-term dependencies in sequential data. The LSTM architecture in the chatbot for disease prediction consists of several key components. First, an embedding layer converts words into dense vectors to capture semantic meaning. This is followed by a bidirectional LSTM layer that processes sequences in both forward and backward directions, enabling the model to learn context from both past and future data. A dense layer with ReLU activation introduces non-linearity to enhance learning. A dropout layer reduces overfitting by randomly dropping neurons during training. Lastly, the final dense layer with softmax activation outputs probabilities for each symptom category. The model is compiled using SGD and trained with categorical cross-entropy loss, ensuring effective learning from sequential data. Upon initiating a consultation, NLTK techniques are used for tokenization and synonym identification. This approach not only improves the accuracy of symptom prediction but also ensures that the chatbot can handle complex user inputs and provide relevant disease predictions based on the collected symptoms.

3. RESULTS AND DISCUSSION

3.1. Chronic disease prediction models

Table 2 show the performance evaluation of the disease prediction models. Upon conducting rigorous experiments, the results revealed that all models achieve accuracy above 90%. To ensure a fair comparison, all models were trained and tested on the same preprocessed dataset.

Table 2. The performance evaluation of the chronic disease prediction models

Models	Recall	Precision	F1	Accuracy
SVM	0.9224	0.9540	0.9287	0.9224
Random forest	0.9223	0.9540	0.9286	0.9223
KNN	0.9157	0.9503	0.9225	0.9157
ANN	0.9152	0.9505	0.9217	0.9152

Remarkably, the SVM model demonstrated the best performance by achieving an accuracy of 92.24%. The significant success probably contributed to its ability to identify optimal hyperplane boundaries for multiclass classification. Following closely behind is the random forest model with an accuracy of 92.23%. By utilizing the power of ensemble learning and decision trees, the random forest model can effectively capture complex relationships in the data. Next is the KNN model which achieved an accuracy of 91.57%. The KNN model, captured the relationships between symptoms and diseases accurately by optimally considering the nearest neighbors. Lastly, the ANN algorithm has also demonstrated its proficiency in learning intricate patterns and relationships within the data by achieving a high accuracy of 91.52%.

One possible contributing factor to the outcome is the complexity of the multi-class dataset. SVM, random forest, and neural networks are particularly well-suited to handle multi-class classification effectively. SVM is adept at managing complex decision boundaries in high-dimensional spaces, while random forest effectively captures intricate interactions among features through ensemble learning. Neural networks are capable of modelling non-linear relationships with their deep architectures. In contrast, KNN relies on distance metrics and majority voting. It may limit its ability to handle complex, non-linear patterns, resulting in comparatively lower accuracy. Furthermore, the lower performance of neural networks could be attributed to overfitting as their ability to generalize was hindered by the dataset's complexity. In a nutshell, SVM demonstrated superior performance across all metrics and was selected for integration into the chatbot application.

3.2. Graphical user interface

Mr. Doctor bot is a disease prediction assistant chatbot designed to predict diseases based on user symptoms. The chatbot operates in three main modes: small talk, consultation, and help. In the small talk mode, users can engage in casual conversation with the chatbot, obtaining general information such as operating hours, name, and age. The help mode provides users with detailed instructions on how to effectively utilize the chatbot's features and maximize their interactions. The consultation mode serves as the primary function of the chatbot, allowing users to input their symptoms and receive predictions about potential diseases (see Figure 10).

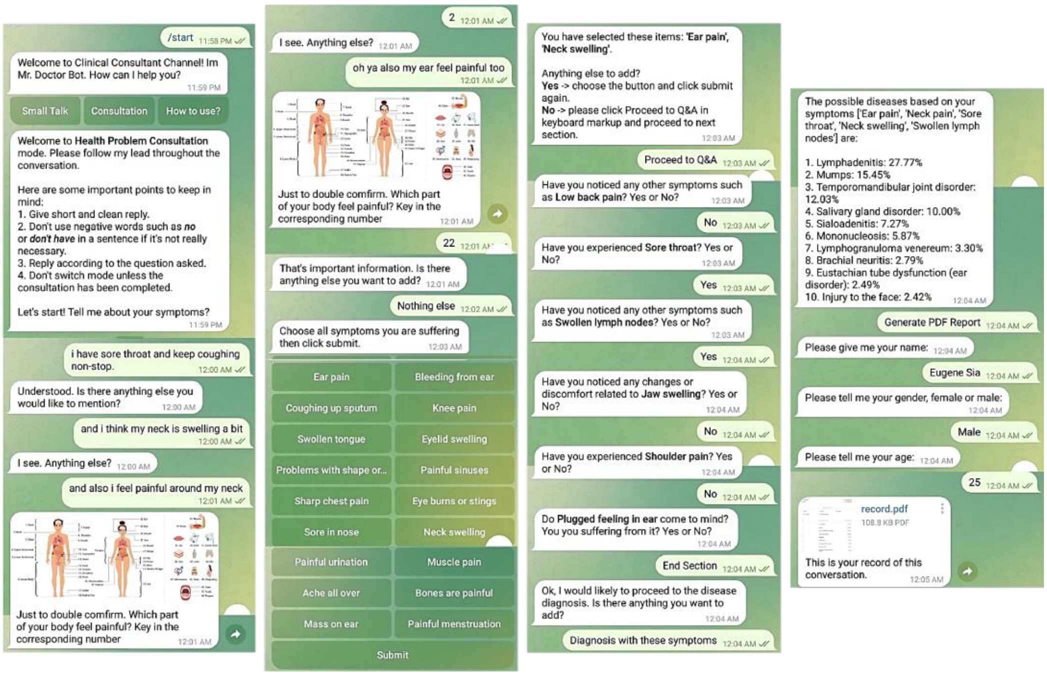

Figure 10. Demonstration of the chronic disease prediction chatbot in consultation mode

During the consultation mode, the chatbot engages users in a structured dialogue flow. Initially, users are prompted to describe their health problems. Based on the user's description, the chatbot generates a list of possible symptoms for the user to select from. Following this, the chatbot asks additional questions to gather more relevant symptoms that could be correlated. with the user's description. Users have the option to continue the question-and-answer section until the chatbot concludes it, or they can choose to end the section themselves. Afterwards, users can opt to return to the initial prompt to provide additional details or proceed to receive a prediction result. The chatbot will then present the top 10 diseases along with their corresponding probabilities based on the symptoms collected. This functionality allows users to gain insights into potential health conditions based on their symptoms, facilitating informed decision-making regarding further medical consultation or self-care measures. After that, the user can choose to generate a PDF report about the symptoms and prediction results.

After that, the chatbot application is evaluated through rigorous black-box testing, user feedback surveys, and application comparisons. Most respondents found the chatbot to be a useful, friendly and time-saving tool. Users appreciated the convenience and cost-effectiveness of accessing medical consultations through the chatbot rather than visiting a physical clinic. However, some feedback indicated areas for improvement. Users noted that the chatbot lacked a degree of empathy and human-like interaction. Other specific suggestions included faster response times, simpler language, and more detailed explanations of diseases. Overall, the feedback underscored the chatbot's potential benefits in aiding in better healthcare decision-making.

4. CONCLUSION

The disease prediction chatbot has taken a significant step towards harnessing the power of artificial intelligence in the field of healthcare. The disease prediction models using SVM, KNN, random forest, and ANN have yielded remarkable results by achieving accuracy above 90%. This high accuracy demonstrates the models' ability to identify patterns and correlations between diseases and symptoms effectively, which also emphasizes confidence in the accuracy of disease prediction. Overall, this chatbot offers significant benefits by enhancing healthcare accessibility, allowing healthcare professionals to receive preliminary diagnostic insights and patients to get immediate guidance based on symptoms. However, the implementation of such a system raises significant data privacy concerns. Addressing these privacy concerns is crucial for maintaining user trust and the overall efficacy of the system.

Further improvements and refinements can be made to enhance the performance of the chatbot. For example, expanding the dataset by incorporating additional data sources such as medical history, lifestyle factors, genetic information, or laboratory test results. Additionally, continuous model monitoring and evaluation are crucial for identifying any performance gaps or biases. Regular updates and retraining of the model using the latest medical knowledge and research findings can help the chatbot stay up-to-date and ensure the accuracy of its predictions. These efforts will contribute to enhancing the chatbot's performance, accuracy, and user satisfaction, ultimately providing a more valuable tool for disease prediction and healthcare assistance.

REFERENCES

[1] N. Anil, H. Vardhana, P. L, and K. R. L, "A Deep Learning Model for Multiple Disease Prediction using VGG-16," *Interantional Journal of Scientific Research in Engineering and Management*, vol. 07, no. 09, Sep. 2023, doi: 10.55041/ijsrem25632.

[2] K. T. Alhamazani, J. Alshudukhi, S. Aljaloud, and S. Abebaw, "Implementation of Machine Learning Models for the Prevention of Kidney Diseases (CKD) or Their Derivatives," *Computational Intelligence and Neuroscience*, vol. 2021, no. 1, Jan. 2021, doi: 10.1155/2021/3941978.

[3] B. Smith, A. Khojandi, and R. Vasudevan, "Bias in Reinforcement Learning: A Review in Healthcare Applications," *ACM Computing Surveys*, vol. 56, no. 2, pp. 1–17, Feb. 2023, doi: 10.1145/3609502.

[4] L. Caruccio, S. Cirillo, G. Polese, G. Solimando, S. Sundaramurthy, and G. Tortora, "Can ChatGPT provide intelligent diagnoses? A comparative study between predictive models and ChatGPT to define a new medical diagnostic bot," *Expert Systems with Applications*, vol. 235, pp. 1-14, Jan. 2024, doi: 10.1016/j.eswa.2023.121186.

[5] S. Dubey, G. Tiwari, S. Singh, S. Goldberg, and E. Pinsky, "Using machine learning for healthcare treatment planning," *Frontiers in Artificial Intelligence*, vol. 6, Apr. 2023, doi: 10.3389/frai.2023.1124182.

[6] S. Badlani, T. Aditya, M. Dave, and S. Chaudhari, "Multilingual healthcare chatbot using machine learning," in *2021 2nd International Conference for Emerging Technology, INCET 2021*, IEEE, May 2021, pp. 1–6, doi: 10.1109/INCET51464.2021.9456304.

[7] R. Goel, R. P. Goswami, S. Totlani, P. Arora, R. Bansal, and D. Vij, "Machine Learning Based Healthcare Chatbot," in *2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering, ICACITE 2022*, IEEE, Apr. 2022, pp. 188–192, doi: 10.1109/ICACITE53722.2022.9823901.

[8] D. M. V. V. Saradhi, K. Tejaswini, A. Kumar, and K. Rajkumar, "Chatbot system for healthcare," *International Research Journal of Modernization in Engineering Technology and Science*, Jan. 2023, doi: 10.56726/IRJMETS-NCASCTE202225.

[9] C. MacKay, W. Klement, P. Vanberkel, N. Lamond, R. Urquhart, and M. Rigby, "A framework for implementing machine learning in healthcare based on the concepts of preconditions and postconditions," *Healthcare Analytics*, vol. 3, pp. 1-9, Nov. 2023, doi: 10.1016/j.health.2023.100155.

[10] V. Ingawale, D. Bartakke, S. Virkar, S. Chavan, and M. Navale, "Smart Hospital Chatbot-Virtual Doctor Consultation and Appointment," *International Journal of Advanced Research in Science, Communication and Technology*, pp. 102–108, Feb. 2022, doi: 10.48175/ijarsct-2517.

[11] R. Sable, S. Pawade, T. Burkul, A. Sarode, and S. Saumya, "A Survey on Chatbots in Healthcare Domain," *Interantional Journal of Scientific Research in Engineering and Management*, vol. 04, no. 06, Jun. 2022, doi: 10.55041/ijsrem14300.

[12] A. Prasad, B. S. S. S. Jennifer, D. Ghsoh, H. Busshetty, and D. T. J.T, "Chatbot in Healthcare," *International Journal of Engineering Research in Computer Science and Engineering*, vol. 9, no. 11, pp. 26–28, Nov. 2022, doi: 10.36647/ijercse/09.11.art008.

[13] K. N. R. Challa, V. S. Pagolu, G. Panda, and B. Majhi, "An improved approach for prediction of Parkinson's disease using machine learning techniques," in *International Conference on Signal Processing, Communication, Power and Embedded System, SCOPES 2016 - Proceedings*, IEEE, Oct. 2017, pp. 1446–1451, doi: 10.1109/SCOPES.2016.7955679.

[14] J.-P. Cheng and S.-C. Haw, "Mental Health Problems Prediction Using Machine Learning Techniques," *International Journal on Robotics, Automation and Sciences*, vol. 5, no. 2, pp. 59–72, Sep. 2023, doi: 10.33093/ijoras.2023.5.2.7.

[15] J. S. A. Tan, Z. Che Embi, and N. Hashim, "Comparison of Machine Learning Methods for Calories Burn Prediction," *Journal of Informatics and Web Engineering*, vol. 3, no. 1, pp. 182–191, Feb. 2024, doi: 10.33093/jiwe.2024.3.1.12.

[16] M. Bali, S. Mohanty, S. Chatterjee, M. Sarma, and R. Puravankara, "Diabot: A predictive medical chatbot using ensemble learning," *International Journal of Recent Technology and Engineering*, vol. 8, no. 2, pp. 6334–6340, Jul. 2019, doi: 10.35940/ijrte.B2196.078219.

[17] E. K. Hashi, M. S. Uz Zaman, and M. R. Hasan, "An expert clinical decision support system to predict disease using classification techniques," in *ECCE 2017 - International Conference on Electrical, Computer and Communication Engineering*, IEEE, Feb. 2017, pp. 396–400, doi: 10.1109/ECACE.2017.7912937.

[18] R. Keniya *et al.*, "Disease Prediction From Various Symptoms Using Machine Learning," *SSRN Electronic Journal*, 2020, doi: 10.2139/ssrn.3661426.

[19] B. Pandey, D. K. Pandey, B. P. Mishra, and W. Rhmann, "A comprehensive survey of deep learning in the field of medical imaging and medical natural language processing: Challenges and research directions," *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 8, pp. 5083–5099, Sep. 2022, doi: 10.1016/j.jksuci.2021.01.007.

[20] S. Barraza-Aguirre, J. Diaz-Roman, C. Ochoa-Zezzatti, B. Mederos-Madrazo, J. Cota-Ruiz, and F. Enriquez-Aguilera, "Segmentation of Lung Lesions Caused by COVID-19 in Computed Tomography Images Using Deep Learning," in *Signals and Communication Technology*, 2024, pp. 237–259, doi: 10.1007/978-3-031-34601-9_14.

[21] Y. Wu *et al.*, "A deep learning method for predicting the COVID-19 ICU patient outcome fusing X-rays, respiratory sounds, and ICU parameters," *Expert Systems with Applications*, vol. 235, p. 121089, Jan. 2024, doi: 10.1016/j.eswa.2023.121089.

[22] I. M. Shofi, L. K. Wardhani, and G. Anisa, "Android application for diagnosing general symptoms of disease using forward chaining method," in *Proceedings of 2016 4th International Conference on Cyber and IT Service Management, CITSM 2016*, IEEE, Apr. 2016, pp. 1–7, doi: 10.1109/CITSM.2016.7577588.

[23] N. Bhagwat, J. D. Viviano, A. N. Voineskos, and M. M. Chakravarty, "Modeling and prediction of clinical symptom trajectories in Alzheimer's disease using longitudinal data," *PLoS Computational Biology*, vol. 14, no. 9, pp. 1-25, Sep. 2018, doi:

10.1371/journal.pcbi.1006376.
[24] V. Nagavallika, "Prediction of Heart Disease Using Machine Learning Techniques," *Journal of Contemporary Medical Practice*, vol. 4, no. 6, Jun. 2022, doi: 10.53469/jcmp.2022.04(06).39.
[25] D. Dahiwade, G. Patle, and E. Meshram, "Designing disease prediction model using machine learning approach," in *Proceedings of the 3rd International Conference on Computing Methodologies and Communication, ICCMC 2019*, IEEE, Mar. 2019, pp. 1211–1215, doi: 10.1109/ICCMC.2019.8819782.
[26] Y. Lim, K.-W. Ng, P. Naveen, and S.-C. Haw, "Emotion Recognition by Facial Expression and Voice: Review and Analysis," *Journal of Informatics and Web Engineering*, vol. 1, no. 2, pp. 45–54, Sep. 2022, doi: 10.33093/jiwe.2022.1.2.4.
[27] M. Ali, F. Khan, M. N. Atta, A. Khan, and A. Khan, "Hybrid Crow Search and RBFNN: A Novel Approach to Medical Data Classification," *Journal of Informatics and Web Engineering*, vol. 3, no. 1, pp. 252–264, Feb. 2024, doi: 10.33093/jiwe.2024.3.1.17.
[28] S. Hamdoun, R. Monteleone, T. Bookman, and K. Michael, "AI-Based and Digital Mental Health Apps: Balancing Need and Risk," *IEEE Technology and Society Magazine*, vol. 42, no. 1, pp. 25–36, Mar. 2023, doi: 10.1109/MTS.2023.3241309.
[29] C. Bulla, C. Parushetti, A. Teli, S. Aski, and S. Koppad, "A Review of AI Based Medical Assistant Chatbot," *HBRP Publication*, vol. 3, no. 2, pp. 1–14, 2020.
[30] Z. Memon, F. Tahir, S. Dehraj, F. Noureen, A. H. Jalbani, and K. Bux, "Multi Interactive Chatbot Communication Framework for Health Care," *International Journal of Computer Science and Network Security*, vol. 20, no. April, pp. 121–124, 2020.

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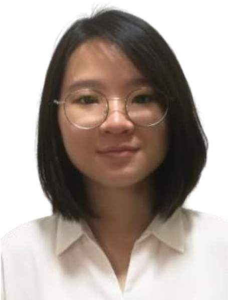

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