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Chatbot-Based Medical Diagnosis Using Natural Language Processing and Classifier

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Abstract

Medical check-ups, illness diagnoses, and treatment suggestions are the most common outcomes of a visit to the hospital. The vast majority of individuals all across the globe have engaged in this activity. Many people believe it to be the most accurate method of determining one's health. Nowadays, individuals are less conscious of their health. In their hectic schedules, people often overlook the need to keep their health in check. The use of Natural Language Processing (NLP) methodologies and their use in constructing conversational systems for health diagnosis boosts patients' access to medical information. Medical chatbots have been developed and applied in various clinical settings to provide conversational tools accessible to a broad range of healthcare providers and patients. In this suggested system, a medical chatbot is designed to be a conversational agent that pushes patients to discuss their health difficulties based on the symptoms presented; the chatbot delivers the diagnosis. Preparation of text-based documents, document tagging, symptom detection, and illness prediction is part of the proposed Chatbot-Based Medical Diagnosis (CBMD) system. The CBMD method encourages people to open up about their health concerns, gives a proper diagnosis, and prescribes treatment. NLP is used in this instance to do text processing. The first step is for the patient to type in their symptoms. All the text in those files has already been preprocessed using techniques like stemming, stopping, and tokenization. The knowledge source's useful content is labeled to identify quality information from a single document. For illness diagnosis, the patient's symptoms are compared to those in the knowledge base. Finally, Deep Neural Network (DNN) classifier is used to classify the patient's symptoms matched to their corresponding ailment. DNN recognizes the signs and symptoms based on the patient's input. To help patients, DNN analyzes their symptoms and provides the most appropriate remedy. In the last step, the outcomes of the classifier are evaluated using several metrics, such as precision, recall, f-measure, and accuracy.

Keywords: Deep Neural Network (DNN), Chatbot Based Medical Diagnosis (CBMD), Natural Language Processing

Overview

Medical diagnosis, treatment, and prevention of disease, illness, injury, and mental impairments in humans are all made possible by remote diagnostic procedures, which are becoming more popular and accurate owing to their affordability, speed, and dependability [1]. An increasing number of healthcare institutions are offering telehealth services, which allow patients with limited mobility and income to get adequate medical treatment from a distance, improving their health outcomes and quality of life [2]. As medical technology advances, there is a growing demand for medical expert systems that can monitor diagnostic and treatment procedures [3]. As computer-related technology continues to advance, clinicians' ability to make accurate diagnoses of illnesses has been enhanced by innovative signal processing methods and deep neural networks [4]. Chatbots have emerged as a viable avenue in easing communication between physicians and patients with AI methods [5]. The use of synchronous text-based conversation platforms for remote health care is becoming increasingly popular [6].

Many long-term diseases can benefit from chatbots that keep track of the patient's well-being and remind them to take their medicines [7]. Conversation engines and linguistic vocabularies must be used by chatbots in the healthcare business, as well as a formalization of medical information (semantics) and the health state of patients [8]. The suggested solution centres on a healthcare chatbot application accessible in several languages that analyzes the patient's symptoms by having a dialogue with the patient and maps these symptoms to the currently available dataset [9]. Patients can communicate with the system through text or voice [10]. The patient can choose the language he desires to converse and to identify symptoms; NLP is used to process patient-provided information [11]. Afterward, the symptoms are sent into a DNN that has been taught to identify illnesses based on their appearances.

An unstructured free text can be mined for information using natural language processing (NLP) technology, which employs linguistic analysis and DNN [12]. Information retrieval is an area where NLP systems have shown their uniqueness and value, especially when it comes to the retrieval and processing of huge volumes of data and the return of structured information through patient-defined queries [13]. For the NLP system's overall purpose, the explicit knowledge expressed in natural language text is reflected [14]. Text-based information taken from patients' self-reports is not being utilized to diagnose diseases [15]. NLP addresses a variety of difficulties with medical data, including inconsistent formatting, missing words and punctuation, strange parts of speech (POS), and medical jargon and misspellings [16]. Coreferences, a linguistic structure, make medical writings harder to understand [17]. It is more difficult to infer information from medical literature since the abbreviations used in such writings are distinct linguistic entities. It's unrealistic to anticipate a diagnosis from a chatbot [18]. However, if given the symptoms, it can offer helpful information. The chatbot is capable of providing a predicted diagnosis [19]. Initial response and referral to a healthcare practitioner can be assisted by this method. It is possible to employ healthcare chatbots as medical helpers for physicians and patients [20].

The main contribution of this paper is,

Chatbots are being used in customer service and life-and-death situations. Chatbots can tackle health concerns in the healthcare industry. A medical chatbot provides a proper diagnosis, which plays a significant role in medicine. The patient discusses symptoms, and the chatbot diagnoses and prescribes therapy. The development of chatbots has recently emerged as a trustworthy strategy for medical businesses. Medical chatbots will communicate one-on-one with patients through the company's information management network. DNN analyzes the patient's symptoms and provides the most appropriate therapy for the disease. This strategy is used at all times and by online chatbots to learn and develop.

Thus, the remainder of this paper is arranged in this way: The section-2 literature review and its effects have also been explored in detail. The CBMD and DNN mathematical model are addressed in Section 3. Simulated findings and discussion are presented in Section 4. The study concludes with future work in Section 5.

Related works

Artificial Intelligence (AI) was one growing area of computer science often tapped for use in commonplace software. Access to physicians and hospitals has been particularly difficult during COVID-19; even with minor health complaints, individuals have avoided going to medical facilities [21]. Regarding healthcare, chatbots are becoming more useful for anything from predicting illnesses and drugs to answering pathology questions and even providing basic medical information. Pre-diagnosis for patients based on symptoms and concerns voiced by the patient can be provided by a conversational chatbot like the one being developed here. NLP and neural networks are included in the model, as are decision tree classifiers, to provide two distinct methods of diagnosis. The process of integrating medical records into a single application is still difficult. There are extra problems when data becomes diverse, and its application is not the same depending on patients. MEDSHARE is a web-based program that combines data from numerous sources and allows patients to access all their health information in one location. In addition to collecting data, this site uses Natural Language Processing (NLP) to aid in diagnosing. An NLP package generates a fuzzy logic rule set used in the process [22]. This data is fed into the SVM classifier, which has the highest accuracy rate of any classifier tested to help in illness prediction. Finally, the analysis results are communicated to the front-end application and the mobile device of the concerned patient through text message in the native language of that patient's choice, using the translation package.

Artificial Intelligence (AI) could be used to help diagnose depressive illness, according to this study's findings [23]. Depressive illnesses could be promptly diagnosed and treated using smartphone-based diagnostic tools. Region-based convolutional neural network (R-CNN), a deep learning approach that detects vector-based information that could be used to help diagnose depression disorder, would be used to create a model that examines eye and lip positions, estimates emotions, and uses images of patients who have previously involved in depressive disorder diagnoses. In pre-diagnosis, medical triage chatbots were extensively employed to enquire about symptoms and medical history. In this research, researchers present the Multi-relational Hyperbolic Diagnosis Predictor (MHDP), a unique multi-relational hyperbolic graph neural network-based technique to develop a disease prediction model [24]. In MHDP, they create a heterogeneous network of symptoms, patients, and diagnosis nodes and then develop node representations by aggregating local features recursively in hyperbolic space. Two real-world datasets show that the proposed MHDP technique outperforms current state-of-the-art baselines.

Kernel extreme learning machine (KELM) had been extensively used in the domains of classification and identification since its introduction. A novel parameter optimization technique based on a dispersed foraging sine cosine algorithm (DFSCA) was developed to increase optimization performance [25]. DFSCA is being merged with KELM to create a new machine learning model termed DFSCA-KELM that would be used to train the model. Two real-world medical scenarios were used to demonstrate that the DFSCA-KELM model could be used successfully to handle practical medical issues. These findings suggest that the proposed method would be an excellent diagnostic method.

Proposed method

The chatbot is a computer program that uses natural language processing to communicate with patients through text to voice. Initially, chatbots are designed to communicate with humans exclusively to entertain them. Present-day India has significant difficulties providing its rapidly expanding population with high-quality, cheap, efficient healthcare. Patients are forced to delay treatment or settle for nearby medical facilities that are not as cost-effective or as well-suited to their medical requirements because of the difficulties of getting to healthcare facilities, particularly in rural regions. An important duty for Medical Chatbots is to link patients with the chatbot so that they can get timely medical care and access and quality care.

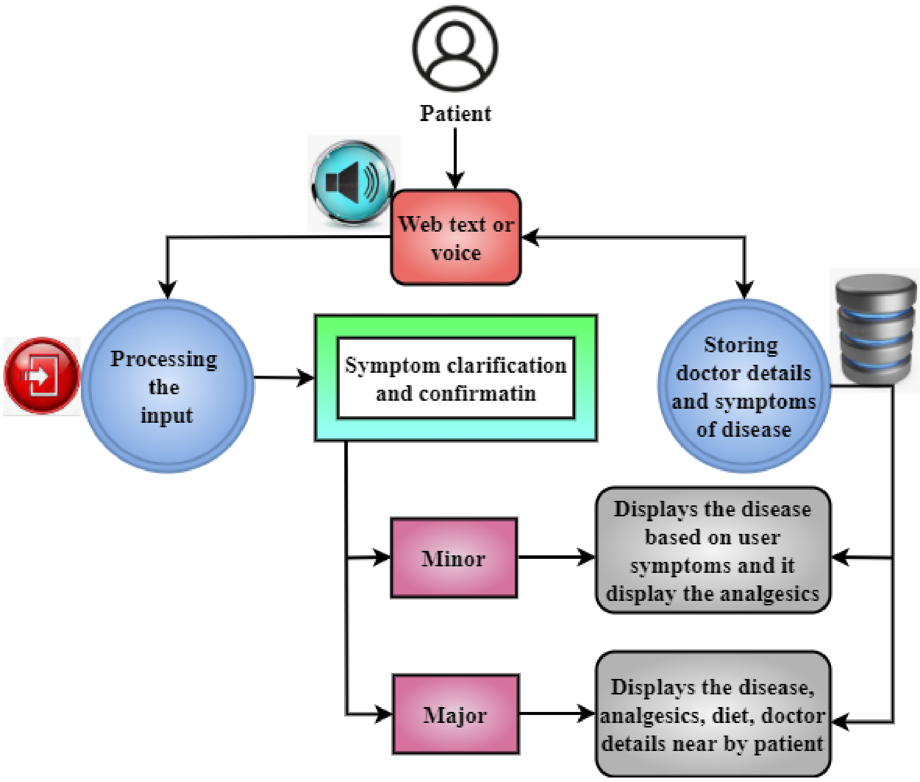

Figure 1: *Architecture of healthcare-assisted chatbot system*

Figure 1 shows the architecture of the healthcare-assisted chatbot system. The patient can interact with the bot through text or voice. System answers questions using a computerized expert system. The patient can see which doctors are accessible to treat that disease. The chatbot's database contains the chatbot's data in the form of a pattern or template. The bot will provide analgesics and nutritional recommendations according to the nature of the ailment. Patients can begin interacting with the chatbot as soon as they like, and this image will be stored in the system's database for future usage. The chatbot will ask a series of questions to help the patient understand their symptoms. The ailment will be categorized as a mild or severe illness. It doesn't matter whether it's a huge or a little illness. A doctor will be advised if it's a serious illness, and the analgesics will be shown, as well as dietary advice that indicates which foods you should eat more to get well.

Using a chatbot, patient can avoid going to the hospital for even the most minor ailments. When they talk about symptom analysis, they try to figure out when the symptoms first appeared, what circumstances led to their emergence, how those circumstances affected the patient's feelings, and, perhaps most importantly, how those symptoms helped the patient. The chatbot will accept the patient's input, which will then process it using algorithms. The algorithms will be applied to any data the patient provides to the bot. Algorithms and a database of symptoms will be used to decipher the input. The patient's symptoms will be described by the chatbot, who will then do the symptoms confirmation. The ailment will be categorized as a mild or severe illness. The patient will be given contact information for a nearby doctor for additional treatment and shown analgesics and dietary recommendations that suggest which foods to consume more to recover from the disease if it is a major one.

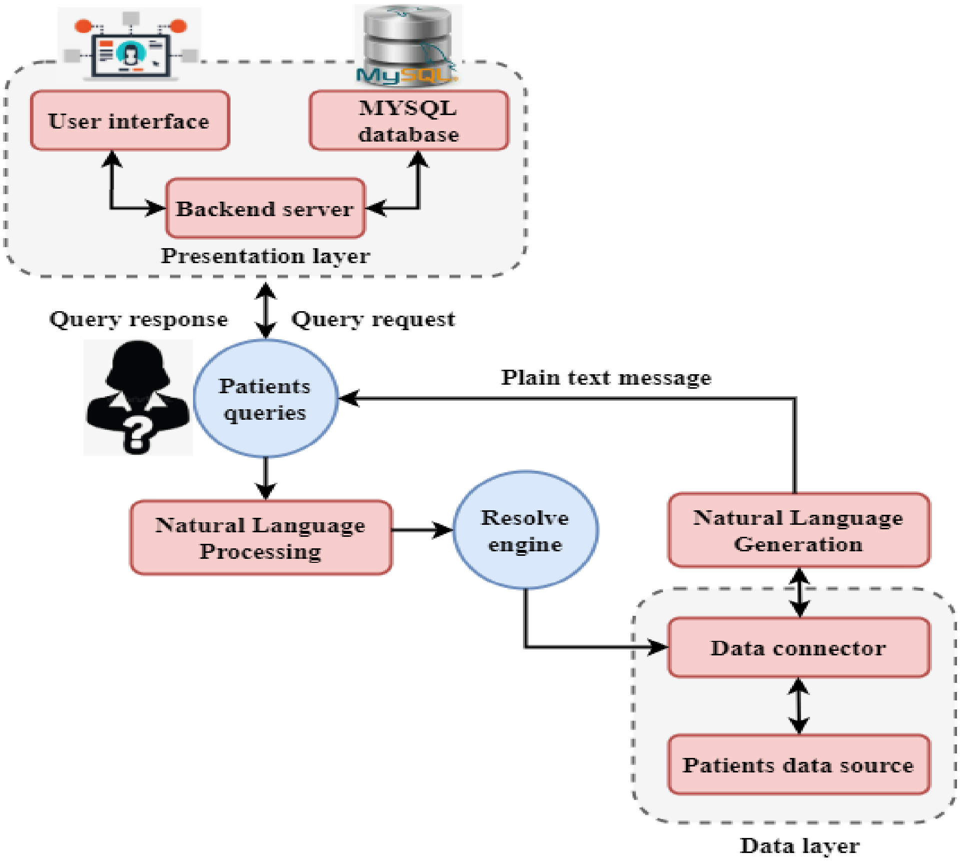

Figure 2: *Chatbot-Based Medical Diagnosis*

Figure 2 shows the chatbot-based medical diagnosis. The system will be built using a web application, as has been recommended as the development approach. A first chatbot is built to assist people in identifying the symptoms of their illnesses. Then, CBMD will add a chatbot link to the hospital's website so that other people can learn about medical reports. The system's database is used to store patient data. To determine the patient's purpose, the patient has to create a chatbot using the Chatterbot Library and teach it to recognize certain sorts of phrases. After that, the data will be sent to the backend.

The chatbot has the potential to be programmed to engage in logical thinking and provide replies independently of the backend. A healthcare application is presented as a means of building the system. The suggested system's commercial elements are discussed in detail. A first chatbot is built to assist patients in identifying the symptoms of their illnesses. That's when the information about a hospital and its personnel are made available online, making it easier for the public to learn about the facility and its employees. The system's database stores patient records and the backend is in charge of converting the processed input from the chatbot into database actions.

There are two parties involved who can access the proposed system: administrators and end-user. An administrator's login credentials are required to access the healthcare web application before it can be used. Questions from patients in the form of text are grouped using natural language processing. The resolve engine aids in making decisions based on input data supplied to a custom data source through the resolve engine. For grammar and syntax checks, the output data is retrieved and passed to the NLG engine. The healthcare chatbot's interface displays the final message, which is sent back to the local host server. The chat records are viewed and altered in the database by the administrator, who can add or remove data.

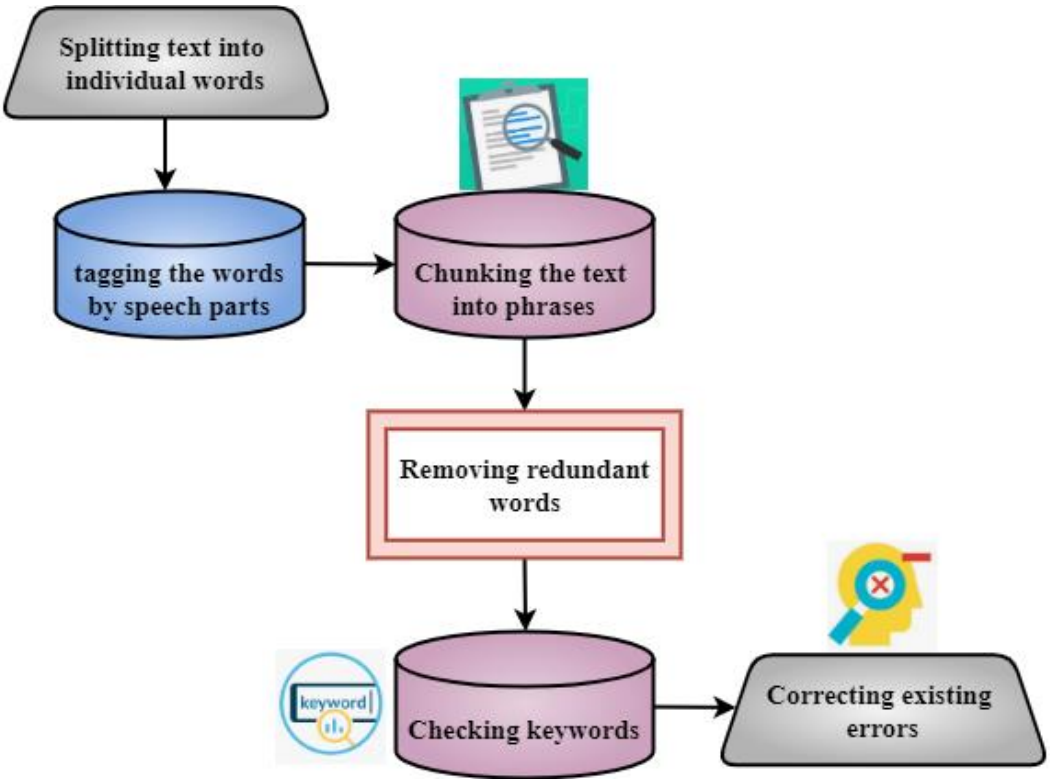

Figure 3: *Processing the input text*

Figure 3 shows the input text processing. A patient can create an account on the site and communicate with a doctor in real-time through live chat. A chatbot is available if a doctor is unavailable. The patient can use voice or text input to describe their symptoms. For the chatbot to fully interpret the patient's query, Natural Language Processing (NLP) will be used. At this point, the bot will ask follow-up questions and establish a diagnosis based on the patient's responses to the first symptoms. This content is broken down into individual words, labelled with grammatical markers based on their position and context in a sentence. In this phase, many types of sentence structures can be used to chunk the selected words and build sentences. These formulations can be made keyword-free by removing unwanted keywords in chinking operations.

On the rare occasion when these catchphrases are incorrect, they can be checked and corrected. It is necessary to have a toolkit to handle the text generated by the speech recognition system properly. For example, stemming and parts of speech tagging can extract the patient's input's semantic meaning by breaking sentences into words. There are several ways to split or separate a sentence or paragraph into individual words, numbers or meaningful full phrases. It is possible to think of tokens as a little chunks, like a word in a sentence and a phrase in a paragraph.

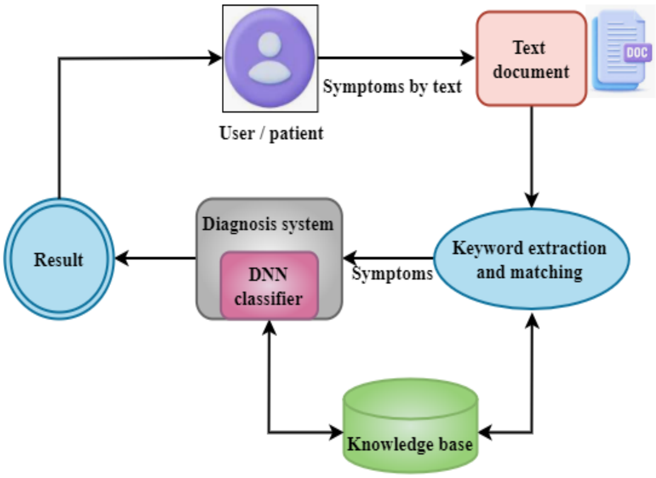

Figure 4: *Medical diagnosis system*

Figure 4 shows the medical diagnosis system. Patients' clinical data from electronic health records (EHRs) or paper records are analyzed to assess the diagnostic data demands and requirements for tropical illnesses. The diagnostic system framework was built in Python because of its cross-platform and wide availability of third-party libraries for activities related to NLP operations. The system uses Python library packages to access the DNN and NLP required for classification. Medical image classification using DNN is a hot topic of study to gain automated clinical diagnostic help. High-risk decisions will be made based on the diagnosis, which necessitates testing the robustness of medical DNN tasks in the face of adversarial assaults. In a question and answer system, the knowledge base is the primary data source, which can be organized or unstructured.

The data from a medical database system is collected and then arranged into categories to develop the knowledge base, referred to as the issue's context knowledge. YAGO (Yet Another Great Ontology), an open-sourced knowledge base, is used to establish a knowledge network of common knowledge items. UMLS (Unified Medical Language System), which incorporates diverse medical vocabularies, is used to link medical words and extract medical concepts, connections, or information. The content extractors use the NLP package to do text parsing. When a text message containing symptoms is sent to the system, the SMS receiver is triggered to receive it and then forward the text to the system's NLP module. It examines the text, makes any necessary edits, and extracts relevant keywords from the text.

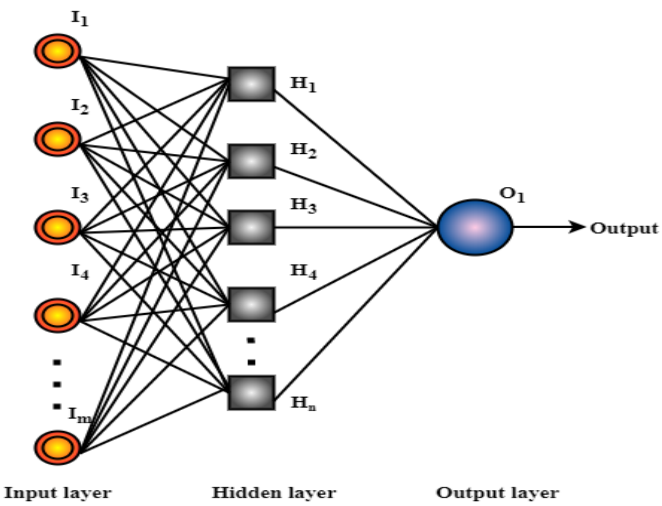

Figure 5: *Deep Neural Network*

Figure 5 shows the DNN with numerous layers is used to analyze input or training data so that the model can identify higher-level characteristics from the data. The dataset is used to train the chatbot, which contains intentions, patterns, replies, and context. Random replies from a collection of responses are used to categorize the patient's message into a certain DNN category. Retrieval-based chatbots are built using Natural Language Processing and Keras. One of the main elements of deep learning is the use of a hierarchical representation of learning to learn features from the lowest to the highest level. Deep learning invalidated shallow networks' higher-level dependency on feature engineering. Using a feed-forward neural network design, this model is built in which input only goes forwards through the network.

The input is transformed, and the output is passed on to the next hidden layer at the end of each hidden layer. The DNN model is mathematically interpreted in the following equations. The input layer is given as

$$\left.\begin{aligned} x^{(m)} &= b^{(m+1)}u^{(m)} - c^{(m)} \\ b^{(m)} &= h\left(X^{(m)}\right) \ (1) \end{aligned}\right\}$$

As shown in equation (1), The mth layer of the neural network is denoted by $x^{(m)}$. There are two layers in the system: the mth layer's activation vector $c^{(m)}$ and the previous $(m+1)$th layer's output b. The activation function $h(.)$ is non-linear. Using ReLU as an activation function $u^{(m)}$ in the hidden layers $X^{(m)}$ is advantageous due to its computational efficiency and rapid learning convergence.

Training:

The objective of training a DNN is to enhance the neural network's current performance. Deep learning employs a cost function to find the model network with the optimal set of input parameters before training.

The hidden layer K is defined as

$$K = \hat{z}\log(z) + (1 + \hat{z})\log(1 + z) \ (2)$$

As shown in equation (2), in this network, the cross entropy function $\hat{z}$ is employed because of the classification type of model. Minibatch training data z is used to calculate gradients of the cost function by varying it for model parameters and backpropagating it to previous layers using a method known as backpropagation.

The network's output is given a probabilistic interpretation l using a Softmax Non-linearity activation function Sm at the network's output layer $X^{(K)}$ is stated as

$$Sm\left(X^{(K)}\right) = \frac{d^{x}K}{\sum_{L=1}^{l} d^{x}L} \ (3)$$

As shown in equation (3), where K, L is used to represent the number of output classes, it means that the output layer has the equivalent of d^{x} neurones.

Optimization

Optimizers adjust the weights and learning rates of the neurones in the hidden layer to lower the network's overall loss. When it comes to effectively and efficiently training a model to provide accurate results, the function that a model's internal parameters play is of the utmost importance. As a consequence, several different optimization strategies and algorithms are used to keep and create values that are acceptable and ideal for the model parameters that influence the learning process and output of the model.

The Function of Activation

A set of input values is fed into the activation function, which then creates the desired output to activate artificial neurones in DNN. This process is continued until the desired result is achieved. There are several strong activation functions, including Gaussian, Multiquadric and Inverse. The most critical features of an activation function are that it be continuously differentiable, desirable when its range is confined, smooth with monotonic derivatives, and monotonic itself. An infinite number of neurons in a feed-forward neural network with a sigmoidal activation function can be used to execute almost any continuous task.

Initialization of the weight

When constructing a neural network, the weight initialization process involves choosing an initialization value for each neuron in the network beforehand to achieve optimization at the most appropriate time. An optimization technique is specified, the cost function is computed, gradients of a cost function are computed using backpropagation to update the initialization parameters, and so on for training. The process concludes by resetting the initialized values.

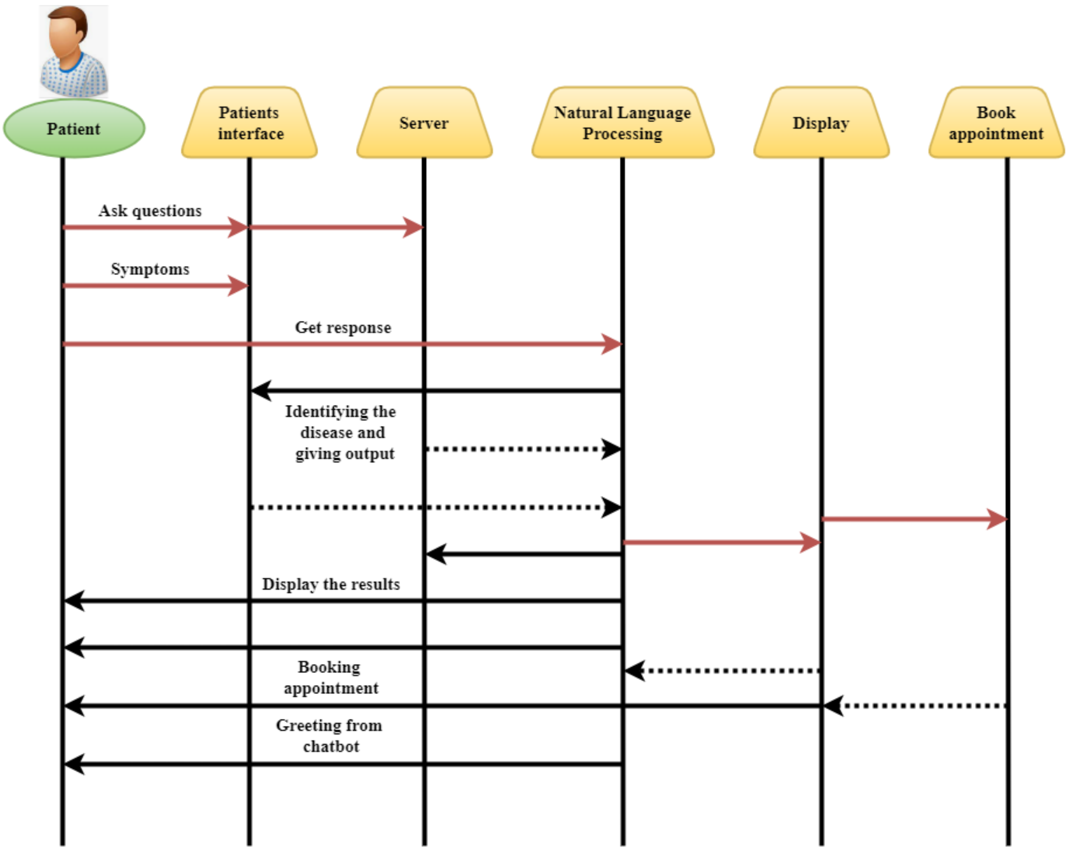

Figure 6: *NLP-based healthcare chatbot sequence diagram*

Figure 6 shows the NLP-based healthcare chatbot sequence diagram. A sequence diagram depicts interactions between objects in sequential order, i.e., the order in which these interactions occur. When referring to a sequence diagram that has been properly formatted, the phrases event diagrams or event scenarios are used. Businesses and software developers often refer to and use this diagram while developing and deciphering requirements for new and ongoing projects. Name, age, date of birth, and phone number are just a few of the personal information that the patient will provide. The chatbot will question the patient about their symptoms and utilize natural language processing to react to the ailment and recommend certain treatments. Booking an appointment at a hospital will be requested after that. At this point, the health care bot will deliver the appointment information and enable the patient to depart the site by completing the chat with it.

Numerical outcome:

From [26], this information utilized in this research has been obtained from a medical database, and written material was obtained through conversations with medical doctors and other patients well-versed in the different disorders under consideration. System files are generated using the retrieved data.

https://www.kaggle.com/code/captaintyping/a-chatbot-to-map-medical-prognosis-to-symptoms/script

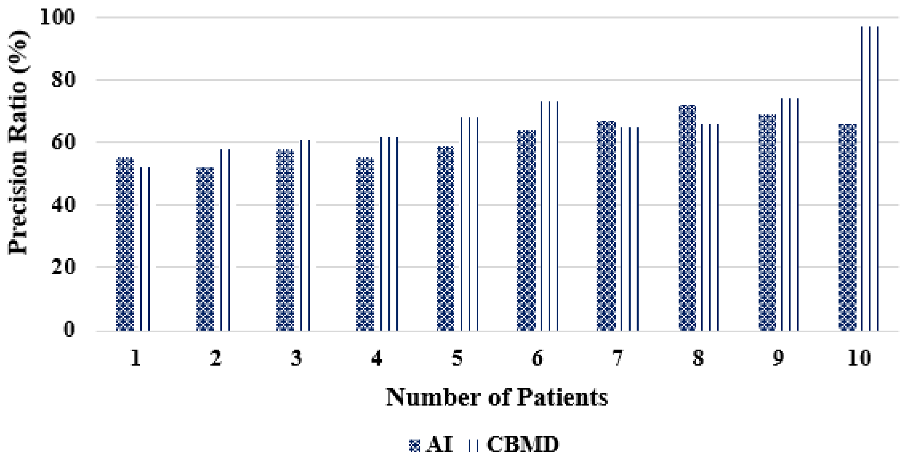

Figure 7: *Analysis of Precision*

The precision Pr is given in equation (4),

$$\mathrm{Pr} = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \quad (4)$$

As shown in figure 7 and equation (4), all predicted positive phrases are considered, and only true positive (TP) is counted as positive. By dividing the total number of real positive statements by the total number of statements expected to be positive, precision can be obtained. An accurate prediction can precisely predict the number of patients in the positive class. Evaluation of training data is necessary to verify that utterances are consistently mapped to the medical intent to improve intent classification accuracy. Data from a collection, corpus, or sample space can be measured in terms of precision and recall in pattern recognition, information retrieval, and classification (DNN). Both false positive (FP) and false negative (FN) errors often occur, although they are the two most prevalent. In contrast to precision, recall measures the proportion of relevant instances that could be located, while recall measures the proportion of relevant instances that could be located. As a result, relevance is the basis of both high accuracy and high recall.

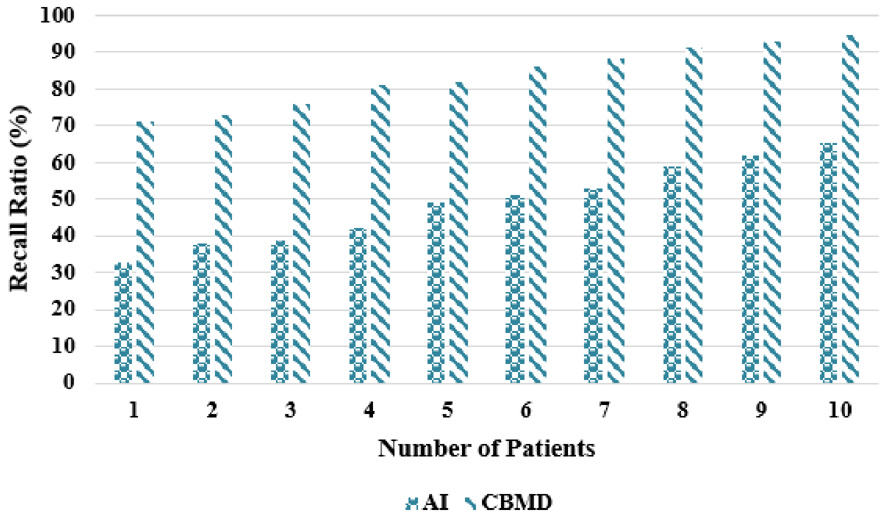

Figure 8: *Analysis of Recall*

The recall Re is given in equation (5),

$$\mathrm{Re} = \frac{\mathrm{TP}}{\mathrm{TP+TN}} \quad (5)$$

True positive (TP) and true negative (TN) outcomes can be defined as the opposite of false positive and false negative errors, as demonstrated in equation (5) and figure 8. (TN). An LLT that has been properly rejected as a solution is a true positive in CBMD, while a non-relevant LLT that has been incorrectly rejected is a true negative. To assess the accuracy of the automated encoding, measures such as the proportion of false positive and false negative results, as well as the impact of relevant solutions on the whole set of retrieved results, are necessary. Specifically, recall is employed as the primary criteria for achieving this goal. The proposed method refers to the percentage of relevant results as a positive predictive value when describing recall as the proportion of all relevant solutions that the system has retrieved.

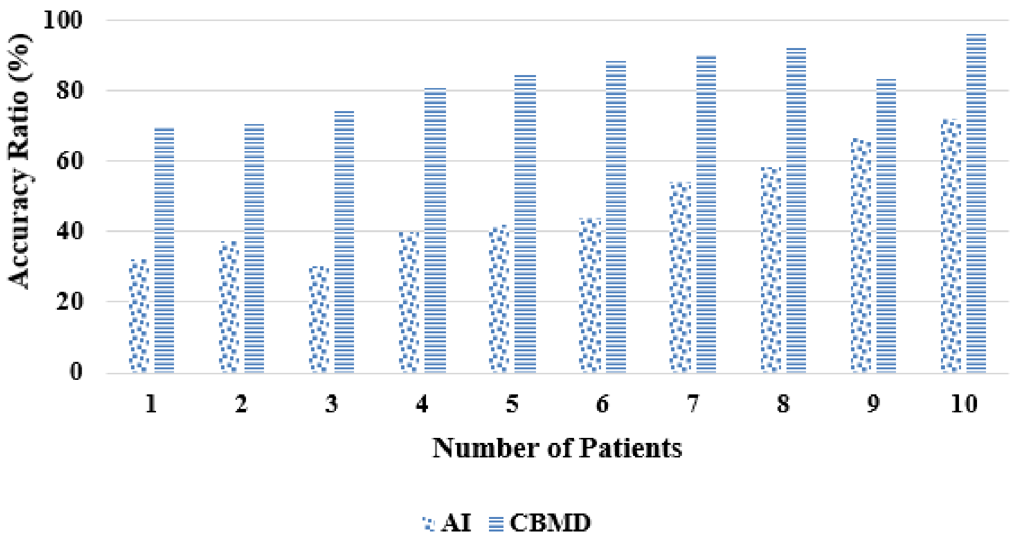

Figure 9: *Analysis of Accuracy*

The accuracy A is given in equation (6),

$$\mathrm{A} = \frac{\mathrm{TP+TN}}{\mathrm{TP+TN+FP+FN}} \quad (6)$$

As shown in figure 9 and equation (6), chatbot-based medical systems often utilize accuracy as a primary parameter to evaluate the performance of DNN. A classifier's forecast accuracy is measured by how many examples it correctly categorizes. It is necessary to investigate each class's correctness while dealing with multiclass problems. Accuracy can be measured by taking the sum of true positives (TP) and true negatives (TN) that pertain to true forecasts belonging to a particular class and dividing that total prediction by its overall effect is false positive (FP) and false negative (FN).

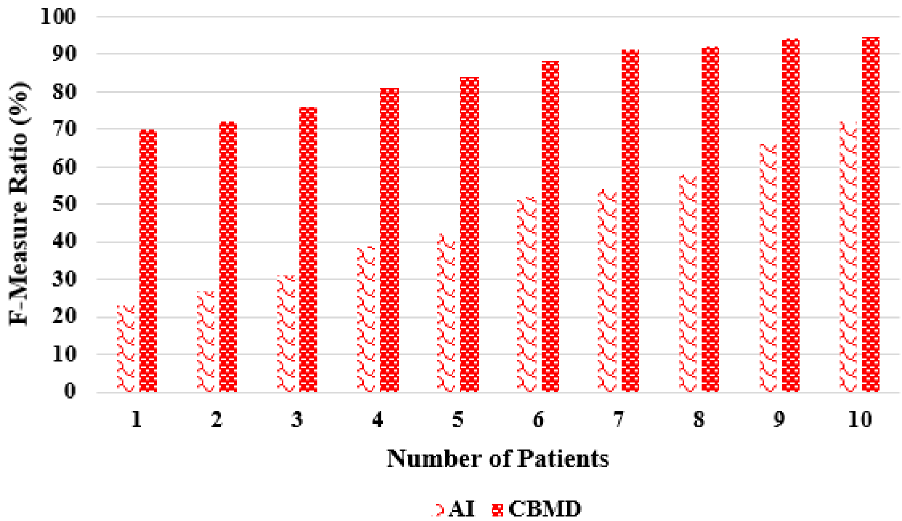

Figure 10: *Analysis of F-measure*

The F-measure F is given in equation (7),

$$F = 2\frac{Pr \times Re}{Pr + Re} \quad (7)$$

As shown in figure 10 and equation (7), a single metric for summarizing model performance in chatbot-based medical systems, classification (DNN) accuracy is extensively utilized. F-Measure is a method for combining accuracy and recall into a single metric. There are two possible outcomes for the suggested method: outstanding accuracy with horrible recall or poor precision with excellent remembering for the patients. It is possible to convey both concerns with a single score using the F-measure method. The F-Measure can be computed after the precision Pr and recall Re of a binary or multiclass classification task have been determined.

Conclusion

One of the biggest challenges is ensuring patients do not even waste time waiting for service. A cost-efficient telehealthcare platform that permits early identification of illnesses and good connection with patients to the diagnostic system is thus critical in light of the exponential rise of mobile patients and the requirement for real-time medical diagnosis help. This became possible to construct a text-based system that gives tailored diagnoses using responses from patients, and this research was able to meet the demands of this study. SMS and Telegram bots can benefit from a system that combines natural language processing (NLP) with machine learning. The system used direct question and response techniques to come up with a diagnosis. Due to its inability to prevent false-positive situations, a final diagnosis must be made by an actual doctor using a medical professional. In the future, this medical diagnostic system should be automated to make it easier to identify illnesses, provide treatment suggestions, write a prescription, and track adherence to that medicine. The system will be made more engaging via the use of audio interaction. Medical practitioners in developing countries will have less work to complete due to these advancements, which will lower costs and increase survival rates.

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