REVIEW BASED OPINION CLASSIFICATION MODEL FOR MEDICAL CHATBOT SYSTEM USING ENHANCED CNN-BiLSTM APPROACH

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Abstract

Artificial intelligence (AI) and other automation technologies that can speak via chat with end users are used to replace or supplement human support agents in chatbots, which are conversational applications that help with customer care, engagement, and support. Chatbots are evolving into complicated software artefacts requiring a high level of proficiency across many technological fields. The software engineering difficulties of creating top-notch chatbots will be covered in this technical briefing. By utilizing the open-source chatbot creation platform, attendees will be able to design their own bots.

Keywords: Natural Language Processing, Artificial Intelligence, Machine Learning, Chatbot, Data, Training.

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1. Introduction

Platforms for instant messaging have become one of the most popular ways to communicate and exchange information. These days, the majority of them offer built-in assistance for integrating chatbot applications, which are automated conversational agents equipped to communicate with platform users. In numerous different situations, such as automated customer service, education, and e-commerce, chatbots have proven beneficial for automating jobs and enhancing user experience. Furthermore, according to recent reports, designing chatbots will soon be a crucial skill for IT recruitment. According to projections, the global chatbot market will reach $2 billion by 2024, expanding at a 29.7% CAGR.

The need to quickly develop complicated chatbot applications leveraging AI-based natural language processing to be able to smoothly converse with the user has been highlighted by the growing interest in and demand for chatbot applications. Additionally, to carry out the required user actions (such as to check and query the data to be presented back to the user or to carry out some processes/actions in response), any non-trivial chatbot requires access to an orchestration of internal and external services.

As a result, chatbots are evolving into sophisticated software creations that call for a high level of technical proficiency across a range of fields, from natural language processing to a thorough knowledge of the APIs of the targeted instant messaging platforms and the third-party services to be integrated.

RELATED WORKS

Prakhar Srivastava and Nishant Singh [1] have proposed an analysis of work done on data from many domains and sizes to learn more about a a user's biological signals as well as the provision of information to the user via a chatbot system. However, this study had limitations for disease prediction and diagnosis utilizing medical information and was just intended to be a simple healthcare counselor based on the biological information and scenario supplied. An artificial intelligence algorithm that reflects and judges the health anomalies from the biological information must be built for the suggested Interactive Health Care Advisor to be more effective in healthcare applications. Future research should focus on "health condition determination algorithms" that take into account biological data and personal life patterns, "health condition change prediction algorithms" that take into account changes in biological data and life patterns, and "Healthcare Advisor Process Algorithms" that use chatbots.

Wilmer Stalin Erazo , German Patricio Guerrero , Carlos Carrion Betancourt and Ivan S anchez patient's illness. Time is needed for training and testing each algorithm, and each algorithm's accuracy can vary. We obtain the class-wise distribution of the record by training a dataset with varying counts. K-nearest neighbor (KNN) and naive algorithms can only handle quick and easy classification, but SVM excels at more difficult classification tasks.

Nudtaporn Rosruen and Taweesak Samanchuen [2] come up with Bibliometrics is a quantitative analysis that measures and evaluates publications using statistics. To develop chatbots and train them on a million Twitter conversations between users and agents, LSTM networks use deep learning techniques. More than 40% of users rated this system and its output favorably. The chatbot is being used in some industries, including education, smart systems, and healthcare. The chatbot for education is made to react to university students and provide a FAQ system to the repository, with the results demonstrating that the conversation's specific topic is also addressed. This approach improves user convenience, expands serviceability, and lowers the cost of operating the medical consultant service.

Tae-Ho Hwang, JuHui Lee, Se-Min Hyun and KangYoon Lee[3] In their study, they used the Interactive Healthcare Adviser System to assess fundamental biological data such as body temperature, blood pressure, pulse, oxygen saturation (SpO2), and electrocardiogram (ECG), as well as to check each user's health using a chatbot. Also, we developed a Healthcare Advisor Use Case scenario and put chatbots into use utilizing Kakao's open builder. We have successfully demonstrated the supervision of changes in
Salazar
[4] proposed that the key component of the approach is the deployment of a chatbot, which will assist in registering potential incidents of COVID-19 and assisting the system outside of regular business hours. The plan calls for incorporating the UDLA Universityhealth system's web services into the architecture. Yet, it gathers this data in order to build a cognitive knowledge foundation. The goal is to define the dialogue through modules of information on suspected cases of the Covid-19 virus and frequently asked questions. The Chatbot then connects directly to the web page using a previously studied decision tree focused on natural language processing with implications for machine learning.

Athota, L., Shukla, V. K., Pandey, N., & Rana, A[5] came up with an application that employs a question- and-answer format, and if you are a new user, you must provide your information on the login page in order to register with the program. It indicates whether the database has the answer to the query or displays alternatives. The website where professionals immediately respond to user questions is called the expert answering page. To speed up query execution, the application leverages bigram and trigram in addition to n-gram text compression. To communicate the responses to the users, N-gram, TF-IDF, and cosine similarity were used.

Gupta, J., Singh, V., & Kumar, I[6] came up with the help of these retrieved indications, the chatbot predicts the condition. This chatbot has been incorporated through the use of the RASA system. The goal of this project is to create a 24/7 chatbot that can effectively diagnose patients by analyzing the primary symptoms and using a conversational approach with the aid of the RASA framework and natural language processing. The state's health industry will be significantly impacted by the chatbot that was created. Accuracy will increase, and manual errors are less likely to occur. Individuals spend a lot of time online, but they rarely look for health- related information. Many avoid visiting to hospitals because they believe it will require a lot of their time and effort. Also, many decide against going since they won't have time to wait in lines or in line for appointments once they are at the hospital. As a result, they ignore minor health issues until something worse occurs. We developed this chatbot to help users forecast their potential diseases easily through a simple discussion in which they would be asked about their symptoms, their moods, and their diets in order to prevent this and to fix the problem. People will become aware of how bad their illness is and whether they need to take measures to combat it.

Ren, X., Spina, G., De Vries, S., Bijkerk, A., Faber, B., & Geraedts, A.[7] They have described an exploratory field study examining a conversational interface (CI)- assisted consultation that aimed to deploy a chatbot assistant to give occupational physicians real-time decision support during consultations. The application of CIs to doctors during the OH consultation may increase their efficiency, particularly through increased information accessibility, guided workflow, and helpful references to decision-making, according to our quantitative and qualitative data analyses. Also, rather than getting proactive recommendations, OH doctors chose to query the chatbot assistance for advice. We now address design implications for a better use of conversational user interfaces in the occupational health setting to help clinical decision-making based on the results of our research.

Madhu, D., Jain, C. J. N., Sebastain, E., Shaji, S., & Ajayakumar, A.[8] They proposed a solution that is, it has to be constructed from several modules. Each module has a task-specific capability. The modules must be accessible and upgradable separately. The system provides a variety of services. They are generally highly complicated. Each module can then be optimized over time. Thus, the system must be designed so that each module can be upgraded on its own. The system must be capable of module-by-module performance improvement. Thus, it is simple to improve the system. The system's capabilities grow together with systemic improvement. It will be able to characterize more medications and anticipate an increasing number of ailments. One of the system's planned capabilities is describing a person's health status by examining their pulse or an ECG (Electrocardiogram). As a result, it can provide an accurate health update. so providing us with predictions of potential illnesses even before they begin to spread.

Mathew, R. B., Varghese, S., Joy, S. E., & Alex, S. S.[9] They proposed a machine learning algorithm is used by the system. KNN is required by the chatbot for it to respond to the user's messages. K closest neighbor (KNN) is a very straightforward and effective machine learning technique. The ideal application for this is pattern recognition. It is a popular classification approach in which the samples of input data, in this case the symptoms, are categorised according to the k nearest neighbours' majority class label. The data samples are classified, and the classes are then saved. As a result, it performs categorization based on similarity measures to existing data samples when a new data sample is collected.

Wongpatikaseree, K., Ratikan, A., Damrongrat, C., & Noibanngong, K.[10] In their study, they used innovative chatbot technology to the field of healthcare. For senior persons, they have suggested a chatbot for daily health monitoring. By communicating via the Line application, they concentrate on daily PHR collection from senior citizens. This is due to the fact that as individuals age, some diseases, including high blood disease, begin to affect them. Some senior people do not take care of themselves until their health is in poor shape. The elderly can interact with the chatbot thanks to this study. To make it easier for seniors to monitor their health, four key features—registration, personal information editing, blood pressure input, and PHR report creation—were suggested. In the Al module, linear regression was suggested as a way to track the blood pressure trend of elderly people.

Kandpal, P., Jasnani, K., Raut, R., & Bhorge, S.[11] In their study Neural networks have been trained on data for this work using a variety of tools that aid in producing better outcomes. To achieve better outcomes, we will combine Deep Learning with Natural Language Processing in this chatbot. Healthcare is a big part of our daily lives; whenever someone is ill, they go to the doctor or a clinic nearby to find out what problems they are having. In recent years, many businesses and institutions have partnered with hospitals to offer support that can help doctors and medical staff deal with patients more effectively and with less effort by using technology.

Talukder, A. K., Chaitanya, M., Arnold, D., & Sakurai, K.[12] They came up with a comprehensive system built on the Ethereum blockchain. This system supports data from numerous 2G sources, including genomics, the Internet of Things (IoT), diagnostic centers, radiology, procedure lists, and clinicians. It will collaborate with a variety of healthcare stakeholders, including patients, physicians, hospitals, laboratories, diagnostic centers, advocacy groups, pharmacists, and insurers, to enable peer-to-peer (P2P) access to and interaction with medical data while maintaining the security, privacy, and anonymity requirements. This system's interactions are all precise, unchangeable, auditable, transparent, secure, and machine comprehensible (based on controlled vocabulary and ontologies).

Mao, G., Su, J., Yu, S., & Luo, D.[13] They stated that, In retrieval-based chatbots, matching an appropriate response with its multi-turn context is a major difficulty. In order to make response choice easier, current research generate numerous representations of context and response, but they employ these representations independently and disregard the connections between them. We suggest a hierarchical aggregation network of multirepresentation (HAMR) to improve valuable information and fully utilize a wealth of representations in order to overcome these issues. Initially, we use self- aggregation to merge the syntactic and semantic representations of sentences that were extracted using bidirectional recurrent neural networks (BiRNN). In order to combine various matching data between each speech in context and response—which is produced by an attention mechanism—we construct a matching aggregation method second.

2. Existing Methodologies

Decision Tree

Models for classification and regression are created using decision trees. It is applied to the development of data models that forecast class labels or values for use in decision-making. The system's training dataset is used to create the models (supervised learning).

A decision tree is a common data mining tool because it helps us visualize the decisions and makes them simple to understand.

Analysis that constructs a model to describe significant class variables is known as data classification. As an illustration, consider a model created to classify bank loan applications as safe or dangerous. Pattern recognition and machine learning both require classification techniques.

Applications of categorization include target marketing, fraud detection, and medical diagnosis. The "Mode" of all observed values for the terminal node is used as the output of the classification issue.

A two-step process is followed, to build a classification model

1. A classification model based on training data is constructed in the first step, learning.

2. The model's accuracy is examined in the second stage, classification, before the model is used to categorize fresh data. Thus, the class names are given as discrete values, such as "yes" or "no," "safe" or "risky."

To predict numerical properties, regression analysis is utilized.

Continuous values are another name for numerical properties. Regression modeling is the process of creating a model that predicts continuous values as opposed to class labels. The "Mean" of all observed values for the node represents the result of the regression analysis.

Long Short Term Memory – LSTM

The purpose of this research is to evaluate the efficacy of a medication feedback analysis system based on an LSTM network. Keras and TensorFlow are used to implement the LSTM model. The major purpose of the suggested model in this study is to give a traditional comparison of time series forecasting. As predicted, it is only capable of making accurate predictions for short time intervals, and the results are time-dependent. With additional, necessary time for model training, notably via CPU, the LSTM could perform better.

LSTM is a kind of recurrent neural network, However, compared with the conventional RNN, the structure of this repeated module A of LSTM is more complicated, as shown in Fig. 1.

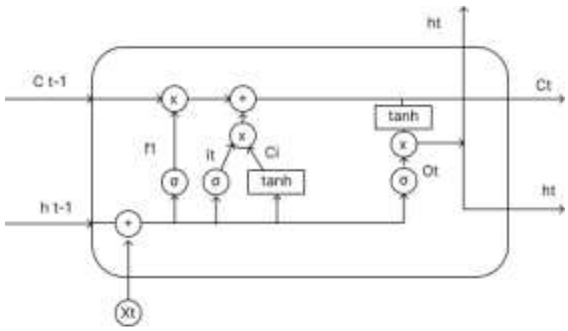


Figure The structure of LSTM cell.

The forgotten gate, the input gate, and the output gate make up this module's three components. The Sigmoid function, whose output ranges from 0 to 1, indicates how much of each component can pass.

Among them, ft determines how much information we want to discard. it determines how much new information we should add. ot determines how much information we want to output. xt is the input at time t. ht−1 is the output of the previous gate, Wf , Wi, Wc and Wo is the weight, bf , bi , bc and bo is the bias, Ct−1 is the cell state at the previous moment, Ct is the cell state at the current moment.

PROS AND CONS

The benefits of LSTM and decision tree classification are stated below in many categories:

Decision tree categorization is useful for the knowledge discovery process since it doesn't require any domain expertise.

Humans may quickly understand and find the data representation in the shape of a tree intuitive.

Data in several dimensions can be handled.

It is an efficient procedure with high precision.

The numerous drawbacks of LSTM and decision tree classification are listed below:

Overfitted trees are decision trees that have gotten too complicated.

The decision tree algorithm might not be the best choice.

In the event that one class label predominates, the decision trees may produce a biased result.

PROPOSED METHODOLOGY

A hybrid bidirectional LSTM and CNN architecture is known as a CNN BiLSTM. The initial formulation used for named entity recognition teaches characteristics at both the character- and word-level. The character-level properties are induced using the CNN component. In order to create a new feature vector from the per- character feature vectors, such as character embeddings and (optionally) character type, the model uses a convolution and a max pooling layer for each word\

Modules

- Data Acquisition
- Pre-Processing
- Training
- Prediction and Evaluation

Data Set Collection

The data set from the social media sites Twitter and Amazon. This data collection includes comprehensive customer ID, ranking, and feedback information, among other things.

Pre-Processing

The information is initially gathered from social media sites via scraping tools, APIs, consumer data feeds, and other methods. It's possible for the data to be structured, semi-structured, or unstructured. Tokenization, a step in the preprocessing process, involves cutting the raw text into tokens. The next step is to identify the set of tags that are most likely to have produced the given word sequence.

Training

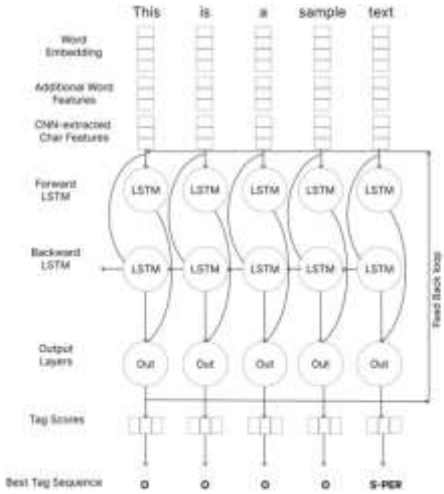
The train test split function from (sklearn.train test split) will be used to randomly split the data into training and testing sets according to the ratio specified.

Enhanced BiLSTM Model

We will briefly introduce the principle of The BiLSTM model. Enhanced BiLSTM is a kind of recurrent neural network, However, compared with

Construction of Enhanced BiLSTM Model

the conventional RNN, the structure of this repeated module A of BiLSTM is more complicated, as shown in Fig. 1



.

The forgotten gate, the input gate, and the output gate make up this module's three components. The Sigmoid function, whose output ranges from 0 to 1, indicates how much of each component can pass. Among them, ft determines how much information we want to discard. it determines how much new information we should add. ot determines how much information we want to output. xt is the input at time t. ht−1 is the output of the previous gate, Wf , Wi, Wc and Wo is the weight, bf , bi , bc and bo is the bias, Ct−1 is the cell state at the previous moment, Ct is the cell state at the current moment.

Enhanced BiLSTM Model

Since the model is difficult to learn information at a time far from the current time, and it may be important for the current value. To overcome the weakness, we tried to add an attention layer to the Enhanced BiLSTM network. Referring to the attention implementation steps of [9], we can apply it to the Enhanced BiLSTM model.

Among them, Xi, i ∈ (1, n) is the input, hi is the intermediate output result of each cell, hi are input into each attention model as H, and the elements of the next layer h i are used as H to calculate the similarity and weight coefficient, and finally get the attention coefficient.

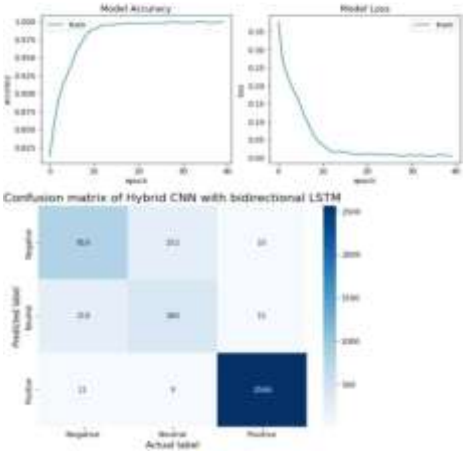
Figure The internal structure of attention model
Finally, a weighted summation operation is performed to obtain the Attention value Ci. The formula used in the attention layer is as follows:

The softmax function is used to normalize the weight in the ai and hi weighted sum equations above. Vector H and H are used to calculate similarity to obtain weights. The attention weight value Ci is the outcome of weighted summation. The Enhanced BiLSTM encoder retains the intermediate output results of the input sequence as part of the implementation of the attention layer. Next, the weight factor is calculated by comparing the similarity between the intermediate output results of the previous layer and the current output.

According to the diagram above, we first create a feature matrix and label vector using the original traffic flow data using a sliding time window method. Then, using an attention layer, we obtain the attention weights based on the correlation between the values of the feature matrix X and the value of the label vector Z, and finally, we produce the final prediction Y.

Proposed algorithm

INPUT: Drug Data

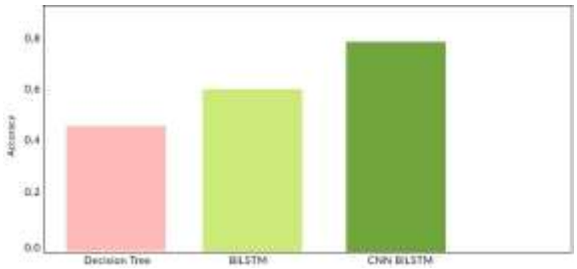


The dataset used for training is structured as,

Unique ID	DrugName	Condition	review
1	Mirtazapine	Depression	Sample review
2	Mesalamine	Crohn's Disease, Maintenanc e	Sample review
3	Bactrim	Urinary Tract Infection	Sample review
4	Contrave	Weight Loss	Sample review

Output: A trained Enhanced BiLSTM model.

1. Construct a dataset with a sliding time window, including Xt and Zt.
2. Normalization Xt and Zt.
3. Input features matrix Xt and current disease vector Zt to A-LSTM network.



4. while training epoch does not reach the set value.
5. Put (Xt, Zt) into the Enhanced BiLSTM network for forward propagation.
6. Calculate the attention weight corresponding to each element.
7. Generate Yt
8. Calculate mean square error.
9. Use RMSProp update weights for BiLSTM network.
10. end while
11. return A trained Enhanced BiLSTM model.

Long time series and significant prediction lag times

are used to verify the effectiveness of the LSTM model based on the attention mechanism. The same data collection is used to create and maintain all prediction models. We set the LSTM model to include two hidden layers, 64 and 64 hidden layer neurons, and a learning rate of
0.05. RMSprop is also used as the network optimizer. Algorithm illustrates the Enhanced BiLSTM model training procedure.

3. Result and Discussion

Nearly 50,000 records are used to train this Algorithm.
By this DrugData we are able to achieve 90 plus percentage of accuracy. The same dataset is tested with other algorithms for comparision.

Accuracy comparision stats,

Models	F1 Score	Accuracy	Precision	Specificity
DT	92.92	89.73	92.13	85.39
BiLSTM	93.84	91.36	92.19	87.35
E-BiLSTM	94.76	94.84	95.60	92.74

4. Conclusion

In this project, By examining patient reviews of common dications they have taken, we study the use of sentiment analysis in the medical field. We suggest an LSTM model built on the FastText word embeddings and tf-idf approaches. We also include linguistic restrictions on the pre-trained embeddings to enhance the word context similarity. Experimental findings on the drug review dataset demonstrate that our suggested technique performs better than the baseline results according to a number of parameters. We also examine the connection between drug popularity and polarity. Our work may be expanded in the future to examine the efficacy of medications based on several domains (conditions) such as anxiety, diabetes, pain, etc. Moreover, developing an emotion language relevant to the medical sector continues to be a crucial field of research.

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