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Precaution Chatbot for Epilepsy Patients using Natural Language Processing and Deep Learning Sequential Model

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Abstract

Epilepsy is a brain disorder that can affect people of all ages which is one of the most common neurological disorders affecting around 50 million individuals. Healthcare Chatbots schedule appointments, respond to patient inquiries, and offer relevant information, freeing medical staff to handle life crises. This paper implements a chatbot for epilepsy patients to increase awareness about epilepsy. Patients may easily access this AI-based healthcare chatbot whenever they have queries regarding precautions to be taken by epilepsy patients. Chatbot uses a rich set of epilepsy-related datasets collected from trusted websites which are preprocessed with NLP techniques to prepare the data for model inputs.DNN, LSTM, and RNN models are created and evaluated to produce answers to user queries related to possible precautions to avoid seizures, safety measures to be taken by patients with seizure history, etc. Evaluation of models shows that the RNN model generates more accurate answers with 94% accuracy. Finally, the epilepsy question answering Chatbot for precaution is concluded with the RNN model.

Keywords: Epilepsy, Seizure, Chatbot, Natutal Language Processing, LSTM Long short-term memory, Recurrent neural network, Deep neural network

1. Introduction

A neurological condition called epilepsy is characterized by aberrant brain activity, which can result in seizures or bursts of strange behavior, feelings, or even unconsciousness. A seizure causes a brain electrical signal. Epilepsy affects all ages, genders, nations, and cultures[1]. Epilepsy can cause uncontrolled shaking and loss of consciousness.

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Sometimes epilepsy can be identified after a single occurrence [2]. Two separate seizures at least 24 hours apart are needed to diagnose epilepsy. Most seizures start without warning, last a few seconds or minutes, then stop on their own[3].Getting to know somebody with epilepsy does not provide any information about their epilepsy or the seizures they experience. Epilepsy can be caused by idiopathic causes up to 50% of the time. This implies that the person is unaware of their origin [4, 5]. The illness can be better managed if detected early and given the appropriate care. Hence it is important to spread knowledge about it [6]. Natural language processing makes it viable for computer systems to recognize user-supplied data. It is a sub-field in artificial intelligence, machine learning, mathematical linguistics, and informatics[7]. A chatbot is an artificial intelligence or computer software that uses natural language processing to interact with customers via text [8]. Due to their 24/7 availability, deep learning-powered chatbots use algorithms to address questions. Following are the major research challenges we found in the latest articles. Chatbots that engage candidates need better writing, content, and data security[9]. The cost of the bot, including hiring engineers, content teams, and agents can be high. However, the bot can prequalify prospects and gather data for businesses to enhance operations. Most applicants are indifferent to chatbot interaction, and top talent may stop conversations. Data security is crucial, and businesses must adhere to clear policies regarding data storage and access [10]. The volume of shared sensitive personal data in the medical and financial industries requires vigilance. One of the most important advantages that chatbots integrate natural language processing provide to the medical sector is the ability to give patients tailored support and engagement. The use of natural language processing algorithms enables these chatbots to deliver rapid responses. The objectives of an awareness and precaution chatbot in epilepsy are to provide users with information on a wide variety of health-related subjects, to encourage participation in preventative measures, and to provide assistance for community health initiatives. In addition to being a trustworthy source of health knowledge, it offers details on the symptoms, treatments, and lifestyle adjustments that may be made to avoid seizures. Furthermore, it offers advice on how to prevent seizures from occurring.
Following Section 2 elaborates Literature review of chatbot systems and different technologies adopted for classification. Section 3 describes the methodology. Section 4 and Section 5 describe the Evaluation metrics and results and analysis implemented in the epilepsy chatbot. Section 6 concludes our research work with the Future scope for improvement.

2. Literature Survey

To evaluate how well the NLUs perform at intent categorization, computing confidence intervals, and extracting entities, use two separate tasks created from Repository and Stack Overflow contexts [11]. The NLU that performs the best for the evaluated tasks is IBM Watson when all three factors, intent categorization, confidence ratings, and entity extraction, are considered. The design of Chatbots and the findings from user studies are two potential future study areas. As chatbots grow over the following years and communication with non-human agents becomes more prevalent in our daily lives, it will be more crucial than ever to further our understanding of human-machine communication's origins, nature, and implications [12]. The EvaTalk System, a comprehensive platform that provides both the chatbot interface and administrative capabilities for post-deployment maintenance, was used to validate the technique. The analysis stage is crucial if the organization's goals and the measurements used in the process are synchronized [13]. To determine whether there is a connection between extroverts' and introverts' preferences for learning, customized VARK surveys are initially used as a chatbot to classify people as introverts or extroverts [14]. According to the Chatbot's categories, visual and auditory stimuli are shown for two minutes to introverts and extroverts.The dataset is validated using machine learning methods, including Nave Bayes, N48, and Canopy. The chatbot specification and platform specifications are separated by Xatkit's domain-specific languages [15]. In addition to the actions and events in the current version of Xatkit, the runtime component is updated to handle new platform-specific activities and events. Each team member's responsibilities are laid out in CMP, making allocating jobs to workers with various skill levels straightforward. The first challenge [16] for a company implementing the CMP is determining what changes must be made to the present architecture or whether a new one must be built. Because every organization has a different set of success metrics, a customized technological architecture may be necessary if all chatbot solutions on the market cannot satisfy the CMP most suitable reply [17] modeling technique was created using a recovered prototype to improve a written answer.The special requirements for seizure detection suitable for everyday use regarding cost, convenience, and social acceptance need alternatives to brainwave patterns EEG-based technologies [18, 19].

3. Methodology

The primary goal of this research work is to create a system for epilepsy and seizure disease management [20] awareness using a chatbot. The chatbot responds to patients independently, providing valuable information about precautionary steps. It can answer complex inquiries in text and numerical formats and handle incorrect spelling and punctuation. The system uses web scraping, JSON files [21], and deep learning models to create a strong user context flow and accurate responses. The system architecture is shown in the following Figure 1.

3.1. Data preprocessing and analysis

With NLP, chatbots can instantaneously understand human speech terminology, language, and meaning. It allows computers to quickly interpret and translate complicated human language and provide accurate responses using deep learning algorithms to mimic human conversation. JSON file provides epilepsy dataset data. Tags: Question categories. Pattern: Dataset questions, Response: Answers to queries, Context: Reference to the dataset, if necessary. The following NLP steps are applied to the JSON dataset with epilepsy details.

3.1.1. Tokenization

The technique of tokenizing involves cutting up the text into smaller fragments. The tokenizer separates the epilepsy precaution query into tokens. It just separates the terms in the question. This reduces the question to a series of words.

3.1.2. Padding

Naturally, any raw text data will contain sentences of varied lengths. Padding is used to make the data to be of uniform length which will be fed into the neural network. Pad sequences uses *sequences padding*, *maxlen*,*truncating*, and *value*. Label encoder is applied to the categorical data to get vectors of tokens with numerical values in the dataset. This output dataset is fed into the model for prediction.

3.2. Deep Learning Models

The deep learning model outlined in the provided algorithm aims to answer concerns about epilepsy safety precautions appropriately. If a user asks questions about epilepsy, the chatbot checks for relevant tags and then sends correct responses to the end user. The following algorithm is used by three models: DNN, LSTM, and RNN.

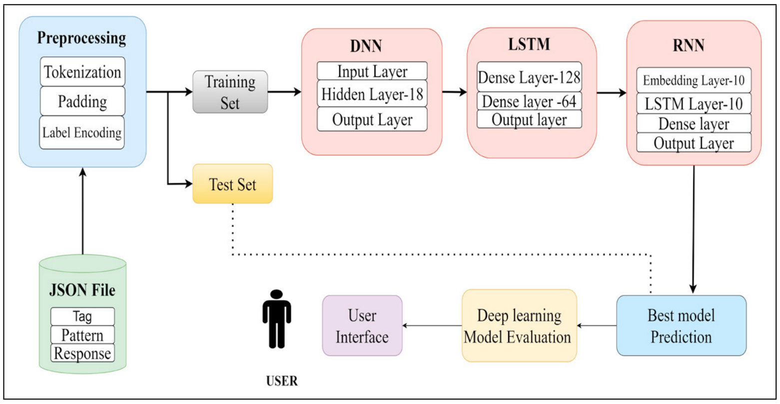

Fig. 1: Architecture of Prediction Chatbot using Deep Learning

3.2.1. DNN Algorithm

A feedforward neural network is a specific type of artificial neural network. The data eventually flows to the input nodes after traveling through the hidden layers and arrives at the output nodes [22]. The feedforward neural network was built using two hidden layers in this Chatbot. After preprocessing, our data are prepared to build and refine a model. Our network aims to examine a word collection and assign each to the appropriate class. The network receives an n-dimensional vector as input. The L-1 hidden layers of the network have n neurons per layer. The input layer is called the 0^{th} layer, whereas the output layer is occasionally called the L^{th}layer. The weight of the layers and bias are designated as $W_i \in R^{n*n}$ and $b_i \in R^n$ respectively. The activation function SoftMax will be responsible for locating the model's prediction and selecting the correct answer from the JSON response file. The DNN architecture comprises 90 layers, each of which has 16 hidden units. With a batch size of eight, the model learning rate is 0.01; overfitting is prevented by a dropout rate of 0.5, in which 50% of neurons are arbitrarily removed from training sessions. The model iterates over the whole dataset many times across 200 epochs to optimize its parameters. Softmax is the activation function used in the output layer. The model's accuracy is 77 percent. The DNN of the chatbot's

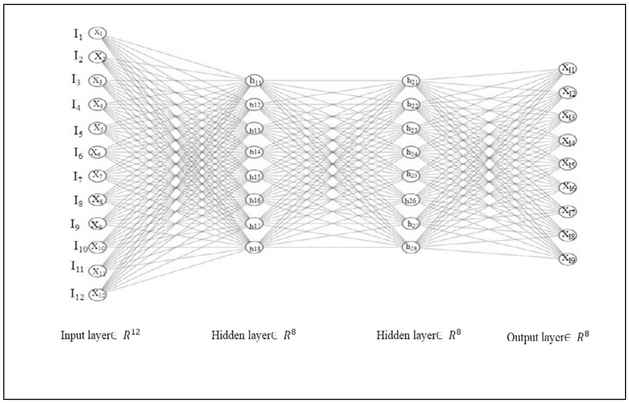

Fig. 2: DNN architecture for Precaution chatbot

architecture is depicted in the above Figure 2
The Preactivation, activation and output at the layer i is given by the following equation respectively

$$x_i = w_i y_i + z_i \tag{1}$$
$$y_i = g(x_i) \tag{2}$$
$$f(x) = y_l(x) = O(x_l) \tag{3}$$

Tables 1 and 2 display definitions of variables in DNN and hyperparameter tunings performed in this dataset.

Table 1:Notation definition for DNN

Notation	Defnition
Z_i	Bias
W_i	Weight
y_i	Hidden Layer
X_i	Input
X_l	output
g	Activation function
O	Output activation

Table 2:Model Parameters for DNN

Hyperparameter	Values
No of DNN layers	90
No of the hidden units in the DNN Cell	16
Batch size	8
Learning rate	0.01
Dropout	0.5
Number of epochs	200
Activation function	Softmax

3.2.2. LSTM Algorithm

An LSTM gate contains the input and hidden state from the previous time step. Three-tier sigmoid activation functions set input, forget, and output gate values [23]. Sigmoid activation gives all three gate values between 0 and 1. This chatbot's network includes 128 neurons, 64 neurons, and intents as neurons. This network should anticipate intent based on data [24]. Train the model using stochastic gradient descent, which is more efficient than normal gradient descent, often determined by the tanh activation function. The input gate decides how much of the input node value to save in the memory cell's internal state. The forget gate either maintains or flushes the memory value. The output gate regulates a memory cell's current-step result change. The model learns slowly using a batch size of 5 and a dropout rate of 0.5 to randomly deactivate half of the neurons during training to reduce overfitting. The model iterates on the dataset for 200 epochs to improve its parameters. When Softmax is the output layer activation function, transforming outputs into class probabilities helps with multi-class classification.

Input Gate:
It selects input parameters for memory modification. The sigmoid function decides whether to send 0 or 1. The tanh activation function prioritizes data by ranking its relevance from -1 to 1.

$$E_t = (C_t\ W_{ce} +\ Y_{t-1}\ W_y + d_e) \tag{4}$$

Forget Gate:
It pinpoints the data that must be removed from the block. The choice is made using the sigmoid function. To generate a number between 0 and 1, it considers the initial state, content input x_t, and each number in the cell state c_{t-1}.

$$F_t = (C_t\ W_{cf} +\ Y_{t-1}\ W_{yf} + d_f) \tag{5}$$

Output Gate:
The block's input and memory define its output. Moreover, the *tanh* function tells us which integers can change from 0 to 1. It also provides the input parameter's weight by dividing these by sigmoid outcome to rank their significance on a range from —1 to 1.

$$G_t = (C_t\ W_{cg} +\ Y_{t-1}\ W_{yg}\ +\ d_g) \tag{6}$$

The LSTM architecture of the chatbot is shown in Figure 3.

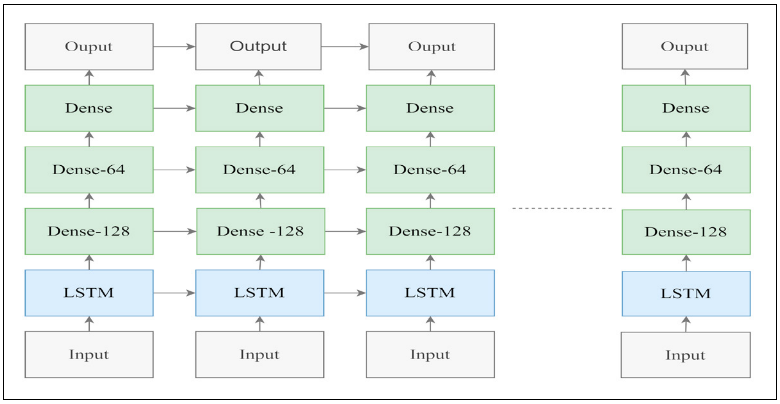

Fig. 3: LSTM architecture for Precaution Chatbot

Table 3:Notation definition for LSTM

Notation	Defnition
C_t	Input
O	Output
D	Bias
E_t	Input gate
G_t	output gate
F_t	Forget gate
D_e, d_f, d_g	Bias Parameter
$W_{ce}, W_y, W_{cf}, W_{yf}, W_{cg}$	weight parameter
Y_{t-1}	Hidden units

Table 4:Model Parameters for LSTM

Hyperparameter	Values
No of LSTM layers	90
No of the hidden units in the LSTM Cell	48
Batch size	5
Learning rate	0.01
Dropout	0.5
Number of epochs	200
Activation function	Softmax

3.2.3. RNN Algorithm

Recurrent neural networks predict future events using past experiences[27]. Import and use a pandas data frame with JSON data. Each separate word receives a different token from TensorFlow's tokenizer. Padding provides data length uniformity before transmitting it to the RNN layer. Target variables also encode decimals. The input and output lengths are clear. The vocabulary size determines how many distinct vector representations of each word the embedding layer produces [28]. The embedding layer's output feeds the repeating layer of an LSTM gate. The embedding layer, which matches vectors for dataset words, is important. A standard dense layer with Softmax activation is applied after flattening the output. The model's accuracy is 100 percent. So added, a dropout layer was to prevent overfitting, and as a result, the model does not overfit and provides an accuracy of 94%. The input at the time step is $c_t \in R$. Assume that c_t is a scalar value with a specific attribute to simplify things. The output at time step t is $D_t \in R$. Despite the network's ability to generate several outputs, this sample only has one $e_t \in R_m$ The hidden unit states values for time t are stored in a vector $W_{ch} \in R_m$. Inputs in the recurrent layer are represented by these weights $W_{hh} \in R_m * m$ are weighted in the recurrent layer connected to hidden units.$W_{he} \in R_m$ are the weights relating hidden units to output units. The RNN-based model architecture and training parameters are summarized in the table. The model comprises an extensive 90 layers of recurrent neural networks, with each LSTM cell containing 48 hidden units. During training, a small batch size of 5 is employed, updating the model's weights frequently. A moderate learning rate of 0.1 governs the step size for weight updates, while a dropout rate of 0.5 is applied to prevent overfitting by randomly dropping half of the neurons during training. The model undergoes 400 epochs and utilizes the softmax. These parameters collectively define the model's structure and training configuration, shaping its learning and predictive capabilities for the given task. Figure 4 above depicts the RNN chatbot's architecture.

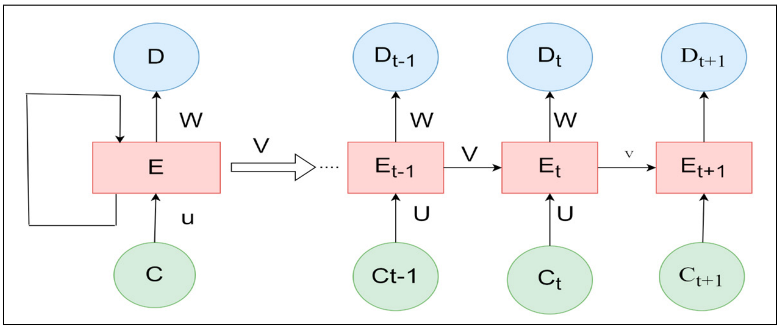

Fig. 4: RNN architecture for Precaution Chatbot

An update hidden state and output state is calculated for each time t using the following formula respectively,

$$F_t = \tanh\left(WW_{ff}^T f_{t-1} + W_{cf}^T C_t\right) \tag{7}$$

It is the calculation of the output state at time t

$$D_t = W_{fd}^T e_t \quad (8)$$

Table 5:Notation definition for RNN

Notation	Defnition
C_t	Input
D_t	Output
F_t	Hidden Layer
e_t	Cell state
W	Weight parameter

Table 6:Model Parameters for RNN

Hyperparameter	Values
No of RNN layers	90
No of the hidden units in the LSTM Cell	48
Batch size	5
Learning rate	0.1
Dropout	0.5
Number of epochs	400
Activation function	Softmax

3.3. Pseudocode

Algorithm 1 Handling Concerns about Epilepsy Safety Measures

```
Input: Concerns about the epilepsy safety measures
Output: A correct reply from the bot
  for all intent in intents do
    for all pattern in patterns do
      if tag = "tips to prevent seizures" then
        Set seizure prevention response.
      else if tag = "Causes for trigger" then
        Set trigger response.
      else if tag = "Kitchen safety" then
        Set kitchen response.
      else if tag = "General Safety at Home" then
        Set general safety response.
      else if tag = "Driving and Transportation" then
        Set Driving and Transportation response.
      else if tag = "Outdoor and Sports Safety" then
        Set Outdoor and Sports Safety response.
      else if tag = "option" then
        Set Helping and safety response.
      end if
    end for
  end for
```

4. Evaluation Metrics

Web scraping is used to collect the data from Healthline and the CHI-Health Neurological Institute Websites, which was then preprocessed and stored as a JSON file. Our dataset has been tested with three deep-learning models:

DNN, LSTM, and RNN. When a user asks a question, the Chatbot begins two important processes. Natural language processing comes first, and then the Deep learning model uses an activation function to predict the correct response. To improve the prediction relevant hyperparameter tuning is done in all models.
Accuracy:
It displays the accurate way in which the model discriminates between accurate and inaccurate tags. This serves as a reliable indicator of the model's functionality.
Recall:
It evaluates how well the model categorizes each class about the overall number of classes in the test set.
Precision:
It is the ratio of correctly classified positive classes divided by the number of predicted positive classes. It displays the correct and incorrect classifications.
F1-Score:
It is intended to give the classifier a score that balances accuracy and recall. The F1-score reveals the model's total performance. A good model has a high F1- Score.

5. Result and analysis

We have implemented DNN, LSTM, and RNN using this dataset and tested its performance. Tokenization is used in these steps to turn text into numerical sequences, and sequence padding is then used for the same length. Categorical labels are converted into numerical representations using label encoding; one-hot encoding then converts these numerical labels into binary vectors, which is essential for multi-class classification problems. Additionally, vocabulary size, input sequence length, and the number of distinct classes in the dataset are also retrieved; these metrics provide important information for setting the input and output parameters of the neural network. This preprocessing creates a logical and quantitative foundation for textual input for neural network classification training. The designated system was set up to monitor its output in various scenarios modifying several factors, including the f1-score, sensitivity, accuracy, and precision. For this dataset, RNN worked well with high accuracy. Overfitting occurred because

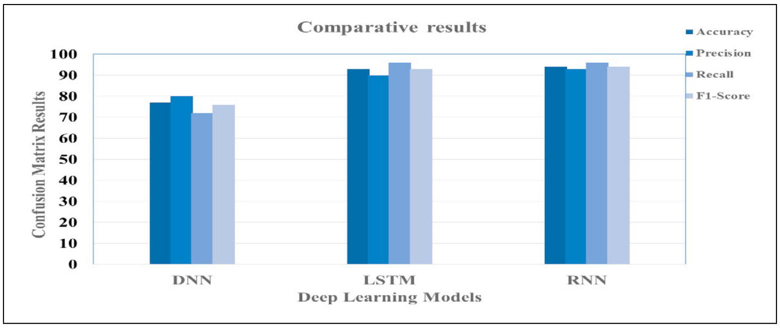

Fig. 5: confusion matrix graph

Table7: Precaution Chatbot's Metrics Scores of Deep Learning models

Algorithm	Accuracy	Precision	Recall	F1-Score
DNN	77	75	72	76
LSTM	93	92	96	93
RNN	94	96	96	94

the RNN model obtained 100% accuracy in the training dataset. After adding a dropout layer, RNN achieved 94% accuracy. Our RNN-based model showcased strong categorization abilities across various tag classes. The model has 94 accuracy across tag classes. This RNN model also answers spelling mistake queries correctly, which is a major benefit. Table 7 shows the performance metrics of all three models used in our Chatbot. Comparative results of those

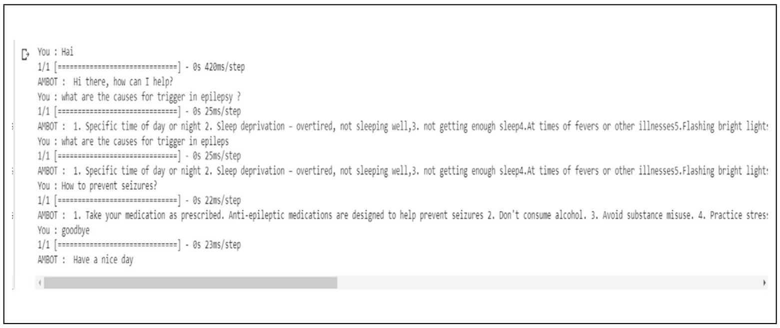

Fig. 6: Graphical user interface of Chatbot

models are highlighted in Figure 5, revealing the Chatbot's general performance. Finally, Chatbot questioning answering is implemented with the RNN model. The chatbot user interface is shown in Figure 6, where the user asks queries regarding epilepsy. Then, the given query is subjected to NLP processing to identify the essential tokens, converted into suitable vector format, and fed into the model, which predicts the tag based on that appropriate answer, which is predicted and displayed in the Chatbot. Thus, this Chatbot can produce more accurate answers for the given user query.

6. Conclusion

The epilepsy chatbot provides valuable information about epilepsy and seizures to the patients and caretakers. It provides information about handling, managing, and taking precautions to avoid untoward incidents during seizures or epilepsy Three deep learning algorithms, DNN, LSTM, RNN, and RNN with dropout layer, are used for model creation. Chatbot responses for user queries are generated with the model's classification output and evaluated with standard precision, recall, accuracy, and F1-score metrics. The dropout layer produces accurate answers without an overfitting problem. Thus, chatbot answer generation is finalized with the RNN model as it produces the highest accuracy of 94 percent compared to DNN and LSTM. To make the system user-friendly, User Interface Design is created and linked with deep learning classification modules to generate and display the most appropriate answer for the given query. The future scope for awareness of chatbots in healthcare holds promise through continuous advancements in NLP, and their integration with emerging technologies. These enhancements will refine chatbots' language comprehension, allowing for more natural conversations, personalized health guidance and chatbot creation that could focus on voice-over contextual-based intelligent chatbots.

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