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ATTENTION MECHANISM CONVERSATIONAL AGENT MODEL FOR DENGUE FEVER ANALYSIS

[1.] Uzoaru Godson Chetachi
uzoarugc@clifforduni.edu.ng

[2.] Francis Chigozie Emmanuel
francischigozie77@gmail.com

[3.] Alozie obidinma
Christian-Obidinmag@gmail.com

ABSTRACT

A conversational agent, often known as a chatbot, is a sort of artificial intelligence (AI) software that can simulate a discussion (or chat) with a user in natural language via messaging programs, websites, mobile apps, or the phone. This work describes a conversational chat system that uses an attention mechanism to react to Dengue requests. The model utilizes the three scoring techniques of the Luong Attention Mechanism: They are dot, general, and concat attention mechanisms: The results demonstrate that the accuracy of the dot attention mechanism is maximum and is 87% when the test questions were taken directly from the database, as determined by an assessment of the results, compared to 38% when the attention mechanism is not used. Furthermore, when the questions are asked with natural changes, human confirmation reliability is 63% as opposed to 16% when the attention mechanism is not applied. According to the study, chatbots may be employed anywhere due to their accuracy and 24-hour availability.

Keywords: Chatbot, Conversational agent, Dengue, Recurrent neural network, Attention mechanism, BLEU score.

1. Introduction

A chatbot is an automated computer software designed to mimic human interaction [1]. It enables people to interact with organizations offering services over the Internet or applications [2]. Chatbots are gaining popularity in the corporate sector for managing client interactions [3]. These bots are commonly employed to respond to inquiries on products and can offer customer support 24/7 without requiring the presence of a human representative [4]. One of the various applications of chatbots is the automation of routine processes for customers, such as banking and retail transactions. Chatbots are employed for automating public sector tasks, such as handling inquiries related to billing matters [5]. As an illustration, there was a significant amount of concern and distress around Dengue [6]. An AI chatbot capable of addressing common requests and providing up-to-date information and recommendations to the public could alleviate the workload on contact center agents. As a result, human agents are capable of managing more intricate calls, including those that may have time constraints [7].

While "chatbot" and "conversational Agent" are often used interchangeably, they have distinct meanings [8]. In the absence of conversational Agent technology, Chatbots often follow a rule-based organizational framework and rely on keywords and language markers to trigger pre-determined responses. Conversational Agent Chatbots, in contrast, faithfully replicate human interactions, resulting in a more favorable user experience. [9]. Deep learning algorithms need to analyze vast quantities of data to interpret user intent and human language. Deep neural networks, which use an attention technique, are essential to use conversational artificial intelligence [10]. This method models how cognitive attention works by putting more weight on some components of the input data while examining other aspects.

This research gives a comparative investigation of the efficiency of attention methods for the conversational Agent built for medical practitioners. Our contributions include (i) Developing a conversational agent model to respond to relevant queries, (ii) Performing an analysis of attention processes, (iii) Developing a repository of question responses specifically for inquiries related to Dengue, and (iv) Developing a model utilizing the Python Flask Library. The paper is divided into multiple sections. The introduction is located in Section 1; Section 2 consists of the literature review. While Section 3 describes the approach and dataset. The findings are presented in Section 4, and Section 5 contains the conclusion.

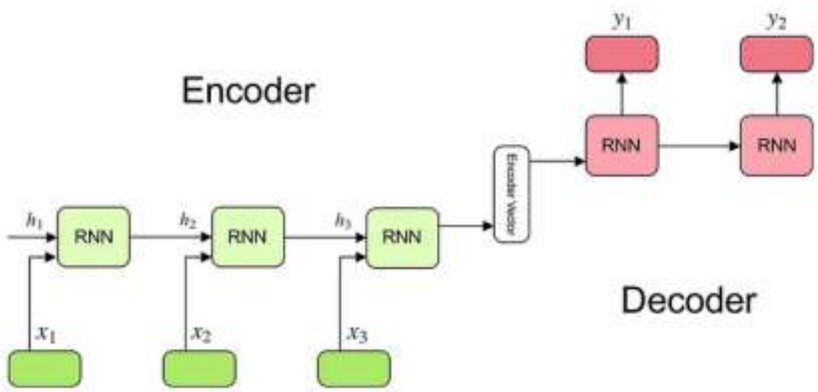
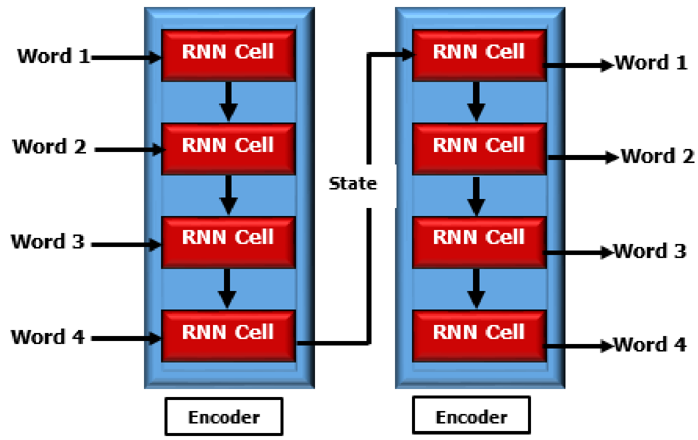
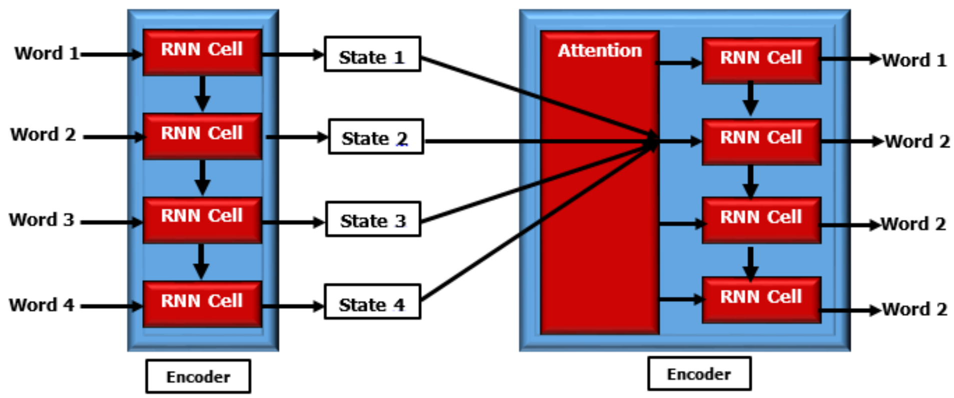


Fig. 1: A recurrent neural network with an encoder that takes words as input and a decoder that produces words.



(a) Without an attention mechanism



(b) With an attention mechanism

Fig. 2: a recurrent neural network where the decoder generates output words and the encoder receives input words.

2. LITERATURE REVIEW

There are two sorts of Conversational Agents [11]: retrieval-based and generation-based. Retrieval-based chatbots employ metrics to match user input, which functions as a query—with likely answers. The inner product of two feature vectors that represent the request and potential responses in a modified Hilbert space is computed to achieve this. In contrast, the generation-based approach uses a model to help the chatbot generate a response rather than pulling data from a repository. A chatbot's implementation can differ depending on the data it uses and the results it wants to produce.

There are debate on the design technique of the modern chatbot pointed out that Sequence-to-Sequence for input processing and Long Short-Term Memory (LSTM) models are typically applied while designing a chatbot [12]. Chatbots are exhibited by employing the Recurrent Neural Network (RNN) LSTM model [13].

Large inputs can be handled by using an attention model and a bidirectional RNN. A bidirectional Gated Recurrent Unit (GRU) RNN encoder and a Sequence-to-Sequence model for input processing are two ways a retrieval-based chatbot can carry out its retrieval-based capability. A bidirectional Gated Recurrent Unit (GRU) RNN encoder is used in these models. [14].

A voice application was created to provide basic healthcare education and counseling to pregnant women and chronic patients using natural language processing. Multiple languages can be supported by the application. [15]. Utilizing Google's Dialogflow Discussion API, an automated chat system is created to comprehend and respond in the user's native tongue. As a result, the user and the application might have ongoing conversations.

An automated communication system that bridges the divide between people and machines is introduced, enabling two-way dialogue. [16]. This method employed a bi-directional LSTM neural network to analyze questions at the sentence level. Furthermore, 1,606,583 conversation materials were created by the scientists in order to train a deep neural network that would assess the applicability of potential responses, postings, and rephrased questions in a variety of scenarios. An artificial intelligence (AI)-based chatbot that analyzes Aedes-borne diseases through natural language processing was developed in a different study that involved the creation of a Thai-language chatbot that employed Jaccard similarity to examine diseases carried by mosquitoes. The study's conclusions showed that the Thai-language chatbot successfully captured users' intentions with an intent accuracy of 85.00%. Additionally, the SUS evaluation revealed a strong usability score of 89.75, indicating that the chatbot was easy to use[17]. There is construction of a hybrid machine learning based prediction model, which helps to discover patients who are infected by vector-borne disease at an earlier stage and also helps with the categorization and diagnosis of severe vector-borne disease [18]. Google and Verily collaborated to create a chatbot that answers questions and addresses concerns about dengue [19]. The chatbot offers answers to 97 of the most popular questions as well as ten to fifteen practice phrases for different conversational techniques. After extensive development, the bot was 75% of the time correct. The results of the investigation indicate that there are 61 chatbots in use across 30 countries. [20]. To assist senior citizens, a chatbot-based mobile support system was created. [21]. Their rule-based approach takes into account each user's preferences while including social, mental, and physical assessments. Every day, the mobile chatbot asks the elderly person one question, to which they can respond by pressing a button or using speech recognition.

Rule-based chatbots are among the several applications for which chatbots have been created. Rule-based chatbots are limited, though, as they are unable to transition between topics with ease. Conversely, artificial intelligence-powered chatbots may link similar questions and provide answers for almost any query. In comparison to rule-based chatbots, this study's conversational AI-based chatbot is more helpful to users because it can handle demands that go beyond the database.

3. Methods

We created a collection with over a thousand frequently asked questions and responses about dengue fever. The opendengue dataset served as the basis for our question-answer database, and our team used a variety of resources to compile the responses. The questions include a wide range of topics, from basic inquiries about dengue to information about different preventative measures and available treatments.

The training process of the sequence-to-sequence network model is shown in Fig. 1. This type of network works well for answering multi-word inquiries and responses. An example of an RNN architecture that can translate an input sequence from one domain to an output sequence in a different domain is a Seq2Seq model. [22]. An encoder and a decoder are the two RNNs in the model. After processing the input sequence, the encoder produces a single vector. After that, the decoder builds the target sequence using the vector. One input word at a time is fed into the encoder RNN, which then outputs an output vector and a hidden state vector.

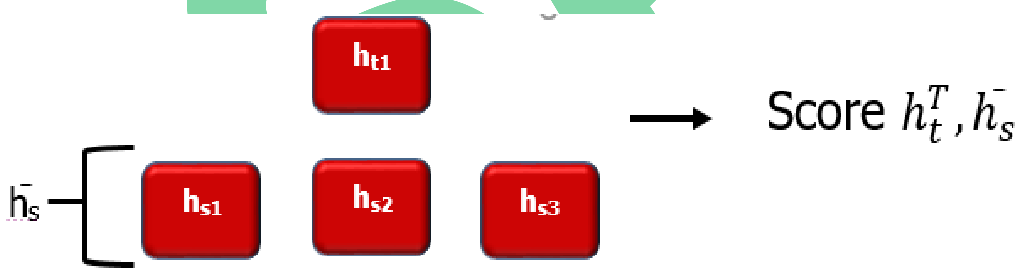


Fig. 3: Calculation of global attention using Equation 2.

This research uses a bidirectional GRU as the encoder, which comprises two RNNs functioning independently. One RNN processes the input sequence in a conventional sequential order, while the other processes it in reverse order. This method allows the encoder to encode both past and future context. The encoder then generates a context vector, which the decoder utilizes to generate a response. The decoder uses a unidirectional GRU to process each word in the response phrase, and it employs the attention mechanism to output a probability score for the next anticipated word. According to Ref. [23], GRU is more economical and easier to utilize than LSTM, especially when working with less training data and shorter sequences.

Fig. 2a depicts how a primary seq2seq decoder leverages a context vector to express the comprehension of a complete input sentence. Nevertheless, this method could lead to a loss of information and restrict the decoder's capability regarding lengthy input sentences. To overcome this issue, an attention mechanism has been introduced, as indicated in Fig. 2b, which helps the decoder RNN to focus on specific parts of the input sequence rather than relying on the complete fixed context [24].

$$score_{alignment} = W_{combined} \cdot \tanh(W_{decoder} \cdot H_{decoder} + W_{encoder} \cdot H_{encoder}) \qquad (1)$$

Bahdanau et al. [25] proposed an attention method that allows the decoder to pick specific elements from the input sequence to generate output. The technique creates a unique mapping between each time step of the decoder output and the encoder's hidden states. The Additive Attention approach uses the hidden states of both the previous time step decoder and the present encoder to calculate alignment scores. The scores are combined using a Linear layer. Equation (1) shows how to apply a tanh activation function and multiply the output by a weight matrix.

This paper uses the Luong Attention Mechanism [26], which improves upon the attention mechanism provided by Bahdanau et al. The major difference between the two approaches is how they use the encoder's secret states. The Luong method examines all the encoder's hidden states, resulting in "global attention," while Bahdanau et al. Only consider the encoder's current hidden state, resulting in "local attention." The "global attention" process determines weights based on the decoder's hidden state at the current time step. The Bahdanau et al. technique uses the decoder's concealed state from the previous stage.

$$Score(h_t^T, \overline{h_s}) = \begin{cases} h_t^T \ \overline{h_s} & \text{dot} \\ h_t^T W_a \overline{h_s} & \text{general} \\ V_a^T \tanh(W_a[h_t; \overline{h_s}\ ] & \text{concat} \end{cases} \quad \textbf{(2)}$$

where Wa stands for trainable weights, hs for all source states, and ht for the current target hidden state.

Equation (2) and Fig. 3 illustrate how the Global Attention mechanism generates a score function by combining the hidden states of each source, hs, with the currently hidden states, ht. This function assists the model in learning the proper alignment weights by calculating the difference between two vectors.

As seen by Equation (2), the model can learn to better align the sequence by concentrating on its most crucial segments.

Minh-Thang Luong et.al. (2015) states that there are three methods for calculating global attention: concat, general, and dot. The dot approach calculates similarity using a dot product. Trainable weights Wa are used in the general method to increase flexibility. Although the encoder and decoder hidden states are merged before being transmitted through a neural network for scoring, the Concat function is comparable to Attention in Bahdanau et al. This indicates that, contrary to what Ref. [27] explains, the weight matrix is shared by the encoder and decoder hidden states rather than being unique to each. This study trained the network

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using the three attention mechanisms—dot, general, and concat—and then compared the outcomes.

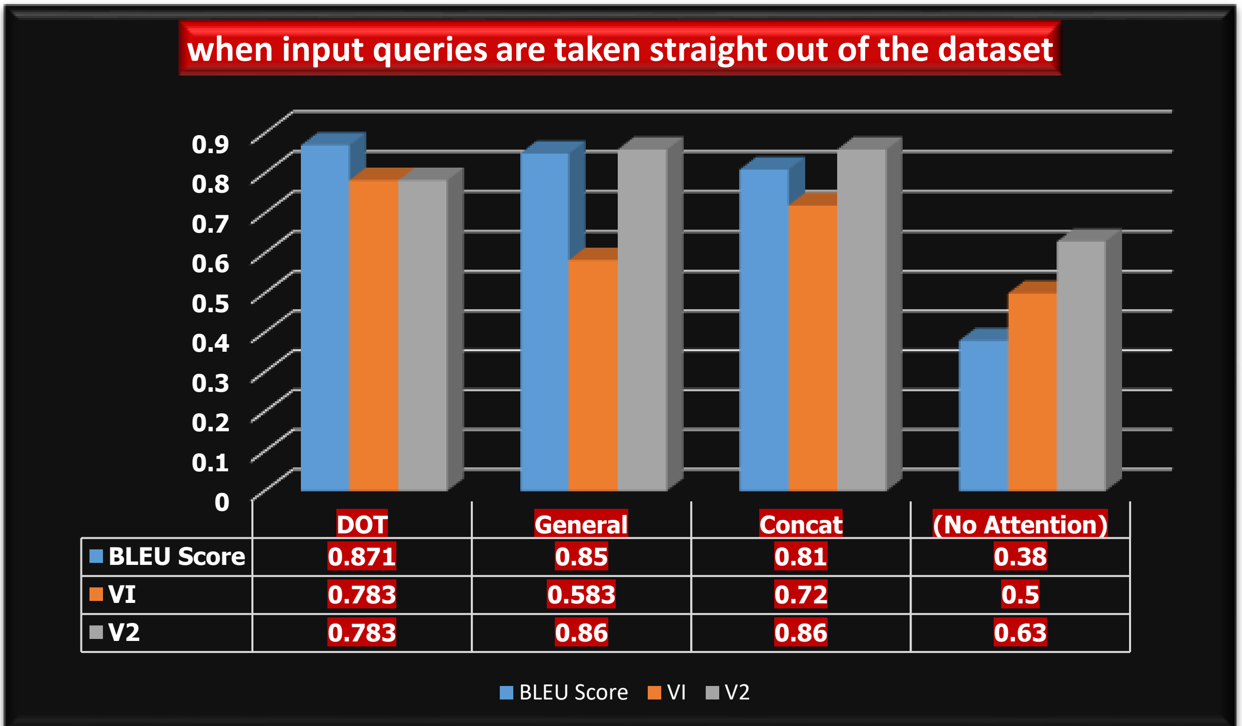
Table 1: Training hyperparameters.

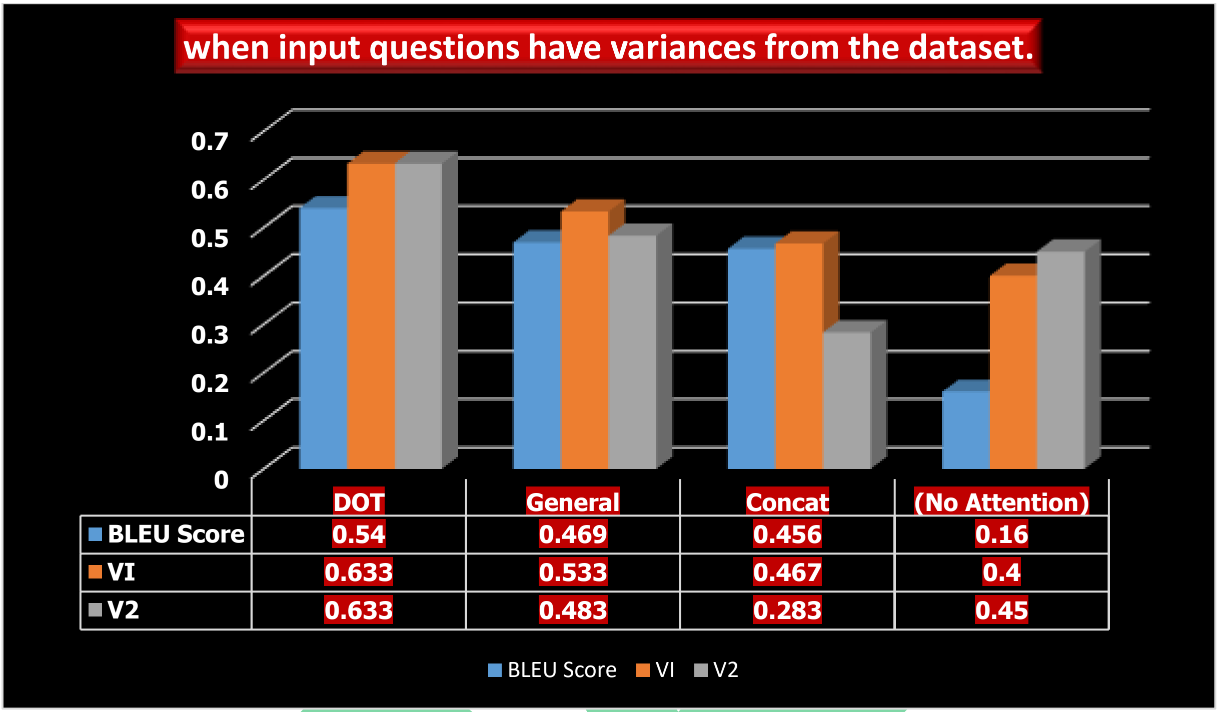
Hyper-parameter	Value
Hidden Nodes	**256**
GRU Layer	**1**
No of Training Iteration	**100,000**
Learning Rate	**0.01**
Loss Function	**NLLLoss()**
Optimizer	**Stochastic gradient descent**

Table 2: Mean BLEU for Luong attention processes and volunteer scores.

(i) when input queries are taken straight out of the dataset			
Function	**BLEU Score**	**VI**	**V2**
DOT	0.871	0.783	0.783
General	0.850	0.583	0.86
Concat	0.810	0.720	0.86
(No Attention)	0.38	0.5	0.63

(ii) When input questions have variances from the dataset.			
Function	**BLEU Score**	**VI**	**V2**
DOT	0.540	0.633	0.633
General	0.469	0.533	0.483
Concat	0.456	0.467	0.283
(No Attention)	0.16	0.40	0.45


when input queries are taken straight out of the dataset
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
DOT
General
Concat
(No Attention)
BLEU Score 0.871 0.85 0.81 0.38
VI 0.783 0.583 0.72 0.5
V2 0.783 0.86 0.86 0.63
BLEU Score
VI
V2



Fast convergence was ensured by using the Adaptive Moment Estimation (Adam) optimizer and calculating the loss using the average log-likelihood. To promote faster convergence, we additionally employ gradient clipping and the teacher-forcing technique. Using this method, the decoder receives the ground truth—that is, the target word—as input for more effective training. To keep the gradient from growing too big, which would interfere with training, we employed gradient clipping in the interim.

The phrases are transformed into numerical torch tensors as part of the model's training procedure. Preprocessing is the initial stage, which entails converting the Unicode string to ASCII, lowercase all letters, and eliminate any characters other than punctuation marks that aren't letters. The sentences are then split up into pairs. To train the model, each phrase pair is then converted into a value that both the encoder and the decoder can comprehend. As a result, every pair of sentences is converted into a tensor that has an end-of-sentence token, an index value for each word, and a start-of-sentence token.

To guarantee that the tensor lengths remain constant, pad the tokens. Following the generation of the sentence pair tensors, the model is trained by passing the pairs through the encoder repeatedly, followed by the decoder iterating the encoder output. The hyperparameters utilized in the training are displayed in Table 1.

In this study, we examine and compare the outcomes of the three distinct scoring systems used by the Luong Attention Mechanism (see Table 2).

Sample answers from Dot attention mechanism when input queries are taken straight out of the dataset

QUESTION	Expected Response	Real Response
Are Dengue and Malaria the same thing?	No, it's not. Dengue is transmitted through a bite from an infected Aedes aegypti mosquito. Malaria is transmitted via the bite of a female Anopheles mosquito.	Dengue fever is a tropical disease caused by the dengue virus. Malaria is a deadly blood illness caused by a protozoal parasite.
Could you describe the origins of the Dengue virus?	During the 1828 outbreak in Cuba, the disease was first known as Dunga, which was later shortened to dengue.	The disease arose from Africa during the slave trade in the 15th-19th century and migrated into the Americas.

Do dengue symptoms appear gradually?	Dengue fever symptoms can appear suddenly or gradually, and the severity of symptoms can vary from person to person.	Dengue fever symptoms typically appear between 3 and 14 days after a person is infected to the virus, with an average incubation period of four to seven days.
Do I have dengue fever?	If you suspect you have dengue fever or are experiencing symptoms associated with the virus, it is essential to seek medical attention promptly.	Consult a doctor if you develop a fever or have dengue symptoms. Tell him or her about your travels. Rest as much as possible. Acetaminophen can help you lower your fever and decrease pain. Consume plenty of water to keep hydrated. Drink water or drinks with electrolytes.
Can I email a description of my symptoms?	Proceed to the nearest health center and receive results.	Proceed to the nearest health center and receive results.
What are the best ways to prevent getting infected with the virus?	Use Mosquito Repellent, Wear Protective Clothing, Avoid Peak Mosquito Activity, Use Mosquito Nets, Eliminate Mosquito Breeding Sites:	Use insect repellent, dress loosely in long-sleeved shirts and slacks, and keep mosquitos at bay both inside and outside your home.

Sample answers from Dot attention mechanism when input queries are with variations from dataset.

QUESTION	EXPECTED RESPONSE	REAL RESPONSE
TELL ME ABOUT DENGUE	Dengue fever is a viral illness caused by the	*Dengue* (break-bone fever) is a viral infection that spreads from

	dengue virus, which is primarily transmitted to humans through the bites of infected Aedes mosquitoes, particularly Aedes aegypti and, to a lesser extent, Aedes albopictus. These mosquitoes are commonly found in tropical and subtropical regions, making dengue a prevalent disease in many parts of the world.	mosquitoes to people. It is more common in tropical and subtropical climates.
WHAT HAS THE ABILITY TO SPREAD DENGUE?	Dengue fever is primarily spread by the bite of infected mosquitoes, particularly Aedes mosquitoes.	The principal vector of the dengue virus is the mosquito Aedes aegypti, which transmits the virus from human to mosquito to human in a cycle of transmission.
METHODS FOR AVOIDING DENGUE	Preventing dengue involves minimizing the risk of mosquito bites and reducing mosquito breeding habitats.	Wear loose-fitting, long-sleeved shirts and long pants, apply insect repellent, and keep mosquitoes both inside and outside your home.
CAN MY DOG CONTRACT DENGUE?	No, dogs cannot contract dengue fever. Dengue is primarily a disease that affects humans and is transmitted by Aedes mosquitoes, particularly Aedes aegypti and Aedes albopictus.	In addition to non-human primates, dengue illness has been reported in dogs, horses, bovids, pigs, marsupials, bats, and birds.
ALLERGIES TO DENGUE MEDICATIONS	Allergic reactions to medications used to treat dengue fever are possible, but they are relatively rare.	With a percentage of 28.6%, pruritus was the most prevalent allergy symptom in dengue patients, regardless of the severity of the disease.

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WHAT SAFETY MEASURES MAY I TAKE?	Use Mosquito Repellent, Wear Protective Clothing, Avoid Peak Mosquito Activity, Use Mosquito Nets, Eliminate Mosquito Breeding Sites:	Use insect repellent, dress loosely in long-sleeved shirts and slacks, and keep mosquitos at bay both inside and outside your home.

4. Results and discussion

Three scoring functions are used to monitor user input and chatbot responses in order to evaluate performance. First, we utilize the BLEU (Bilingual Evaluation Understudy) score, which gauges how closely a machine's output resembles a human's, to assess the quality of the machine-generated response. A common and reasonably priced metric, the BLEU score is like a language teacher rating a student's response against a reference answer. A score of one represents a perfect match, and an absence of match is denoted by a value of 0. We use unigrams to compute accuracy. For example, the accuracy score would be 3/5 if the goal sentence were "Dengue is an infectious disease" and the model predicted, "Dengue is a disease."

For human verification, we asked two volunteers, V1 and V2, to score the replies produced by the model on a scale of 1 to 10. Two tests were carried out, one in which the user input perfectly matched the dataset used to train the model, and the other in which there were discrepancies or departures from the dataset's questions. The average performance scores for answering questions that matched the dataset exactly are shown in Table 3a. The average performance scores for answering questions that differed from the dataset (see Table 4) are shown in Table 3b.

The model can react to non-scripted user inputs based on the findings. Out of the three models, the one with the dot-scoring function fared the best. In contrast, performance declined on questions with deviations. This suggests that the AI chatbot is making an effort to produce responses that are consistent with the queries posed, much as how people would modify their responses accordingly.

5. Conclusion

An attention mechanism in our conversational Agent allows it to reply to Dengue queries. We compare attention variations for different contexts using a recurrent neural network. During testing, our dot attention mechanism achieved 87% accuracy when questions were taken straight out of the database. However, accuracy fell to 54% when questions included natural fluctuations. However, after human testing, the model was shown to be 63% accurate during human verification, making it usable. We intend to add more questions on other diseases to our dataset and use other language models, such transformers that are better suited for big datasets in order to increase our performance.

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