A Proposed Chatbot Framework for COVID-19

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***Abstract*—In recent years, chatbots have gained traction in a variety of fields, including health care, education, marketing, cultural heritage, support networks, entertainment, and many others. To manage the large number of user requests during pandemics, chatbots have become a must-have piece of equipment. In this paper, we present a smart chatbot system that can communicate with people and provide them with answers about the COVID-19. To tackle the popular role of question answering, our model used the pre-trained Google BERT language model. On top of the BERT, we add two architectural phases for the question-answering task. The first step is a text classification technique that employs the BERT Transformer to categorise text input into various categories based on the meaning of the words themselves. The actual application of the BERT model, as well as the query domain for answers, is the second step. Our proposed system is trained and tested on Stanford University's SQuAD V2.0, a well-known question-answering dataset.**

***Index Terms*—Chatbot, COVID-19, BERT, SQuAD.**

I. Introduction

Human-computer interaction (HCI) is a technology which enables users and machines to communicate using natural language [1]. An intelligent communication device (chatbot) is one solution to human-computer conversation that has been developed to persuade people that they are conversing with a human rather than a machine. Chatbots have been commonly utilised in a variety of domains, including customer care, website assistance, and schooling. According to recent reports, 80% of businesses expect to deploy chatbots by 2020 [1].

The biggest advantage of utilising chatbots for businesses is that their customer support systems are streamlined and the chatbot will address queries about goods or services from consumers. Building a smart chatbot, on the other hand, is difficult since it necessitates contextual comprehension, text entailment, and language-understanding technologies. Therefore, artificial intelligence and natural language processing also are needed for a variety of applications [2], [3].

It is still necessary to define AI's role in providing viable solutions to the defined epidemic. Surprisingly, a global research program must be developed to begin measures against this — but rather potential — epidemic without blaming anyone.

Recently, we have observed an increasing interest in conversational agents, as well as in software that interacts with humans through natural language. Text-based chatbots (or simply chatbots) have proliferated in a wide range of application environments for about the last ten years, allowing humans to communicate with machines using natural written language [4].

During a pandemic, people become unsure about what to do. Taking insufficient precautions (for example, failing to take prophylactic measures) will increase everyone's risk of infection. Heading to the emergency room for minor symptoms, for example, can overburden the healthcare system, wasting valuable resources. As a result, trustworthy information sources are critical for preventing a "misinfodemic": propagating a disease aided by viral misinformation.

To manage the large number of requests from citizens during pandemics, such as COVID-19, organizations should have new communication mechanisms. As a result, organizations such as the Centers for Disease Control and Prevention (CDC) and the World Health Organization (WHO) have started to use chatbots to exchange knowledge and suggest behaviours in order to relax the overwhelming majority of nervous individuals [5]. Chatbots are software-assisted intelligent services that converse with people in their native language via voice or text. Such well-known examples include Amazon's "Alexa," Apple's "Siri," and Microsoft's "Cortana." The Chatbot use for health-related purposes has grown significantly in recent years, from assisting clinicians with clinical interviews and diagnosis to assisting customers in self-managing chronic conditions.

Chatbot systems are the latest digital interface developments, following the growth of the web and smartphone apps [6], [7].It is well documented for these applications to use automatic conversational agents that operate on software creation or a kind of artificial intelligence (AI) relationship between users and automated systems with the intervention of natural language processing (NLP) [8]. A chatbot, on the other hand, reflects the technical advancement of Question Answering systems that are primarily focused on Natural Language Processing. Among the most popular examples of Natural Language Processing being used in various enterprises' end-use applications is producing answers to user requests in human-like natural language.

Since the healthcare industry is so closely linked to human interaction, it seems counterintuitive that conversational AI applications such as chatbots are becoming more popular. The majority of a hospital administrator's day is spent arranging appointments and responding to routine patient inquiries. It is neither necessary nor effective to continue or repeat the same actions and phrases. Bot applications can easily perform such activities. User feedback assessments are, of course, possible by gathering user comments in order to ensure good patient flow. Health bots are useful as a complement to personal clinical treatment or urgent drugs in the event of severe pandemics like novel Coronavirus (nCOV-19) [9], [10].

A. Emergency Response and COVID-19

In an emergency, a few minutes will be the difference between life and death. In certain ways, improved health care and accessibility services can result in the saving of numerous lives. The emergency paramedical end-to-to-end intervention device was recommended to be semi-automated. In the event of an emergency, it will deliver medical supplies on-site. To make sure that the mechanism stays reliable, it uses decentralised methods of delivery and doesn't depend on outside entities. In urban, semi-urban, and rural areas, the response system may be used. It enables community hospitals to offer specialist health care even when a specialized doctor is not available. Some of the classifiers used in the answer method are K-nearest neighbor, SVM, and ANN. Drones are used by the answer method to access distant locations that humans find impossible to enter. The drone can detect objects thanks to the deep neural network, which improves accuracy and reduces failure. The chatbot reviews user responses before passing them on to the administration if necessary. The chatbot uses NLP to optimize input responses.

Healthcare staff must be screened for COVID-19 symptoms and exposure for infection prevention to spread before any shift. The screening method must be effective and transparent for this to work. An AI-based chatbot-based workflow was developed and introduced by the University of California, San Francisco Health. In the first two months of use, it performed over 270,000 screenings. It resulted in better physical distancing, stopped potentially infectious individuals from accessing the facility, and provided valuable live data for decision-making personnel [11]

As a result, our proposed chatbot for medicare recipients would serve as a medical consultant while also providing easy and relevant preventative measures against COVID-19 infection. Additional advantage of this application is that it is usable around the clock to evaluate the patient's situation. Besides, also possesses back-end reasoning that identifies the virus's seriousness and facilitates real-time physician consultation in life-threatening situations.

II. Related Work

A. patient care

Through enhancing contact between clinic–patient and doctor-patient, healthcare chatbots have a lot of potential in medical communication. Remote testing, prescription follow-up tracking, and telephone appointments will also help meet the high demand for health services. A chatbot will conduct short and easy health surveys, set personal health-related reminders, communicate with clinical teams, plan appointments, and retrieve and review health data [12]. When looking for specific signs or patterns that can be used to diagnose illness, chatbots can react quickly or immediately to patients' healthcare-related queries.

For example, the Internet-based Doc-Bot communicates via mobile phone or Messenger. The bot can be personalised to suit unique health conditions, demographics, or habits [13]. The bidirectional information exchange between chatbots and patients could be used to test for medication commitment or to gather data.

B. Education and Knowledge Transfer System

Inter-professional education is critical for developing a realistic, inclusive healthcare workforce. When more than one profession learns with, from, or about each other, it is called inter-professional education. Its key aim is to enhance healthcare quality by increasing cooperation. It offers a basis for collaboration and understanding of how each discipline relates while retaining its unique identity [14]. Although more text sources are being opened up to analyze text mining and computational linguistics, other text corpora are becoming more applicable. Text analysis in these systems does not necessitate a deep understanding methodology.

This research is related to health communication and the use of emerging technologies. For example, [15]identifies three major areas where computational analysis and health communication intersect, which are the use of big data for analyzing public perceptions of health conditions or incidents, exploring network-related aspects of health phenomena, and disease tracking.

Another major boost to AI development was the integration of personal voice assistants, which enabled them to use voice commands such as operating home appliances, scheduling meetings, and completing other activities on smartphones or home speakers and then adding to that by allowing them to have a digital personality, such as speaking like a virtual assistants.

For example, Apple Siri [16], Google Assistant [17] are the most commonly used voice assistants. There are also a plethora of less well-known voice assistants, each with their own distinct personality but performing the same basic functions. They link to the Internet and, unlike their predecessors, produce substantive responses easily [18].

Apple chatbot Siri, published in 2010, made personal assistants more mainstream. There are numerous voice queries and calls for information on Messenger, which connect with audio, video, and picture and file submissions. Siri will also provide recommendations and responses, but it actively adapts to the use of internet services. Siri, despite its sophistication, is not without flaws. It necessitates the use of an internet connection. It is multilingual, but several languages are not supported, and navigation directions are only available in English. It also has difficulty hearing the interlocutor if he or she has a heavy accent or if there is background noise [19].

Watson was labelled after Thomas J. Watson, IBM's CEO and founder. IBM's DeepQA project developed Watson, a rule-based AI chatbot [20]. It's a framework that blends natural language processing (NLP) and hierarchical machine-learning methods for information retrieval and question-answering. To generate an answer, Watson employs a wide range of techniques to recognise and configure features such as names, dates, geographic locations, age, gender, and other characteristics. For each answer produced, the machine learning model learns how to combine the values of all of the features into a final number. It then ranks all possible answers and chooses the most correct one based on the ranking.

Watson uses a number of technical features, such as the Apache Unstructured Information Management Architecture (UIMA) system, to define and understand the entire sentence structure and grammar of the query, allowing it to fully comprehend what is being said. Watson may be used in a variety of ways in real-world applications. Since it can process text and conduct complex analytics on massive amounts of raw data, it can manage massive amounts of data. Watson is built in such a way that as the interaction continues, the programme learns more about the consumer. If Watson can find enough trends, it will be able to make accurate predictions.

Among the obvious benefits of Watson chatbot, there are certain disadvantages, such as the fact that it does not process data structure and does not understand relational databases. Finally, the drawbacks include higher maintenance costs, Watson's focus on larger businesses, and the length of time it takes to train Watson on the field and data that would be used by the chatbot [19].

Cleverbot [21] is one of the most common chatbots in the entertainment category, as we previously discussed. Clever uses detailed senetence-based artificial intelligence techniques to have a conversation with a person. It was planned, developed, and deployed to collect a large amount of data from people who use chatbots and interact with machines. Cleverbot's strength lies in the fact that it imitates natural language communication by learning from the user's feedback and then monitoring the interaction after it responds.

Cleverbot splits a phrase into keywords when the user initiates a conversation by saying a particular input, such as a sentence. It responds to the question posed by going at its saved datasets of interactions and determining how a user reacted to the question when it was asked. Cleverbot is unique because it does not rely on pre-programmed responses to respond to users; instead, it produces new ones. To make the chatbot more human, an avatar picture was added to make the conversation more relaxed.

Finally, Cleverbot's disadvantage is the undescribed responses, since it generates responses on its own. As a result, you have little influence of what is being replied to, as well as the abrupt change of subject and reacting without any meaning or reference.

III. Proposed Work

A. Pre-processing

The pre-processing on the data is performed by removing null values and unnecessary spaces to help the model to be able to classify the questions in a more accurate manner.

The major steps for data pre-processing are summarized below.

1) Removal of unnecessary spaces and null values through regular expressions.
2) Converting all text into lowercase
3) Customizing the length of questions and answers.

B. Overview of BERT

One of the most significant problems of natural language processing is a scarcity of training data. Although there is an immense amount of text data accessible in aggregate, if we want to build task-specific datasets, we must divide them into numerous disparate fields [22], [23]. Furthermore, as a consequence of this process, we have either several thousand or a few hundred thousand cases of human labeling. Unfortunately, deep learning-based natural language processing models need even more data to work well — they achieve significant changes when educated on millions, or even billions, of annotated training instances [24].

Special techniques have been developed to help general-purpose language models learn from the vast quantities of text accessible on the internet (this is known as pre-training). Pre-trained models can be tailored to different tasks, such as parsing queries, for example, emotion analysis. It gives greater accuracy than devising something designed from scratch, which usually results in task-specific details. In recent years, BERT has gained popularity because it has demonstrated state-the-of-the-the-the-art success on a wide variety of NLP tasks such as part-of-of-speech tagging, phrase extraction, named entity recognition, and language modeling [25].

Traditional machine learning models and neural networks are incapable of capturing the text's sequential content. As a result, recurrent neural networks (RNN and LSTM) were developed to model the sequential knowledge contained in text [26].

Nevertheless, those recurrent neural networks introduce further complications. A significant problem is that RNNs cannot be parallelized since they only accept one input at a time. An RNN or LSTM will handle single token at a time as input in the case of a text series. As a result, it can go through the chain one token at a time. As a result, training a model on a large dataset can take a long time.

In summary, the classifier may decide the type of a query in two ways: by the use of keywords inside the question or by the question's meaning. This enables the model to be more intelligent in deciding the correct response to a given query.

C. challenge

In our work, we aimed to employ a BERT model to generate a proper answers regarding users questions. However, we could land ourselves in disappointment when we discovered that the number of text strings exceeded the allowed by BERT (usually 512 tokens). The whole scenario may be unusual in normalised benchmarks like SQuAD [27] and GLUE [28], but it is very usual in more complex tasks [29] or real-world textual results.

We resolved the aforementioned challenge in our work by dividing responses into categories based on the type of question. As a result, based on the extracted keywords or the meaning of the given query, we used the BERT classifier to decide which response category to use. The parts that follow will go through our model architectural phases in more detail.

D. Text Classification using BERT:

Our augmented data-set [30] consists of 4115 questions all of them are categorized into 14 different categories which are ('Speculation','Transmission', 'Nomenclature', 'Reporting','Societal Response', 'Societal Effects', 'Origin', 'Prevention', 'Treatment', 'Testing', 'Comparison', 'Economic Effects', 'Symptoms', 'Having COVID', 'Individual Response'). In our experiments, we used 75% of our data in training while the remaining 25% were used for testing. We start the pre-processing part as implemented in [31] where we collected all the questions associated with a specific category which corresponds to the column in the data-set and then we train our model on all the questions. In our experiments, wee

TABLE I: Classification Accuracy of different classifiers aganist BERT

ID	Classifier	Accuracy
1	KNN	43.3%
2	SVM	72.2%
3	Naive Bayes	75.5%
4	Decison Tree	85.7%
5	**bert model**	**96%**

experimented with different classifiers. Results as shown in Table I showed that the BERT classifier outperformed other classifiers. Our classification showed training accuracy of 98% and testing accuracy of 96% [32] The implementation of the BERT model here is after we train our model and start using it by giving it the questions as an input and the model will respond with the right category in which we take the context file associated with it and feed it to the next part.the objective from this step is to classify the type of inquiry the user want so it would be easier and faster for the Q&A model to answer the question with good accuracy as well as allowing as to have more organized and suitable data set.While training we reached accuracy about 98% and testing about 96% as shown in Fig. 2.

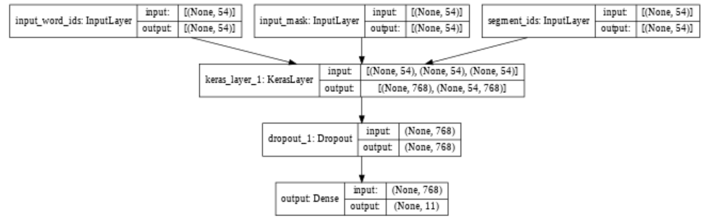

Fig. 1: Keras Layers

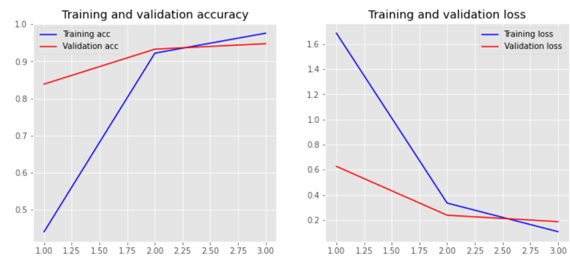

Fig. 2: Training and testing accuracy

E. Answering questions using BERT:

The second model (Q&A with BERT) is pre-trained to accept 512 tokens as the maximum number of tokens in the form of text. BERT is used to understand the meaning of a paragraph, as seen in Fig. 3. Furthermore, the BERT model is fed questions as input and then returns answers based on the context given. The model forecasts the paragraph's beginning and ending tokens. Normally, the paragraph is fed into the BERT model as the background that will most likely address the query.

IV. Work Model

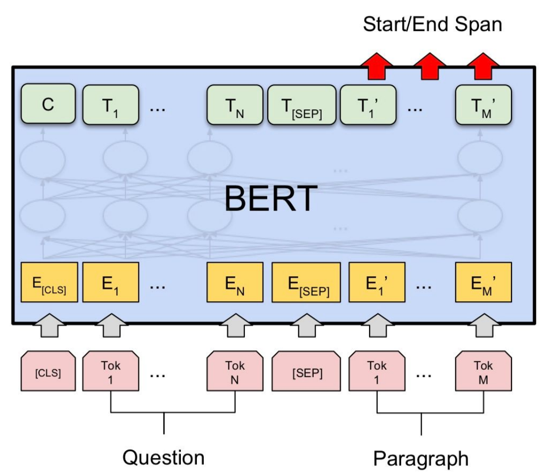

Fig. 3: BERT Model

Bidirectional Encoder Representations from Transformers (BERT) is considered a Transformer based on machine learning techniques for natural language processing purposes (NLP) already pre-trained and developed by Google researchers. BERT was developed to help with Q&A tasks using a

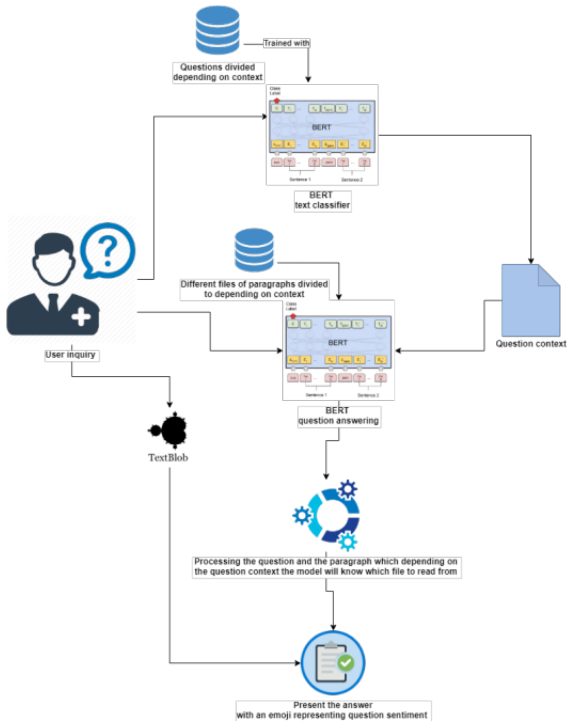

Fig. 4: Our Chatbot Model

question-and-answer dataset like SQuAD v2.0. BERT is different from other deep learning models such as LSTM, where it takes the whole sentence as the input in a sequential way. Therefore, it takes both the question and the context in specific tasks like question answering ones that need to be fine-tuned after being pre-trained.

V. Results Of BERT Model

In this section, we are going to show some preliminary results regarding our proposed model. Table II shows sample common user questions along with the responses generated by our model.

We Managed to achieve accurate responses from the BERT model by categorizing user questions into categories, making it's easier for our Q&A model to receive larger quantities and a more organized dataset. Accordingly, we classify the user question into a category and take it as a context and the question to provide the proper answer. Our experiments over the mentioned workflow have achieved training accuracy of 98% and testing accuracy 96%. These results are considered too optimistic toward improving the development of an accurate prediction model. And diagnosing the symptoms of the coronavirus COVID-19 and helping in raising awareness on this new disease and its impact on our lives. Our proposed model showed reliable answers for common questions that users frequently ask regarding COVID-19. Table II provides some questions along with our system answer. As we mentioned previously, our proposed work that is introduced here is the preliminary version of our system. Therefore, we are still in the process of providing our system with other capabilities to ensure its robustness.

We think that the provided workflow that is used in this paper can be applied on other fields to increase the spreading and usage of chatbots. By using the suitable dataset and the necessary pre-processing techniques, Similar results can be achieved.

VI. Conclusion

In this paper, we have introduced our preliminary COVID-19 chatbot paradigm. We have relied on the pre-trained Google BERT language model to tackle the COVID-19 question-answering challenge. We have tested our proposed chatbot over COVID-19 sample questions-answers dataset. Preliminary results have shown that our proposed model generates a suitable answers regarding the asked question. In the future work, we will try to incorporate more datasets to enrich our model accuracy and robustness.

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TABLE II: Sample answers that are generated by our chatbot system

Question	Answer
What is COVID cure?	By delivering a viral vaccine that causes the person being vaccinated to make an immune response.
Where did COVID start?	Wuhan. China
What is the COVID symptoms?	fever, cough, shortness of breath, and potentially respiratory distress
What is the incubation period for COVID?	1-14 days
When will corona end?	Speculation Category is not available yet
What is the difference between flu and Covid?	covid-19 is caused by a new coronavirus called sars-cov-2
How to prevent spreading corona?	you should use a mask for as long as you are still coughing or sneezing
What are types of vaccine to cure corona?	mRNA vaccines
How to cure covid?	by delivering a viral vaccince
what is the diff between covid and flu?	covid - 19 is caused by a new coronavirus called sars - cov - 2 while flu is caused by influenza a and b viruses
What causes flu?	influenza a and b viruses
What is sars?	severe acute respiratory syndrome coronavirus 2

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