Acta Scientific COMPUTER SCIENCES

Volume 6 Issue 4 April 2024

Research Article

AI Application in Health Care (Chatbot)

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Received: February 02, 2024

Published: April 30, 2024

Abstract

The influence of Artificial Intelligence (AI) has left an indelible mark on diverse aspects of human existence, offering profound automation in a daily activities. This paper undertakes a focused exploration of the applications of AI in healthcare services, a domain where its impact has been transformative. Within healthcare, AI applications have ushered in revolutionary advancements encompassing disease diagnosis, medical record management, treatment protocols, and medical administration.

This paper centers on developing a healthcare chatbot An AI-driven application designed to interact with users, providing valuable medical information and assistance. The motivation for the focus on the chatbot technology is to understand how AI chatbots are able to generate their responses when a prompt is given. Other uses of chatbots for medical applications include medical diagnosis, appointment scheduling, and medication-related inquiries. The chatbot was trained on an extensive Kaggle dataset from The Devastator, [1], comprising 47,603 rows of medical-related questions and corresponding answers. Dataset is the foundational knowledge base for AI models (chatbot's responses) [2].

Before the development of the model, several critical operations were conducted on the dataset to ensure its efficacy. Data cleaning procedures were implemented to rectify inconsistencies and inaccuracies, bolstering the dataset's integrity. Comprehensive data analysis unveiled insights crucial for understanding the dataset, while feature-engineering techniques were employed to enhance the dataset's suitability for training. Python, its libraries, and dependencies were the primary toolkit for executing these operations and building the model.

This paper showcased a versatile approach by incorporating various models; the paper achieved a well-rounded analysis by integrating modern deep learning methods and conventional machine learning approaches' architectures spanning from cluster models such as random forest to advanced neural networks like RNN and LSTM. This diverse model selection facilitated a more comprehensive exploration of the dataset, harnessing the strengths of each model type for a nuanced and effective solution.

Keywords: Artificial Intelligence; Healthcare; Chatbot; Natural Language Processing; Machine Learning

Abbreviations

AI: Artificial Intelligence; RNN: Recurrent Neural Network; LSTM: Long Short Term Memory; NLP: Natural Language Processing; BERT: Bidirectional Encoder Representation from Transformers

Introduction

Background

An entirely new definition of automation and efficiency has emerged as a result of the growing importance of Artificial Intelligence (AI) applications across a range of industries. In this regard, the goal for this research paper is to create an AI chatbot model tailored for use in healthcare settings. Artificial intelligence (AI) has a profoundly revolutionary effect on daily activities in a wide range of disciplines, highlighting its position as a keystone for work automation and efficiency in the modern world.

AI is a multidisciplinary field that integrates science and engineering to endow systems with intelligence characteristics similar to those of humans. Perception, natural language processing, planning, problem solving, learning and adaptation, and environmental action are all included in these qualities [3].

The AI world is rapidly evolving, introducing new, cutting-edge ideas regularly. Modern technologies like self-driving cars and facial recognition are designed to do mundane tasks. However, the primary goal of artificial intelligence is to develop more advanced and intricate systems that may outperform humans in any way [4].

The health industry is one area where artificial intelligence is being more widely used. The usefulness of AI-powered tools in the future generation of healthcare technology is recognised by the industry. AI can improve any stage in the healthcare management and delivery process. For example, one of the primary reasons for deploying AI technologies is to save money in the healthcare industry. By 2026, AI applications are expected to save the United States $150 billion in healthcare costs per year. These cost reductions are primarily due to the transition in the healthcare strategy from reactive to proactive, with an emphasis on health maintenance rather than sickness treatment [5].

Chatbots are one example of how artificial intelligence technologies are used in healthcare. Healthcare conversational AI use cases are versatile and may be tailored to a certain industry. Patients who want to learn more about their ailment, available therapies, or insurance coverage can utilise them. Numerous healthcare organisations are exploring incorporating healthcare chatbots into their operations, since research has shown that they may significantly reduce wait times and boost patient satisfaction. Use cases for conversational AI in healthcare are customisable and may be tailored to the industry. Patients who want to learn more about their ailment, available therapies, or insurance coverage can utilise them. Numerous healthcare organizations are exploring incorporating healthcare chatbots into their operations, since research has shown that they may significantly reduce wait times and boost patient satisfaction [6].

Problem statement

Healthcare professionals have experienced various challenges in delivering services. Some of these challenges, At the time of financial constraints, we tend to look for means and systems to decrease our expenditure. Healthcare is no exception. Currently, the Middle East is suffering from significant [7].

financial constraints. Many governments are developing systems by which the cost of all services provided is decreased, including the healthcare.

Another critical challenge experienced in healthcare is the efficiency and accuracy of disease diagnosis. Due mostly to inadequate local diagnostic capability, inadequate diagnostic readiness had caused considerable delays in the diagnosis of recent epidemics of several diseases, including Lassa fever, Zika, Ebola, and yellow fever. Three months passed between the discovery of the causative agent and the index case in the West African Ebola epidemic of 2013–2016. According to post outbreak analyses, diagnosing 60% of patients in a single day instead of five days could have cut the attack rate in half, from 80% to almost 0%. The diagnostic data and the right treatments ultimately resulted in the outbreak's control. Nevertheless, the reaction cost billions of dollars, and thousands of lives were lost due to the delays [8].

Also, another challenge, as highlighted [9-11], is the workforce shortage. To support this point, they stated that another significant issue facing the healthcare industry now and in the future is a labor shortage since clinical, allied, and management healthcare workers are in short supply in practically every nation. By 2035, there will be a deficit of 12.9 million qualified healthcare personnel in both developed and developing nations, according to the World Health Organization (2014), (2017). (2018).

Objectives

Some of the questions this research seeks to answer is whether lemmatized text data performs better that stemmed text data in when used to build our chatbot model and also which algorithm performs best when used to build our chatbot model.

- This project aims to develop a chatbot model capable of generating accurate and contextually appropriate responses to various prompts. For this model, we employ advanced natural language processing techniques to create a chatbot that can engage in meaningful conversations and provide users with exceptional interaction.
- This project will also investigate and compare the performance of stemming and lemmatization techniques in generating accurate responses, determining which approach yields the highest level of accuracy. This evaluation will provide valuable insights into the effectiveness of these methods in chatbot development and their ability to enhance the overall accuracy of chatbot responses.
- This project will also comprehensively evaluate various natural language processing (NLP) models, including neural networks and other machine learning algorithms, to determine the model that produces the most accurate and contextually appropriate responses for chatbot interactions. This comparative analysis will provide valuable insights into the strengths and weaknesses of different NLP approaches and guide the selection of the optimal model for building an effective and user-friendly chatbot.

Literature Review

Overview of artificial intelligence application in healthcare

Artificial intelligence has flourished due to improvements and the availability of large amounts of data. However, before discussing this further, let us define artificial intelligence. It is the science and engineering of creating intelligent machines, particularly intelligent computer programs, while the aim of utilizing computers to comprehend human intellect is comparable, artificial intelligence (AI) is not limited to techniques that can be seen through biological means. Artificial intelligence is the branch of technology that develops programs to comprehend information and occasionally behave intelligently [12].

Artificial intelligence has become an integral part of today's world due to the vast amount of data available today. Artificial intelligence (AI) has seen increased integrated into our daily lives in recent years in ways that we might not even be aware of. It has spread so far that many people are still ignorant of its effects and our dependence on it. AI technology powers many of our daily tasks as we go about our daily lives, day in and day out. Many of us grab our computers or cell phones when we get up to begin our days. We automatically do this in our planning, information-seeking, and decision-making processes.

AI now permeates every facet of our online personal and professional life. In business, global communication and interconnectedness have always been crucial. It is crucial to make the most of data science and artificial intelligence, and their growth potential is endless [13].

Big data and machine learning affect most facets of modern life, including commerce, healthcare, and entertainment. Google knows what symptoms and ailments people search for, Amazon knows what products people like to purchase when and where they want to buy them and Netflix knows which films and television shows people love to watch. With all of this information, a comprehensive personal profile may be created, which might be very helpful for targeting and analyzing behaviour [5].

Healthcare is not exempt from the effects of artificial Intelligence. In his review [14] believed that artificial intelligence is revolutionizing and strengthening modern healthcare through technologies that can predict, grasp, learn, and act, whether employed to identify new relationships between genetic codes or to control surgery-assisting robots. It can detect minor patterns that humans would completely overlook.

In addition, [5] opined that there is a lot of hope that using artificial intelligence (AI) would significantly advance healthcare in every facet, from diagnosis to therapy. AI technologies will support and improve human labor, not replace doctors and other healthcare professionals. Artificial Intelligence is prepared to assist healthcare professionals with various duties, including clinical documentation, patient outreach, administrative workflow, image analysis, medical device automation, and patient monitoring.

Application of Artificial Intelligence in Healthcare

- **Artificial Intelligence Powered Disease Diagnosis:** Medical diagnosis is one area where artificial intelligence is applied [15]. Suggested a method for identifying brain tumors. A system that uses the Fuzzy C Means clustering method to diagnose brain tumors from MRI data. Particle swarm optimization and genetic algorithms are used with fuzzy C means algorithms. Two techniques were used to fragment the suspicious block: PSO and GA. Brain tumors are then confirmed and correlated in the diagnostic process using a computer-aided system. Brain tumor fragmentation adaptive threshold was found with the use of Fuzzy C Means.
- **Artificial Intelligence Powered Medical Records Keeping:** Around the world, most hospitals are now utilizing AI technologies to improve their processes in what is now known as 'smart hospitals [16]. This has also been reflected in improving medical record-keeping processes, which has gone beyond keeping records for reference to using those records to build solutions that can predict conditions based on historical data. By digitally recording patient data and creating a digital database that can be utilized for diagnosis, treatment, and routine Medicare visits, artificial intelligence (AI) helps healthcare staff save time when documenting cases [17].
- **Application of Artificial Intelligence in Medical Treatment:** AI might also be used to track the directed delivery of medications to certain organs, tissues, or tumors. According to [18], current research in AI and precision medicine shows the possibility of highly personalized medical diagnostic and treatment information being added to the activities that medical professionals and consumers perform concerning their health. Other areas of AI application treatment, according to [19], are oncology, radiography, pathology, and biomedics.

Artificial intelligence-powered chatbots in healthcare

(IBM) defines a chatbot as a computer program emulating human conversation, often incorporating artificial intelligence like natural language processing (NLP). Chatbots aim to bridge communication gaps between patients and healthcare providers in the medical realm. Responding to user queries, they leverage Q&A forums, proving more effective than navigating lengthy web resources. Internet addiction is on the rise, leading to reluctance to seek medical help for minor ailments. Chatbots, equipped with conversational AI, address this by providing accessible and prompt healthcare information, potentially preventing minor issues from escalating [6].

Use cases of chatbots in healthcare

- **Diagnostics Chatbot:** Diagnostics chatbots are built to diagnose symptoms in the interface. [20] state that these chatbots utilize extensive datasets, including vast medical literature and clinical cases, and cutting-edge AI techniques like deep learning and knowledge graphs; DoctorBot processes user inquiries and offers personalized medical advice. Users can engage with DoctorBot through text inputs or by recording voice messages that are instantly converted into text. The range of health services DoctorBot provides includes self-diagnosis, drug usage instructions, diet suggestions, and more. Self-diagnosis stands out as a particularly popular and sought-after service, reflecting the growing demand for efficient diagnostic chatbots in the medical field [21].
- **General Purpose Chatbots:** A general-purpose chatbot is a chatbot that is built to deal with recurring patient inquiries; they can also be referred to as FAQ (frequently asked question) chatbots. Illustrating this concept is the Aapka Chikitsak chatbot, an exemplary instance. Our platform serves as a virtual doctor, delivering preventive measures, home remedies, healthcare tips, symptom insights, and diet recommendations tailored to users' locations. Emphasizing the adage "prevention is better than cure," our application acts as a personal healthcare assistant, ensuring users have access to valuable health information and guidance [22].
- **Appointment Scheduling Chatbots:** These chatbots are used to set up medical appointments for the users. Patients

can seamlessly book, reschedule, or cancel appointments with their needed doctors using an AI-powered doctor appointment chatbot. This, in turn, boosts the patient experience, reduces operational costs, and provides privacy (Tars).

Materials and Methodology

Data preprocessing and visualization

Data Cleaning: Using a data-driven methodology, we examined gathered data from Kaggle to build our medical chatbot. The dataset contained 16407 rows of data and 3 columns, namely, qtype, answer, and question. There were no missing rows in the dataset; In addition, we dropped 48 duplicated rows.

- **Remove Contractions:** Our next step was to deal with word contractions. A word contraction is creating contractions that involve merging two words with an apostrophe. For instance, (We're) is expanded to its complete form, (We are).
- **Digit Removal:** In this crucial preprocessing stage, all numerical values are excluded from the dataset. This step is undertaken as numerals contribute minimally to the textual meaning.
- **Remove Special Characters:** This takes any characters that aren't alphabetic from the text. Like the numerals, these special characters will not significantly improve the meaning of our algorithm; therefore, we eliminate them. To recognize

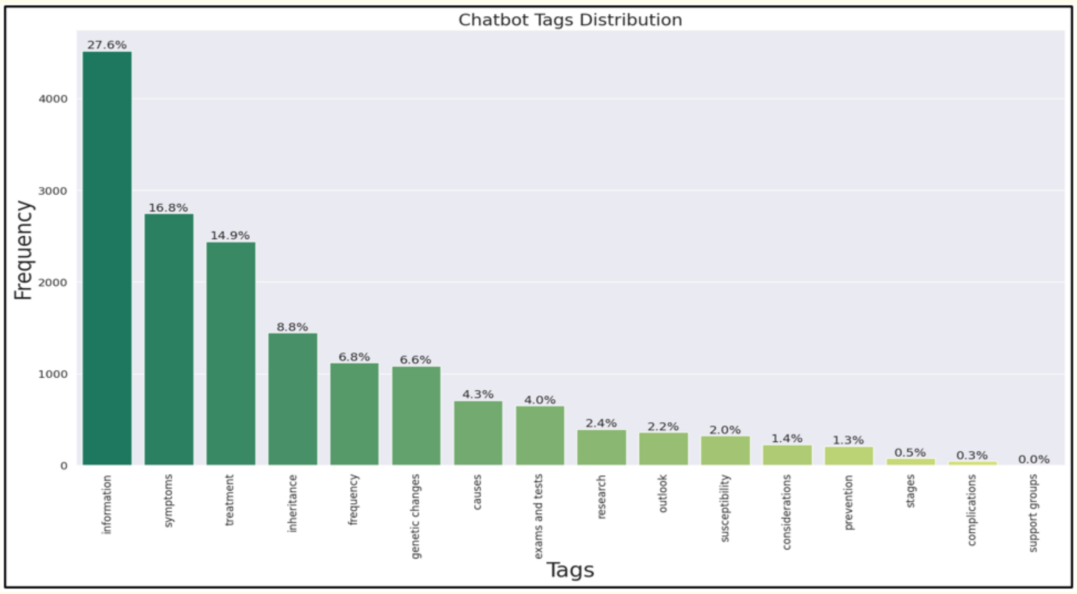

Figure 1: Distribution of intents (qtype).

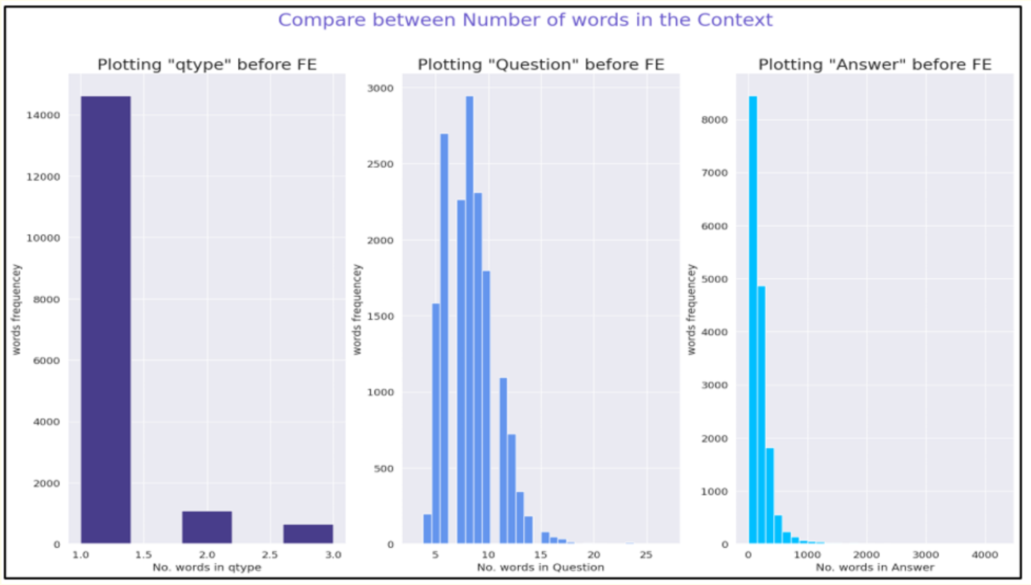

Figure 2: Distribution of word counts per columns.

and remove these special characters, we built a function. A few examples of these special characters are $%" £*(&^). In addition, we converted all our words to lowercase.

- **Removal of Stop Words:** The necessity to remove stop words from our text arises from the fact that stop words are commonly utilized in English phrases and are typically less significant when performing NLP. To name a few, "a," "is," and "are" are some examples of these stop words. Eliminating stop words can assist the algorithm in minimizing processing time and the dimensionality of the data and reducing noise in the data. Stop words inserted. Stop words deleted.
- **Tokenization:** Throughout this process, we divide the text into discrete, stand-alone words or tokens. The algorithm's ability to comprehend and provide weights to individual words is made possible by this fundamental procedure. This procedure may be used for specific words or phrases. Tokenization has several benefits, including faster processing times and aiding the algorithm in feature extraction.
- **Lemmatization:** By using this NLP method, words are reduced to their dictionary or root form. The normalized word forms that represent these root forms, sometimes called lemmas, convey their essential meanings. Lemmatization has the benefit of considering the context of a word's usage. This project utilized the Word Net Lemmatize tool.
- **Stemming:** In NLP, another method for word reduction is stemming, which involves removing prefixes and suffixes, retaining only the word's stem. Compared to stemming, lemmatization takes longer to process as it does not subject words to dictionary or corpus tests.

Creating the word embedding

Machine learning algorithms draw meaning from numerical data. Therefore, all non-numerical data are converted through a process called vectorization. [23] focused their work on word embedding and how they learn semantic meaningful representations for words from local co-occurrences in sentences. For this project, we used Bag-of-words embedding (BoW). In a document's Bag-of-Words (BoW) vector representation, each element signifies the normalized frequency of a basis term. BoW employs precise word matching to calculate basis term occurrences, representing a sophisticated mapping from words to the basis term [24].

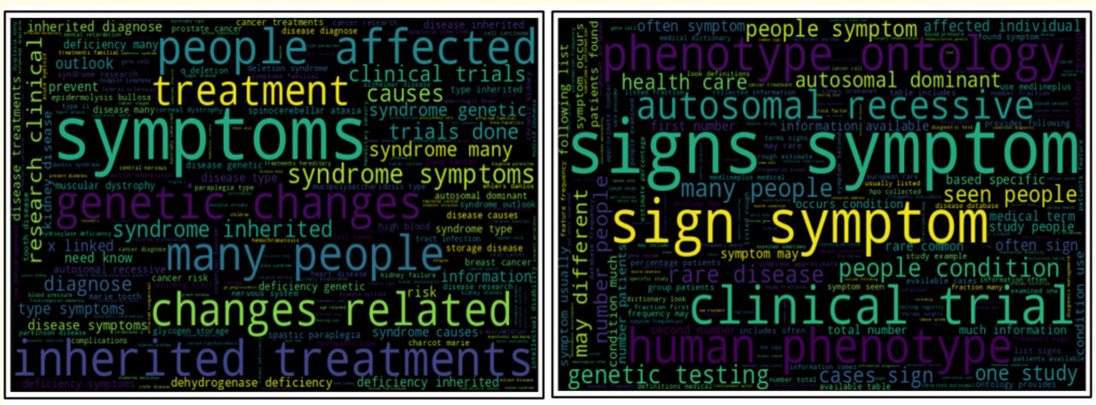

Figure 3: Word cloud for Answer and Question Columns.

Building the chatbot

We are using the machine learning approach to build our chatbot. An example of a similar chatbot is Dodo the chatbot [25]. Designed and implemented a chatbot module as a part of a web application for learning-path recommendation. The proposed module accommodates the potential of LLMs for providing information and explanations on learning recommendations and provides the student with a channel to connect with human mentors.

Algorithms

- **Random Forest Algorithm:** The Random Forest Algorithm can be considered one of Machine Learning's representative algorithms. Random forests, as described by [26], constitute a supervised machine-learning method that relies on the computation of numerous decision trees. The Random Forest Algorithm uses multiple decision trees to mitigate overfitting. It constructs multiple trees during training, considering different data subsets and features. The final prediction is determined by aggregating the outputs of these trees. This ensemble approach enhances predictive accuracy and generalization capability, making it a versatile tool.
- **Recurrent Neural Network:** A recurrent neural network (RNN), as defined by [27], is characterized by neurons that exchange feedback signals. Representing a sequence through a high-dimensional vector known as the hidden state, with a constant dimensionality, RNN incorporates new observations using a complex nonlinear function. RNNs are exceptionally expressive, enabling the implementation of arbitrary memory-bounded computations. Consequently, they have the potential to be configured for significant performance

on intricate sequence tasks, as suggested by [28]. The choice of RNNs is because it excels at sequential data problems due to the ability to capture temporal relationships while maintaining a hidden state, making them excellent for natural language processing.

- **LSTM Model:** [29] Define the LSTM architecture as linked memory blocks, each designed to keep its state across multiple time steps and govern information flow via non-linear gating units. The justification for using LSTM stems from its ability to manage long-range dependencies, making it especially effective for solving text categorization issues. The detailed construction of memory blocks enables LSTMs to successfully acquire and maintain contextual information across long sequences, making them ideal for jobs requiring understanding links and dependencies in sequential data. This capacity is critical for improving the performance of text classification models, as contextual awareness plays an important role in effectively reading and categorising different textual material, hence boosting accuracy.

Results

From the above result, we can see that our base line model gave a performance of 88% across the lemmatized and stemmed text data. Also our RNN model performed 70% at the lemmatized text data and 61% on the stemmed text data. The LSTM model performed 86% on the lemmatized text data and 85% on the stemmed text data.

Model (Accuracy)	Data (Bow) Lemma	Data (Bow) Stem
Random Forest(RF)	0.88	0.88
RNN	0.70	0.61
LSTM	0.86	0.85

Table 1: Summary Of Model performance (Accuracy).

The diagrams below show the graphical representation of the results.

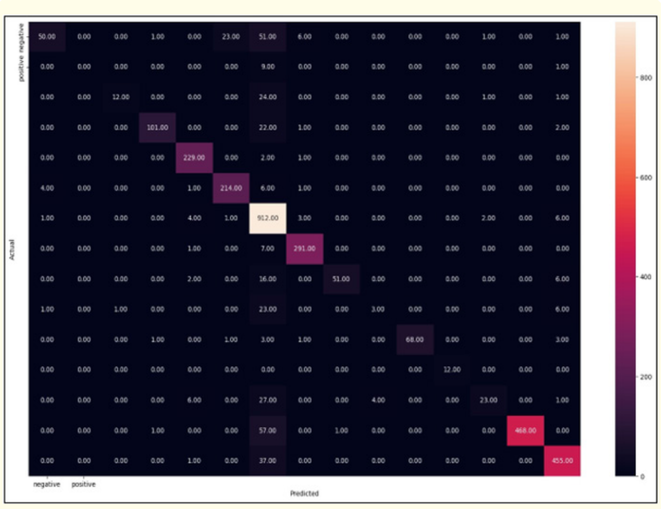

Figure 4: Random Forest Model Evaluation With Lemmatized Words.

We can see that there are few misclassifications of the target by our Random Forest model using the lemmatized text data. These misclassifications was observed in words like complications (100% misclassification) and preventions (75% misclassification). We had 100% classification for words like consideration, research, stages and symptoms.

	precision	recall	f1-score	support
causes	0.90	0.35	0.50	133
complications	0.00	0.00	0.00	10
considerations	1.00	0.34	0.51	38
exams and tests	0.98	0.78	0.87	126
frequency	0.93	0.98	0.95	232
genetic changes	0.90	0.95	0.92	226
information	0.75	0.98	0.85	929
inheritance	0.97	0.97	0.97	299
outlook	0.98	0.64	0.77	75
prevention	0.25	0.06	0.10	34
research	1.00	0.83	0.91	77
stages	1.00	1.00	1.00	12
susceptibility	0.90	0.31	0.46	61
symptoms	1.00	0.89	0.94	527
treatment	0.94	0.91	0.92	493
accuracy			0.88	3272
macro avg	0.83	0.67	0.71	3272
weighted avg	0.89	0.88	0.86	3272

Figure 5: Random Forest Model Evaluation With Lemmatized Words.

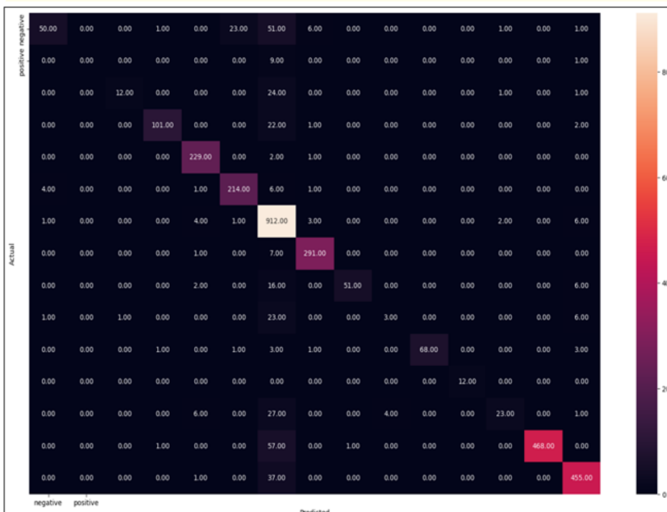

Figure 6: Random Forest Model Evaluation With Stemmed Words.

	precision	recall	f1-score	support
causes	0.90	0.28	0.43	133
complications	0.00	0.00	0.00	10
considerations	0.92	0.32	0.47	38
exams and tests	0.98	0.75	0.85	126
frequency	0.94	0.98	0.96	232
genetic changes	0.90	0.94	0.92	226
information	0.72	0.99	0.83	929
inheritance	0.98	0.95	0.97	299
outlook	0.98	0.57	0.72	75
prevention	0.40	0.06	0.10	34
research	1.00	0.83	0.91	77
stages	1.00	1.00	1.00	12
susceptibility	0.95	0.30	0.45	61
symptoms	1.00	0.88	0.94	527
treatment	0.94	0.89	0.92	493
accuracy			0.86	3272
macro avg	0.84	0.65	0.70	3272
weighted avg	0.88	0.86	0.85	3272

Figure 7: Random Forest Model Evaluation With Stemmed Words.

We can see that there are there is a slightly similar result from Random Forest model using the stemmed text data compared and the lemmatized ones. We still got 100% misclassification for the word complications and 60% misclassification for prevention. In addition, we had only 3 words with 100% classification (symptoms, stages and research).

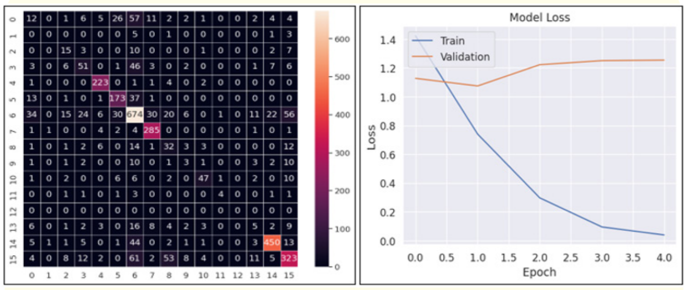

Figure 8: RNN Evaluation of lemmatized Words.

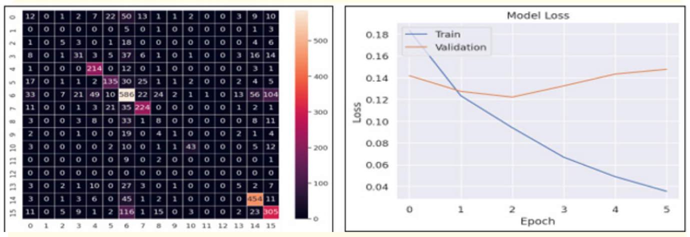

Figure 9: RNN MODEL Evaluation with Stemmed Words.

We can see from the result that we had more misclassification on the simple RNN model. Although we observed that, the lemmatized text data performed better with an accuracy of 70% compare to the stemmed text data with accuracy of 61%.

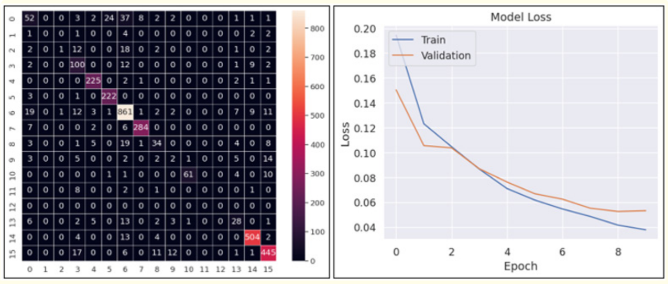

Figure 10: LSTM Model Evaluation with Lemmatized Words.

From our results, our LSTM model performed better than our simple RNN on both the lemmatized and stemmed text data, we can see fewer misclassifications compared to the former. Our lemmatized text data did better with a 86% accuracy, while the stemmed text data has an 85% accuracy.

Discussion

In our experimental journey, the initial step involved preprocessing our dataset, creating both lemmatized and stemmed versions of our text data. This dual approach aimed to evaluate model

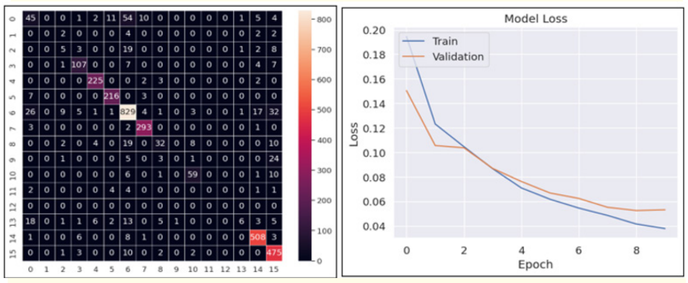

Figure 11: LSTM MODEL Evaluation with Stemmed Words.

performance on distinct datasets. Leveraging the Bag of Words Vector sparse Model, we successfully vectorised our text data. For our baseline model, we employed a Random Forest classifier without predefined parameters, achieving 88% accuracy on both the lemmatized and stemmed text data.

To enhance our Random Forest Algorithm, we turned to Lazy Predict, generating hyper-parameter variables for tuning. Surprisingly, the tuned model exhibited a slight dip in accuracy when applied to the stemmed text data, recording 86%, a marginal decrease from our robust baseline.

Moving beyond traditional machine learning, we delved into the realm of deep learning, employing the simple Recurrent Neural Network (RNN) on both lemmatized and stemmed text data. We ran our model with 10 epoch given our computational resources. On the lemmatized text, our RNN yielded a respectable accuracy of 70%, showing its ability to capture intricate patterns in the data. However, on the stemmed text, the accuracy dipped to 61%, suggesting potential challenges in handling the nuances of the more condensed, stemmed representation.

Undeterred, we explored a more advanced deep learning model, the Long Short-Term Memory (LSTM) network. Recognized for mitigating the vanishing gradient problem inherent in Simple RNNs, the LSTM was also trained with 10 epochs and exhibited commendable performance compared to the simple RNN. On the lemmatized text data, the model achieved an accuracy of 86%, affirming its capability to capture long-range dependencies and intricate relationships within the data. Similarly, on the stemmed text data, the LSTM demonstrated robust performance with an accuracy of 85%, further validating its efficacy in handling the challenges posed by the condensed representation.

Although 88% accuracy may not be good enough for some aspect of medicine like diagnosis and treatment, where a slight mistake can cost a life, it is therefore important in these scenario that steps to improve the model should be taken. One of the step includes training the algorithm with more data, tuning the hyperparameter among others.

In summary, our experimentation journey revealed the strengths and limitations of various models on both lemmatized and stemmed text data. The Random Forest Algorithm gave the best results, while the deep learning models, particularly the LSTM, performed efficiently in capturing complex patterns and dependencies within the textual information, laying the foundation for nuanced text data analysis in future endeavors.

Conclusion

The population's health is one of the major areas most economies should focus on. As the saying goes, health is wealth. In this paper, we highlighted some of the significant factors that affect healthcare delivery, and we mention three factors: inadequate finance, lack of human resources, and inaccuracy of disease diagnosis.

We also highlighted how AI can be applied in various areas of healthcare, like diagnosis, treatment, and administration. We talked about the application of AI, like chatbots; we also looked at the different types and some of the use cases, like the diagnostics chatbot, the appointment scheduling chatbot, and finally, the general-purpose chatbots, which our paper focused on.

We discussed how we got our dataset from Kaggle and carried out data preprocessing to enable us to use it in building our models. We also carried out word rooting like stemming and lemmatization to help our algorithm associate words to their word roots. We used Bag-of-Words embedding to create word embedding for our data.

Finally, we used the random forest algorithm, recurrent neural network, and long short-term memory algorithms to build our chatbot models. Using our embedded data, we compared the results for both our stemmed and lemmatized data.

Limitation

A limitation of this study was the computational resources available, which precluded the training and evaluation of the BERT model on our dataset alongside our machine learning and deep learning models. This prevented us from directly comparing the performance of the BERT model against our existing approaches.

Future Work

In future initiatives, our plan is to conduct comprehensive evaluations to assess the BERT model's performance alongside our established machine learning and deep learning approaches. This would allow for a comprehensive comparison of the model's strengths and limitations, enabling us to determine its suitability for our specific application.

In order to achieve this, collaborations with businesses, academic institutions, or cloud service providers may overcome the constraints on computer resources. Another way to get around the problem of lack of computational power is by reducing resource requirements by increasing the BERT model's efficiency or by applying model distillation techniques.

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