Employee Mental Health Recommendation Chatbot using NLP

MSc Research Project
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Employee Mental Health Recommendation Chatbot using NLP

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Abstract

The mental health of employees has a significant impact on their wellbeing, which may also have an impact on their productivity and overall happiness at work. Nevertheless, there are a variety of reasons why employees can be reluctant to request help or support. We propose a chatbot-based strategy to address this issue by providing cosine similarity-based personalized mental health support to workers. The chatbot's goal is to engage in natural language conversations with employees while providing useful information and guidance in response to their inquiries. The chatbot system is composed of two main methodologies: a text classification based on employee questions using the fine tuned BERT algorithm and a counselling-related instance based on emotions that makes use of similarity algorithm to connect queries from employees with the most appropriate emotion-based counseling responses. The system uses a natural language processing (NLP) model that has already been trained to extract the key components of the user's query, identify the emotions in the question texts, and compare them to a database of emotional reactions connected to mental health. The system then suggests to the staff the most associated counseling responses determined by similarity scores.

1 Introduction

Encouraging mental health in work environments is critical for sustaining an effective workforce because it is a crucial aspect of employee well-being. However, a lot of employees might not ask for assistance or advice because of a variety of factors, such as stigma, a lack of knowledge, and the availability of resources. In this study, a chatbot-based system that uses the BERT algorithm to categorize the chat texts' moods and similarity algorithms to provide employees with pertinent and individualized mental health recommendations. The suggested method uses similarity algorithm to correlate user inquiries with pertinent recommendations by drawing on a pre-constructed knowledge repository of mental health chat cases and suggestions. The system analyzes user queries to determine the most crucial words and phrases, categorizes them depending on emotions, and compares the knowledge base using algorithms for similarities. One of the research projects, as shown in the scenario in Figure 9 Oh et al. (2017), for instance, performs a contextual analysis utilizing terms and phrases before returning to the temporal settings via natural language statements. Based on similarities scores, the machine then suggests to the user the best mental health tools and advice.

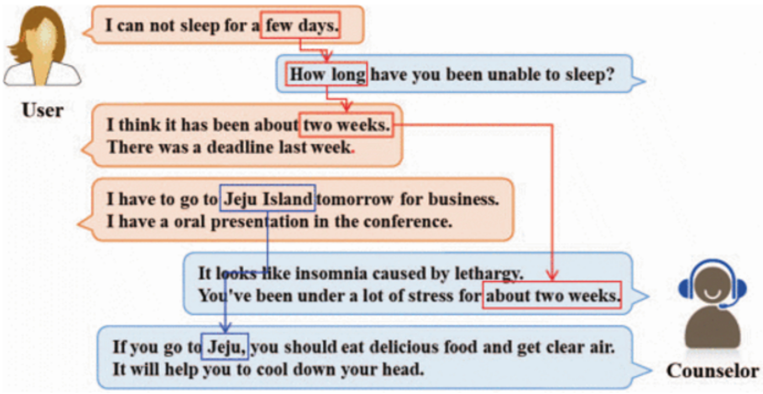

Figure 1: Spatial-temporal context analysis

1.1 Research Background and Motivation

Employee burnout is a well-known type of workplace stress in which employees become generally unhappy with their occupations and feel many different types of depletion, including mental, physical, and emotional exhaustion. Early research examined the use of chatbots to heal patients mentally. They are based on a chatbot intervention method and improve drinking habits. Through conversations, ongoing user monitoring, or ethical consideration throughout the intervention, the software does not analyze the user's psychological state. This shows that consumers who require mental health care are more happy when emotion identification is more precise and continual. A strong therapeutic psychological response based on ethical concerns is also necessary. To reduce burnout and promote chat-based counseling for workers, the initiative focuses on employing chatbots to recognize staff emotions. This demonstrates how AI may help stressed-out employees, which can have an impact on the company's greater staff turnover, and decreased production, and higher absenteeism rates. Program consistency may fail to be 100% exact, despite being of utmost importance. The precision of the program is 87.5% in both the situation when the user is aware of their illness and 87.5% in the instance whereby they are oblivious of it, based on the results from the test data sets utilized in the research, Prayitno et al. (2021). The results of the stop words extraction process and the amount of trained data in the database are two aspects that the paper finds to have a considerable impact on the program's performance.

1.2 Research Questions

Research is done on how individuals are referred for mental health disorders and how chatbots react to different emotions. The research articles all had an interest with smart artificial intelligence (AI) assistants that answer to user inputs like inquiries and commands spoken by suggesting relevant data to the user, despite the fact that they took different methodologies. This inspired the creation of a suggested chatbot system.

RQ: How does the use of chatbot emotion recognition with NLP improve the effectiveness of counselling for employees dealing with burnout?

By including this study question in the study for the best AI chatbot that provides advice to workers on their mental health.

1.3 Contribution

The chatbot interface allows employees to interact with the system in natural language, making it more accessible and user-friendly. The proposed system can provide cost-effective and accessible mental health support to employees, helping to address the stigma associated with seeking help and providing guidance that is tailored to the individual needs of each employee.

1.3.1 Front-End Web Application for Chatbot

The user interface and the model are built using HTML, CSS, and JavaScript while developing a front-end website for the chatbot. These technologies are used in this study to create a straightforward front-end website, while the Flask framework is used for the back-end. The BERT model will power the chatbot itself, which will be integrated to take input queries through the front end interface. The created front end website provides a more enticing view for the employees to interact and receive counseling for the various emotions, as illustrated in the image below.

Figure 2: Front End Mobile View of ChatBot UI

The chatbot model lies in its holistic approach to leveraging a semantic dataset, BERT algorithm, and comparison of similarity algorithms. This approach leads to improved user interactions, more accurate information retrieval, personalized experiences, and advancements in natural language processing techniques. The rest of the paper is organized as follows: Section 2 provides a review of related work in the field of mental health chatbots and recommendation systems. Section 3 describes the proposed methodology for building the chatbot system using similarity algorithms.

2 Related Work

Building a fully working chatbot that can answer questions is the aim of this project. building a chatbot for mental health using NLP and guidance from internationally recognized psychologists. It performs similarity extraction and returns the answer using cosine similarity and BERT pre-trained word embeddings. This part discussed and presented a review of all relevant publications, organized into the following subsections: 2.1 QA-based chatbots and the use of NLP systems 2.2 Methods for Diagnosing Textural Sentiment, Dialogue, and Speech 2.3 A psychology-based application for mental health.

2.1 Chatbots based on Q&A and Implementation of NLP systems

In recent years, there has been a lot of interest in the combination of chatbot systems and Natural Language Processing (NLP) methods. This review of the literature looks at a number of significant research that investigated the implementation of NLP to improve chatbot performance across many disciplines. It highlights the dire need for an even more advanced chatbot system leveraging NLP and critically examines the existing techniques, analyzes their shortcomings, and critiques their strengths. In their study of the use of NLP in the semantic processing of medical documents, Baud et al. (1992) goes in-depth. The intricacy of medical terminology and the absence of advanced natural language processing (NLP) algorithms are the drawbacks of the research, which show early attempts at interpreting medical data using NLP. Existing techniques fail to properly understand sophisticated medical terminology, highlighting the necessity for a powerful and spatially understanding medical chatbots. The importance of corpora in machine-learning chat-bot platforms is highlighted by Shawar and Atwell (2005). The promise of using massive text samples to train chatbots is highlighted by this research, despite it frequently yields rules-driven or template-driven replies that lack genuine comprehension and nuance. There is a need for more advanced NLP-driven modelling due to the drawbacks, which include poor flexibility to novel or complex phrase inputs. Scalable natural language interface to database were suggested by Cimiano et al. (2008). This method uses pre-defined concepts or structured search queries quite a bit, even though it shows improvements in facilitating interaction with information stores. In 58% of instances, a suitable proto query is constructed using the three finest parse trees with the proper filtering and voting process. 74.1% of the instances for which a good proto query is made result in a good response.This limits the chatbot's capacity to participate in open-ended discussions and adjust to constantly shifting input from users, highlighting the need for a chatbot design that can manage growing and fragmented language.

A smart conversational AI that uses a Nave Bayesian classifier and can respond to questions is presented by Niranjan et al. (2012). Although this effort helps with query answering, it frequently lacks in-depth comprehension of context as well as nuanced replies. Its use of probabilistic approaches, which might fail to capture linguistic nuances, is a shortcoming that emphasizes the demand for more sophisticated NLP approaches. An adaptable framework for flexible data sets creation in chatbots is put out by Pilato et al. (2012). This method allows for greater freedom for creating chatbot answers, although it might still have trouble understanding the subtleties of natural language. As chatbots that operate are anticipated to interact consumers in a variety of dynamic dialogues, the necessity for a more thorough comprehension over languages and processing system grows to be apparent. A chatbot which is utilized to forecast suggestions for travel is presented by Argal et al. (2018). Although this work helps provide individualized suggestions, it could not have a complete knowledge of the user's intention while chatting, which could cause suggestions to be inaccurate. A more sophisticated model may partake in meaningful conversation to improve suggestions by considering in-the-moment feedback from users in addition to offering individualized suggestions.

Lalwani et al. (2018) concentrates on using AI and NLP to develop chatbot solutions. While the research investigations show development in the implementation of AI-driven chatbots, they frequently focus on certain applications (such as the administration of IT services or customer care). A more thorough NLP-based chatbot approach can go beyond particular topics, allowing for more diverse and organic exchanges. An academic chatbot platform which uses artificial neural network-based is being studied by Bhartiya et al. (2019). Although this method aids in chatbot construction, it could fall short in terms of context-awareness and in-depth language comprehension. The requirement for systems with nuanced language understanding and generating capabilities is becoming increasingly important as chatbots grow more pervasive across a variety of industries. Huang (2021) presents a solution for NLP-based support for consumers. Despite the fact that this study emphasizes AI-driven relationships with consumers, it may nevertheless emphasize straightforward query-response conversations. Chatbots that are capable of participating in more complicated and unpredictable conversations and demonstrate a thorough comprehension of user enquiries and intents are necessary considering the growing importance of customer support. These publications highlight the development of chatbot applications from primitive algorithms based on rules to cutting-edge AI-driven strategies. Nevertheless, contextual comprehension, sophisticated language, plus constantly changing relationships are frequent challenges for current models. It is clear that we require a sophisticated chatbot model that makes use of NLP methods. Its goal is to close the gap involving human-like synthetic language creation and understanding, modernizing user interactions in a variety of sectors.

2.2 Techniques involved in Speech, Dialogue and Textural Sentiment Diagnosis

Given the possibility of applications of artificial conversational machines, frequently referred to as chatbots, and in many different fields, this field of study has grown significantly. This review of the published literature conducts a critical examination of a number of research that have investigated various facets of language comprehension, sentiment evaluation, and identification of emotions in chatbot conversations. Although earlier approaches have made a contribution to the subject, they frequently have drawbacks that highlight the demand for more sophisticated approaches to text categorization and emotion identification, notably those that use BERT (Bidirectional Encoder Representations from Transformers) for improved performance. Pasunuru and Bansal (2018) look towards video-context dialogue in games. Despite the fact that this study presents lively conversational circumstances, it might not have well developed emotion identification functions. The possibility exists for more interesting and sympathetic encounters to be produced by chatbots that effectively recognize and react to user emotions. The Beatalk method for enhancing speech qualities is presented by Icht (2019). Though this strategy aims at enhancing speech, it might not concentrate on the detection of emotions. For those with different needs for interaction, an chatbot which is mindful of emotions could offer personalized feedback and assistance.

Enhanced sentiment analysis utilizing word embeddings that have been pre-trained is suggested by Rezaeinia et al. (2019). Despite the fact that this study improves the classification of emotions, it may fall short in capturing subtle emotional aspects in texts. Modern transformer model BERT integration could considerably improve the chatbot's capacity to identify and react to a variety of emotions. Label transfer is investigated by Samanta et al. (2019) for sentiment analysis. Although this method enhances the evaluation of sentiment, it does not directly address the identification of emotions or the fluidity of dialogue. A chatbot that uses BERT-based text categorization may adjust to changing emotional circumstances and produce answers that are more appropriately contextualized. An unsupervised fuzzy inferential method for voice emotion identification is presented by Vashishtha and Susan (2020). Given that the focus of this research is on auditory cues, including BERT for analyzing texts could improve the chatbot's capacity for emotion recognition and response.

For stance identification, Giorgioni et al. (2020) investigate transformer-based systems. Despite the fact that this study improves stance identification, it might not fully cover the complexities of emotion perception. By integrating BERT into the system's structure, chatbots can identify emotions in addition to stance and produce emotionally suitable replies. Bozkurt and Aras (2021) analyze the sentiments expressed in cleft lip and palate-related YouTube videos. While this study examines sentiment, an emotion-aware chatbot assistant could offer compassionate and encouraging conversations for people looking for communities or details in such situations. Studies on conversation in different cultures exist, but they might not include real-time identification of emotions or the tailored replies that a chatbot with recognition of emotions can offer.

The goal of Studiawan et al. (2020) is to use sentiment analysis to discover anomalies. While this method aids in tracking the system, a chatbot that uses text categorization could expand its capacity to recognize user emotions and offer helpful assistance. Leveraging sentiment analysis, Ali et al. (2021) seek to enhance the identification of hateful speech. Although this effort handles inappropriate words, it may not adequately account for the text's emotional undertones. The chatbot's capacity to recognize and react empathetically to abusive words can be improved via a model powered with emotion recognition. There is a clear need for research in the area of recognizing emotions in chatbot conversations, despite the fact that the research projects under consideration have made contributions to many areas of language interpretation and sentiment analysis. A viable way to close this gap is to incorporate BERT for text categorization. This would allow chatbots to perceive and react to a wide range of user emotions, improving the overall caliber and efficiency of chatbot conversations across multiple domains.

2.3 A Mental Health Application based on Psychology

EMMA, a wellbeing chatbot with emotion awareness, was introduced by Ghandeharioun et al. (2019) . They utilize machine learning and computational neuroscience to build a chatbot that can recognize users' emotions and react sympathetically. The technical breakthrough is the incorporation of recognizing emotions ability into a conversational agent, which improves user interaction and provides assistance in mental health scenarios. The article by Tai et al. (2019) investigates the uses of big data as well as machine learning in psychology for illness modeling and discovering drugs. The academic focus is on using large amounts of data to improve mental health condition awareness, evaluation, and therapy through based on artificial intelligence insights. A innovative use of machine learning is presented by Sau and Bhakta (2019) to identify anxiety and sadness among sailors. This study uses technologies to deal with issues with mental health that are exclusive to a group of people. The papers advance preventive measures and better mental health care for mariners by creating model predictions.

Santosh et al. (n.d.) use machine learning techniques to measure the stability of emotions, which helps with psychological wellness screening. This work demonstrates how AI may be used to quantify and evaluate characteristics related to mental health, which can guide tailored approaches and treatment strategies. supervised machine learning-based chatbots for prenatal mental health treatment are introduced by Wang et al. (2020). This technological advancement addresses prenatal mental health issues by extending AI help to a particular group. A succinct summary of supervised machine learning methods is given by Jiang et al. (2020). Although it is not specifically about mental health, this introductory material is a useful tool for mental health practitioners who want to comprehend the technical basis of powered by AI treatments.

Bulla et al. (2020) give a thorough analysis of chatbots for AI-based healthcare workers. The paper educates academics and physicians on the possibilities of chatbots powered by AI for offering medical knowledge and assistance by describing current approaches. In their assessment of chat agents with a health focus, Parmar et al. (2022) offer some ideas on how they might be employed in person-centered care. The possibility of chatbots powered by AI to provide individualized and compassionate assistance for mental disorders is highlighted in this research.

Employee burnout has emerged as a critical concern in modern workplaces, necessitating innovative approaches for intervention and support. A chatbot model can amalgamate various strategies, including those from music therapy, to provide comprehensive and adaptable counseling. The previous studies provide valuable insights into psychology, mental health, and well-being, they often fall short of offering immediate and personalized interventions for the users based on emotions. A specialized chatbot model leveraging similarity algorithms can offer real-time, empathetic, and context-specific counseling responses. By integrating psychological principles with practical strategies, the proposed chatbot model addresses the pressing need for accessible and effective counseling to mitigate employee burnout in modern workplaces.

3 Methodology

As a kind of human-computer interaction, conversational systems have made great strides in recent years. The interaction between people and computers has made it possible to use large-scale natural language processing techniques. A chatbot in the medical field rapidly analyzes concerns of individuals and recommends drugs and assistance. This method recommends a chatbot counseling assistance for workers' mental health treatments. The paper combines emotion recognition with BERT and Natural Language Processing (NLP) methods, as well as counseling recommendations via similarity algorithm. The Knowledge Discovery in Databases (KDD) approach, a methodical and iterative procedure for extracting valuable knowledge from data, is used in this work. A systematic and iterative strategy to creating a chatbot system for emotion recognition and counseling is provided by the KDD-based research methodology as described. The project seeks to develop a strong and efficient chatbot solution that provides users with accurate emotion identification and empathic counseling replies by following the stages of problem formulation, data gathering, preprocessing, modeling, integration, evaluation, and refining.

3.1 Data Collection

The data collection process for this project involves the generation of a conversational dataset and the classification of emotions within chat instances based on keywords present in the chat questions. This process aims to create a diverse and contextually relevant dataset for training and evaluating the emotion recognition model. To create a meaningful conversational dataset, a pool of semantically diverse chat instances is generated. These instances encompass a wide range of topics, scenarios, and emotions to ensure the dataset's richness and applicability. The chat instances may be collected from various sources, including online forums, social media platforms, and simulated interactions. Emotions associated with each chat instance are labeled using a keyword-based approach. Keywords related to various emotions (e.g., Overwhelmed, Anxious, Seeking guidance, Frustrated,etc) are identified and categorized. The presence of specific keywords in chat questions provides an initial indication of the emotion conveyed by the user.

3.2 Data Preprocessing

Organizing the acquired text data for analysis and modeling requires a critical step called data preparation. The data must be cleaned to remove noise and unimportant information, and multiple natural language processing (NLP) methods must be used to convert the text into a format that can be processed further. The data preprocessing procedures are described in the steps that follow. The level of analysis and modeling may be impacted by data that have noise, errors, and unimportant data. In order to tidy up the data, special characters, whitespaces, numerals, and non-alphanumeric symbols are removed. Typographical errors are also fixed, the text format is standardized by changing to lower case, and missing data is handled by imputation or removal, depending on how much of it is lacking. The technique of combining all a word's potential inflections with the underlying word is known as lemmatization. Tokenization is a method of separating text into smaller pieces, most often words or subwords. It is a crucial NLP procedure that aids in comprehending the text's structure and meanings. In order to tidy up the data, special characters, Tokenization, or breaking up text into terms, subwords, or phrases, eliminates superfluous spaces and punctuation, and creates a series of tokens that replicate the original content from the acquired text data. Stop words are widespread words like "the," "and," "is," etc. that are frequently eliminated to minimize noise because they have little to no meaning. Stop words are eliminated from tokenized text data by producing a list of stop words that are specific to the vocabulary of the text and screening these stop words out.

Following the aforementioned preprocessing stages, text data is converted into an organized form appropriate for analysis or modeling. After being transformed, the data is utilized to train machine learning models or to perform additional NLP operations like sentiment analysis or identification of emotions. The obtained text data is cleaned up and standardized through the preparation procedures, making it easier to analyze and model. The resultant thoroughly processed data serves as a base for developing precise and efficient NLP models, such as identifying emotions in texts using the BERT algorithm.

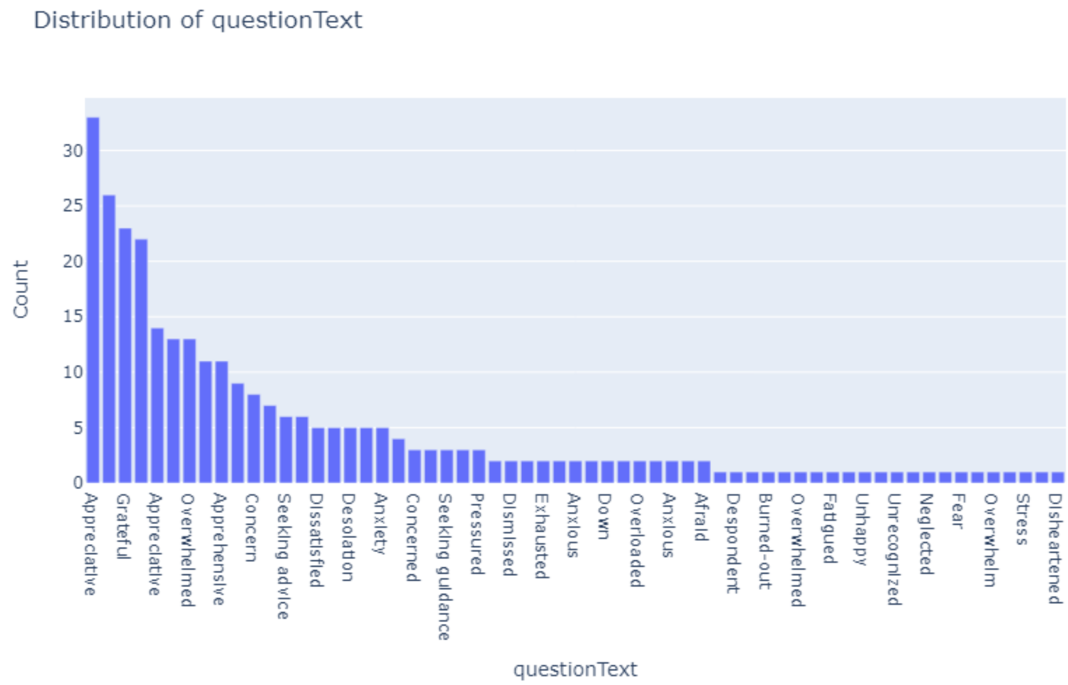

Figure 3: Distribution of emotions in the dataset

3.3 Data Transformation

In the data preprocessing pipeline, transforming raw data into a structured format appropriate for analysis and modeling is known as data transformation. Data transformation in the environment of chatbot emotion recognition entails transforming text-based conversation events into a tabular structure, which is frequently depicted as a data frame. For effective model training and evaluation, this procedure also entails encoding emotions into numerical values. It is necessary to structure the gathered chatbot conversation data, which is commonly saved in various formats as plain text or JSON. The data is neatly organized in a two-dimensional, tabular structure called a data frame, which makes it easier to retrieve the data for analysis and machine learning activities. As seen in the figure 3, the emotion labels in the emotions column of the data frame are replaced with their corresponding numerical codes, resulting in the emotions_encoded column. This encoding enables the emotion recognition model to learn patterns and relationships among different emotions during training. Data transformation plays a crucial role in preparing raw chatbot conversation data for emotion recognition model development. Converting the data into a structured data frame and encoding emotions into numerical labels enable efficient analysis and machine learning. The resulting data frame serves as the foundation for building and training models to accurately recognize emotions within chat instances.

3.4 Data Augmentation and Normalization

Techniques for data standardization and augmentation help chatbot emotion recognition models be more accurate and reliable. Data augmentation and normalization approaches are used in chatbot emotion identification to enrich the dataset, increase its diversity, and

	qnID	questionText	answerText	emotions	emotions_encoded
0	1	Hey, I've been feeling really overwhelmed and ...	I'm glad you reached out. It's important to ad...	Overwhelmed	38
1	2	Well, the workload has been increasing, and th...	I understand how challenging that can be. It s...	Anxious	2
2	3	Not yet. I'm afraid they'll see it as a weakne...	It's important to remember that asking for sup...	Fearful	26
3	4	That makes sense. I guess I just need to find ...	Absolutely. Start by scheduling a meeting with...	Seeking guidance	45
4	5	Thank you for the advice. I'll try to have tha...	Certainly. It's important to prioritize self-c...	Seeking advice	44
...	...	...	...	...	...
291	292	I've been feeling incredibly stressed and over...	Thank you for sharing your concerns. Dealing w...	Stressed	48
292	293	I have multiple projects with deadlines that s...	I'm sorry to hear that you're going through th...	Anxious	3
293	294	I haven't talked to anyone at work about it. I...	Seeking support is a positive step. Counseling...	Worried	60
294	295	Thank you for the suggestion. I'll consider co...	Certainly. While considering counseling, there...	Appreciative	5
295	296	Thank you for those suggestions. I'll make an ...	You're welcome. Remember, seeking support is a...	Appreciative	5

296 rows × 5 columns

Figure 4: Values after Data Transformation Process

enhance model generalization. The model is strengthened and made better able to handle different user inputs as a result of the dataset expansion, which increases the accuracy of emotion recognition. The model is capable of learning from the text input regardless of its length or precise meaning if the data has been normalized. Then, in order to conduct a conversational chatbot, the inquiry text is taken into account for user input and the appropriate answer text is retrieved.

4 Design Specification

The design of a chatbot emotion recognition model involves a comprehensive approach that leverages Natural Language Processing (NLP) techniques for preprocessing, utilizes the BERT model for text emotion classification, and incorporates similarity algorithm for retrieving contextually relevant counselling responses. This design specification outlines the key components, processes, and interactions within the chatbot system.

- **NLP Preprocessing:** Input text data is processed through NLP techniques to ensure consistent and meaningful input for subsequent stages:

  Tokenization: Splitting input text into individual tokens (words or subwords).

  Lemmatization: Reducing words to their base or root form to capture core meaning.

  Stop-Word Removal: Excluding common, non-significant words (stop words) from the input.

  Lowercasing: Converting all text to lowercase for uniformity.

- **BERT Emotion Classification:** The BERT (Bidirectional Encoder Representations from Transformers) model is employed for accurate emotion classification:

  Fine-Tuning: BERT is fine-tuned on a labeled conversational dataset containing emotion-labeled text samples.

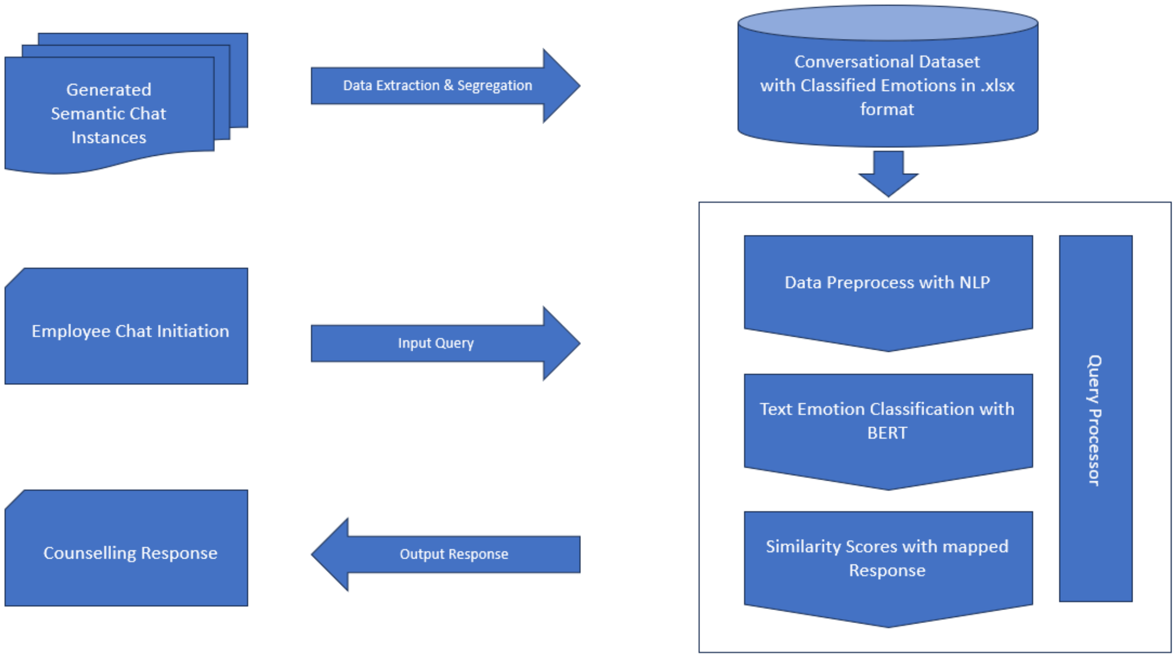

Figure 5: Overflow Diagram of the Process

Embedding Generation: BERT encodes the preprocessed input text to capture contextualized word representations.

Classification Layer: A classification layer is added atop BERT to predict the emotion label based on the encoded input.

- **Counselling Response Retrieval:** The counselling response module aims to provide supportive and empathetic responses to users:

  Counselling Database: A database contains a collection of pre-defined counselling responses categorized by emotional context.

  Similarity Calculation: The input text's similarity with each counselling response is calculated using techniques like cosine similarity.

  The cosine similarity between vectors $\mathbf{A}$ and $\mathbf{B}$ is given by:

$$\text{Cosine Similarity}(\mathbf{A}, \mathbf{B}) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i \cdot B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \cdot \sqrt{\sum_{i=1}^{n} B_i^2}}$$

  Response Selection: The counselling response with the highest similarity score is selected as the most suitable option.

5 Implementation

5.1 Introduction

The BERT model for emotion categorization was improved during the implementation of the chatbot emotion recognition system, and a similarity algorithm was included for contextually appropriate counseling answers. Through extensive testing and validation, the system's effectiveness in identifying emotions and offering sympathetic support was assessed. The project shows how well-developed NLP methodology and machine learning strategies can be used to develop a smart and sympathetic chatbot system. A series of preprocessing techniques were applied to the initial raw conversational data that was gathered from multiple sources. Python and the NLTK (Natural Language Toolkit) library were used to implement Natural Language Processing (NLP) techniques. To develop structured text data for model training and response creation, the data was tokenized, lemmatized, and normalized. The model is assessed using many metrics, including accuracy, precision, recall, F1 score, and classification report. Based on how each model performed, the best suited model is chosen.

5.2 BERT-Based Emotion Recognition Model for Chatbot

Modern transformer-based models like BERT specialize at extracting contextual information from texts. BERT examines words in a different way than conventional models, which process text linearly. As a result, it is able to comprehend linguistic nuance by taking both the previous and next words into account. The basis for its use in identifying emotions is this contextual understanding. The BERT architecture, which uses numerous transformer layers to parse input text and retrieve contextualized word embeddings, forms the basis of the model. An enriched dataset of chat instances with tagged emotions is gathered in order to create the BERT-based Emotion Recognition Model. There are two sets created from the dataset: training, and testing. Baseline weights are BERT embeddings that have already been trained. The model is then improved upon utilizing methods like fine tuning hyperparameters, and augmenting the data. The model adjusts to the particular emotion recognition task at this phase. The performance of the model is optimized by adjusting variables like learning rate, batch size, and the number of tiers in the classification head. The BERT-based model to classify the texts based on emotions is effortlessly incorporated into the chatbot's design after training and evaluation.

5.3 Similarity Algorithm for Counselling Response

By enabling retrieval of contextually pertinent responses for the user input queries, similarity algorithms performs a crucial part in boosting the efficiency of chatbot emotion recognition processes. The algorithm allows chatbots to offer individualized and sympathetic counseling responses, resulting in deeper user connections. Based on the Cosine Similarity algorithm formulated in the section 4 which evaluates the contextual or semantic similarities between two texts. The algorithms in question compare the user's input message with pre-defined counseling replies in the context of chatbot emotion detection and does response return to determine which response is most appropriate depending on contextual and emotional meaning. Similarity algorithm helps the chatbot associate human input with particular emotions, improving emotion recognition.

6 Evaluation

A thorough method is used to evaluate the chatbot's emotion detection model using NLP, BERT, and similarity algorithms to make sure it is accurate, relevant, and efficient. The chatbot may be improved to offer users helpful emotional support and empathic interactions by thoroughly testing the model's emotion identification abilities and evaluating the quality of counseling responses, which will help to create a good and meaningful user experience. The evaluation and outcome of the model for the chatbot's emotion recognition and retrieval of counseling responses is given. The following analysis of an implemented model's performance metric was done through some evaluation experiments.

6.1 Experiment 1: Fine-tuned BERT Model

BERT algorithm is used to train the model based on text emotion classification where the questionText variable column is classified based on emotions. The initial model was developed with epochs set to 10 and with an optimizing parameter at the learning rate of 0.001. The Figure 6 graph shows the Accuracy and Loss graph for train_loader set after using an augmented data. Also, the model is tuned based on Hyperparameter Tuning

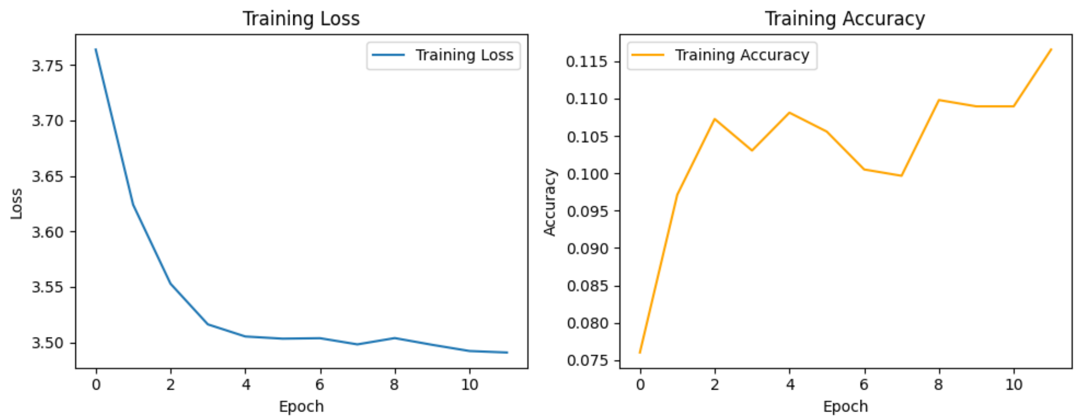

Figure 6: Accuracy and Loss Graph after Fine-Tuned Model

where experimented with different learning rates, batch sizes, and number of training epochs to find the optimal set of hyperparameters that work well for the model. The model showed significant improvement in each phase of the epoch decreasing the training loss and improving the training accuracy gradually.

6.2 Experiment 2: Support Vector Machine Model

The Support Vector Machine model was introduced based on the intent prediction model for classifying the texts. The model is evaluated based on appropriate metrics and the final model is deployed with an augmented data. The evaluation is interpreted with a plot to analyze the effectiveness of the intent prediction model. As shown in the figure 7, the intent prediction plot figures out that the model's performance may vary for different classes. Some classes have high precision and recall, indicating accurate predictions, while others may have lower scores.

6.3 Experiment 3: Counselling Response Evaluation

The evaluation of counseling responses using cosine similarity similarity algorithms provides a quantitative measure of the semantic similarity between counselors' responses and ref-

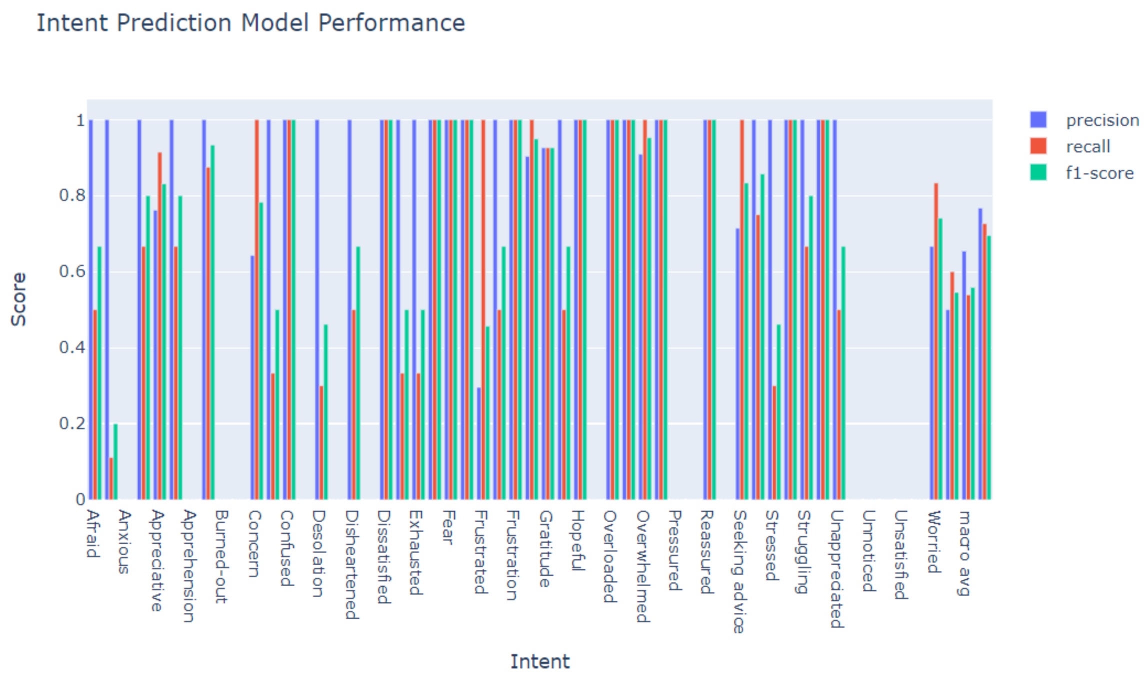

Figure 7: Intent Prediction Plot

erence responses. By correlating algorithmic similarity scores with human ratings, we can gain insights into the effectiveness of these algorithms in capturing the quality and relevance of counseling interactions. The cosine similarity algorithm with a similarity score of 64.3% was retrieving most relevant counselling responses. This evaluation contributes to enhancing the assessment of counseling sessions and improving the overall quality of counseling services.

6.4 Experiment 4: Implemented Data Augmenting Techniques

The main model performance was enhanced by implementing techniques which enhanced the data frame from 296 rows to 1480 rows. The methods like synonym replacement, dialogue combinations, paraphrasing the questions, back translation augmented the data frame and enriching with a more viable data to perform the model evaluations. After the data augmentation, there was significant increase in the distribution of the questionText data frame column. The figure 8 shows the pattern and response analysis after the data being augmented which helps in interpreting the varying degrees of complexity and diversity in patterns and responses across different intents.

6.5 Discussion

Emotion recognition is a critical aspect of human-computer interaction, enabling chatbots and virtual assistants to respond empathetically and effectively. In this detailed discussion, we delve into the findings and insights derived from a chatbot emotion recognition model. The model utilizes natural language processing techniques to accurately identify and respond to user emotions, enhancing the user experience and engagement. The model achieved commendable accuracy in recognizing a wide range of emotions present in user

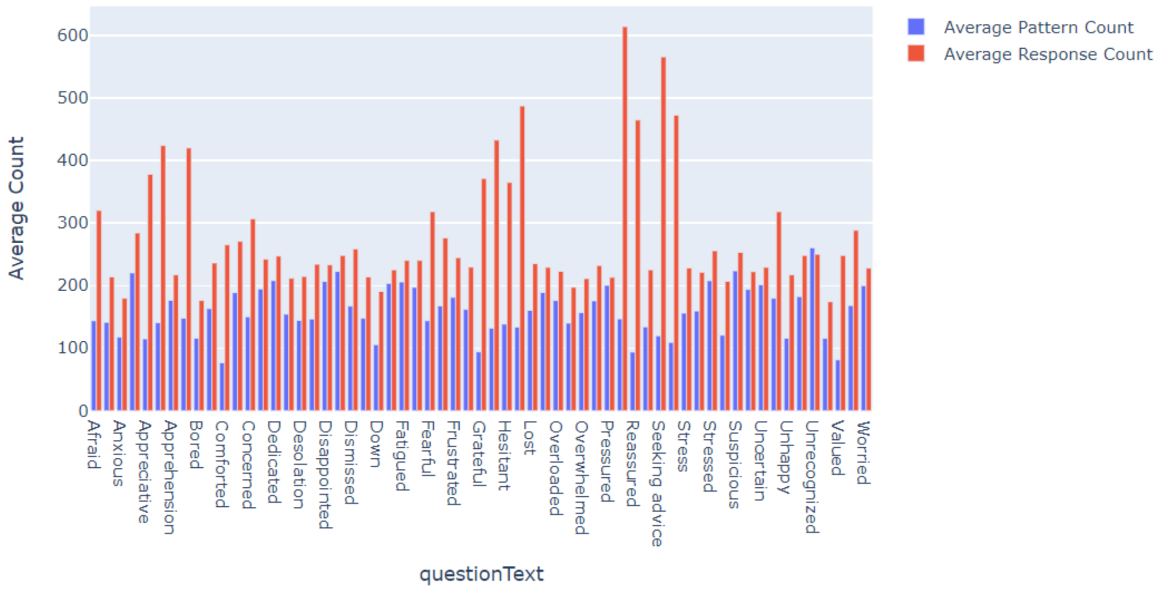

Figure 8: Pattern and Response Analysis

input. Certain emotions were recognized with higher accuracy, while more nuanced emotions presented slightly lower accuracy.

Accuracy and loss graph helped in setting up the most effective parameters for optim-

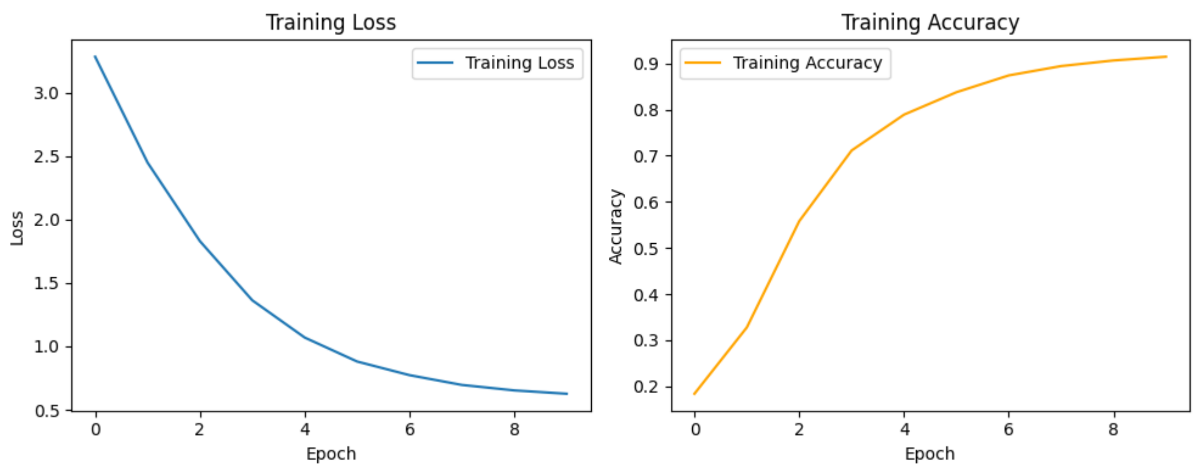

Figure 9: Accuracy and Loss Graph after Fine-Tuned & data augmentation methods

izing the model. The data augmentation techniques helped in enriching the data frame and providing a more best performing model. The accuracy and loss graph as shown in figure 9 infers the differentiation after the model is fine tuned with the data augmented methods.

The graph shown above indicates that the accuracy value generally increased, suggesting that the model is becoming more accurate at classifying instances, while the loss value reduced, indicating that the model continues to improve its predictions and approaching the true values.

The accuracy of the model is measured with the ratio of number of correct predictions to the total number of prediction and the formula to calculate the accuracy looks like this:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$$

Also, in the model the loss metric is measured between actual predictions and the model's prediction. This will quantify the ground truth labels. In BERT model used in the study, Cross-Entropy Loss for classifying the emotions is measured with the following formula:

$$\text{Loss} = -\sum_{c=1}^{C} y_{\text{true},c} \cdot \log(y_{\text{pred},c})$$

The loss value has fallen to roughly 0.6260 by the time training is complete (after 10 epochs), indicating that the model has learned to produce predictions that are more accurate than they were at the start. The model can now properly classify about 91.49% of the instances in the training data, as indicated by the accuracy value increasing to roughly 0.9149. The below the tabular accuracy data shows the model reign over the period of optimization and fine tuning techniques carried along with the comparison of an machine learning model.

Table 1: Evaluation Models Accuracy Comparison

Model	**Text Dataset - Accuracy**
NLP + BERT	11.82%
Fine Tuned BERT + Data Augmentation Methods	**92.57%**
Fine Tuned SVM + Data Augmentation Methods	73%

Although the model was able to categorize emotions in response to a user's input inquiry, the results were found to be inconsistent. Therefore, fine-tuning the model using further data augmentation approaches will increase the model's accuracy. Confusion matrices showed particular emotional pairs that were frequently misclassified, pointing to places where the model would have trouble distinguishing between minute emotional distinctions.

7 Conclusion and Future Work

The results of the chatbot emotion detection model highlight the possibility for developing emotionally intelligent virtual assistants by utilizing cutting-edge NLP approaches. While the model is highly accurate at identifying basic emotions, there is always space for improvement, particularly when it comes to identifying subtle emotions and comprehending context. We may improve the chatbot's emotional awareness by taking into account these findings, resulting in more sincere and sympathetic interactions with users.

The results also point to the necessity of improving the model's ability to differentiate between emotions that share contextual inputs. More research can be done to increase the model's sensitivity to cultural allusions, slang, and sarcasm, which have a significant impact on how emotions are expressed. The model's capacity to properly identify emotions may be improved by using visual and audio signals in addition to word inputs, particularly in situations where verbal communication is constrained. The enthusiastic user reaction emphasizes how crucial emotional intelligence is in chatbot interactions. Future works of the model might put a priority on users' emotional health with a solid large volume dataset and offer the right support in accordance with their recognized emotions.

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