International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 10 No. 6s, 2024
https://theaspd.com/index.php

Mood Lens: AI-Driven Sentiment Detection And Mental Health Monitoring From Social Platforms

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Abstract: *This paper presents an advanced computational system designed to assess sentiment patterns and analyze mental health trends related to depression and anxiety. The increase in microblogging and social media updates has increased companies to public sentiment extraction practices. We want to extract information from both the sentiments we analyze and a vast amount of data that will classify the user perspective for a positive or negative sentiment. Further, we would like to improve classification by using hashtags as an additional means of filtering results. We will use ML algorithms, such as XGBoost, SVC and Random Forest to train the machine learning models to detect sentiments and then determine which model works best, based on accuracy. Finally, we would like to create a chatbot, using NLP, to determine sentiments with the users, while maintaining user and bot confidentiality. This will allow individuals to gain an understanding of their mental state, while obtaining a proper line of action for self-regulation. All this will require secured, end-to-end encryption due to the sensitive nature of the data to keep chats between him/herself and the bot completely private and secure.*
Keywords: *Anxiety , Chatbot, Depression, Mental Health, NLP,Sentiment Analysis*

I. INTRODUCTION

Sentiment analysis, a vital subfield of natural language processing (NLP), focuses on the computational study of thoughts, emotions, and subjective attitudes expressed in textual data. Widely applied across domains such as business intelligence, social media monitoring, and web analytics, sentiment analysis classifies the polarity of opinions—categorizing them as positive, negative, or neutral. Beyond polarity detection, advanced techniques extract deeper insights, enabling organizations to gauge public sentiment, track emerging trends, and inform data-driven decision-making.

As online platforms continue to emerge as the leading way for people to communicate ideas and emotions, sentiment analysis has become increasingly significant. Much investigation has been conducted on sentiment analysis in product appraisals and news articles, but we will be analyzing the sentiment in user-generated content during the Depression and Anxiety. The pandemic affected the world accordingly and dramatically affected people's mental health. We will be using public APIs from social networking sites, including Twitter, Reddit, and Facebook, to mine user-generated content, classify the content, and assess whether it depicts positive or negative sentiments. Social media posts often reflect users' psychological states, and therefore monitoring sentiment changes will provide an opportunity to examine potential distress signals and potentially diminish the dissemination of undesirable opinions that lead to social disruption. This analysis will provide public health officials with valuable data to inform their actions. Additionally, we will also build an NLP-supported chatbot that generates real-time emotion classification to aid in sentiment assessment. The chatbot will assist users by identifying the emotional responses and providing emotive prompts for responses. The chatbot will be constructed to decrease stress, anxiety, and health symptoms associated with depression through guided interactions.

A structured decision tree will be adopted to map responses to pre-determined answers based on the output of the sentiment analysis. The NLP algorithms will control conversational flow and log sentiment data based on keyword presence and sentiment classifications, making the interaction feel natural for the user. Sentiment analysis is unprecedented and unique for social media monitoring and encompasses the ability to speak about public sentiment about any issue with a wider lens. Not only can discussion sentiment be identified, _but_ even strong discussion sentiment can identify _people_ in need of intervention for a severe negative emotion and personal mental challenges (like severe depression by identifying posts of severely negative sentiment). However, strong positive sentiment posts can be identified, on the contrary. Once sentiment can be classified, then the actions of the virtual chatbot will support potential users for a smooth onboarding process, cost-effectively, and the automation of self-therapy for mental issues. The virtual chatbot will be _trained_ through iterations to interact with target audiences and provide emotional support along with key insights regarding their mental health.

II. LITERATURE REVIEW

Public Sentiment During Crisis Events: Exceptional circumstances, such as periods of widespread depression and anxiety, underscore the need for real-time public sentiment analysis to address emerging societal challenges [15]. Studies identify five dominant themes during such crises: business economy, healthcare systems, social change, emotional support, and psychological stress. Analyzing these sentiments provides critical insights into public concerns, guiding policymakers and mental health interventions.

Chatbots in Mental Health: Limitations and Potential: Chatbots interact via text, voice, and visual inputs, offering unique opportunities to expand access to mental health support, particularly for users hesitant to seek help due to stigma [1]. However, current mental health chatbots lag behind other sectors; 92.5% rely on static decision trees, while only 7.5% employ machine learning for response generation [24]. Rule-based systems dominate due to their simplicity in handling structured tasks, but their rigidity limits user autonomy compared to AI-driven alternatives capable of nuanced, context-aware dialogue [6].

Evolution and Applications of Chatbots: Chatbots are automated systems designed to simulate human interaction, offering dynamic cross-communication through natural language interfaces [19]. These systems serve diverse roles—from marketers and sales representatives to counselors—delivering efficient, scalable services. In telecommunications and marketing, scripted chatbots streamline customer inquiries via predefined workflows [22]. Ongoing research aims to enhance chatbot interactivity, moving beyond rigid, rule-based responses to more adaptive, naturally spoken dialogue .12]. The optimal chatbot model depends on factors such as training domain, functional capacity, language, and target audience.

Sentiment Analysis as a Survey Alternative

Feature-based sentiment analysis is increasingly replacing traditional surveys in gauging public opinion about products or services [2]. This structured approach involves: Feature Extraction: Identifying product/service aspects discussed in user text [18]. Sentiment Prediction: Detecting the presence and polarity (positive, negative, neutral) of opinions [5]. Summarization: Aggregating results to generate actionable insights [20]. This method enables companies to derive real-time, scalable feedback without reliance on formal surveys.

Online Networks and Mental Health Modeling: The rise of online group networks has introduced innovative ways to overcome challenges across diverse fields through advanced data-driven approaches [25]. Traditional psychological research relies heavily on questionnaires to assess mental health status. However, microblogging platforms now provide vast datasets that enable the development of association models linking linguistic features to depression indicators [4]. Such models not only facilitate early detection but also identify the most significant features influencing mental health assessments [14].

III Proposed Methodology

Sentiment analysis, particularly in the field of microblogging, is still evolving and remains an ongoing challenge. To enhance existing methods and bridge the gaps in sentiment analysis, our approach delves deeper by specifically analyzing individuals experiencing depression and other mental health issues during the Depression and Anxiety.

Factors such as loneliness, job loss, and anxiety related to the virus contribute to mental distress. Instead of merely classifying tweets and posts as positive or negative, our analysis will leverage hashtags such as #depression and #mentalhealth to refine sentiment detection and achieve more accurate results. This analysis will then be applied to develop a chatbot designed to engage with users, offering emotional support and uplifting their spirits. The ultimate goal is to assist individuals in managing universal downheartedness, nervousness, apprehension and other mental health conditions effectively.

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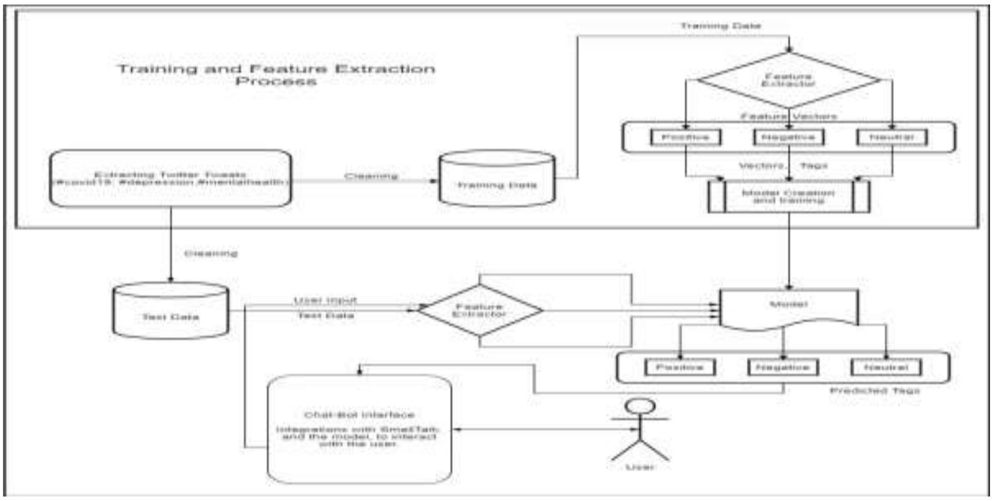


Fig. 1: Behavioural Diagram

A. Preparation and Prediction Process

During the activity (a), our prototypical studies to map a given response (i.e., text) to its subsequent output (tag) based on the training dataset. A feature extractor converts the text input into a feature vector, which is then paired with a corresponding tag (e.g., neutral, negative or positive). These feature-tag pairs are fed into a ML algorithm to develop the predictive model. The accomplished feature extractor converts unseen text inputs into feature vectors in the prediction process. These vectors are then processed by the model, which assigns the most appropriate predicted tag— neutral, negative or positive —based on the learned patterns.

B. Feature Extraction From Text

The elementary step in constructing a ML text classifier is to convert the text through extraction or vectorization. Currently, advanced feature extraction procedures such as word embeddings (also known as word vectors) have been developed. This depiction allows words with similar meanings to possess similar vector representations, enhancing the accuracy and effectiveness of text classification models.

C. Classification Algorithms

The classification step in a ML text classifier normally encompasses using statistical models such as Naïve Bayes, Logistic Regression, Support Vector Machines, and Neural Networks. In Naïve Bayes a sequence of probabilistic procedures that applies Bayes' Theorem used to predict the category of a given text. Linear Regression is most commonly employed statistical algorithm that predicts a target value (Y) based on a given set of characteristics (X). SVM is a non-probabilistic model in which points in a multidimensional space indicate text examples. The various distinct regions within this space represents different sentiment categories. New contents to be classified based on their similarity to existing examples. Deep Learning is a collection of advanced algorithms that simulate the person brain using artificial neural networks to check, process and analyze data.

Bidirectional Encoder Representations from Transformers (BERT) are a significant advancement in NLP pre-training. This method allows users to train state-of-the-art question-answering systems, as well as other NLP models, in about half an hour on a single Cloud TPU or in a few hours on a single GPU. BERT is a direct extension of previous work on contextual representation pre-training, particularly semi-supervised sequence learning and generative pre-training. But BERT possesses a distinguishing feature from prior models: BERT is the first "deeply bidirectional," unsupervised language representation model to be trained solely on text corpora without any specific task to solve, which allows it to understand more subtle aspects of language.

IV. System Design

System building is a abstract framework that outlines the structure, performance, and various perspectives of a system. The proposed system comprises modular components designed for seamless integration and interaction within the broader framework. Each component is engineered to ensure interoperability, scalability, and efficient data flow, enabling cohesive operation across the entire system.

A. Data Acquisition

Data collection is done using Twint, an advanced scraping tool for Twitter written in Python which allows the extraction of tweets without the use of Twitter's AP. Twint uses Twitter's search operators to scrape tweets from specific users, to follow topics, hashtags, and trends, as well as to filter out sensitive data, such as emails and phone numbers. In this paper, we scrape tweets using the hashtag "covid19 depression sad" using Twint, which provides a dataset saved in CSV format, and the end result is a very large collection of tweets which can be used to performed your analysis.

B. Pre-Processing Data

Before model training, raw input data must undergo rigorous cleaning to ensure optimal feature extraction. The preprocessing stage involves: Text Normalization- Convert all characters to lowercase to maintain consistency, Remove numerical values, special characters, and punctuation marks Eliminate hyperlinks, HTML tags, and non-textual elements. Noise Removal- Strip emojis and emoticons (unless preserved for sentiment analysis), Filter out stop words and irrelevant boilerplate text, Remove duplicate entries and empty records. Content Filtering-Extract and discard embedded media (images, videos), Handle or remove code snippets and technical artifacts, Address encoding issues and Unicode normalization. This standardized cleaning process ensures the model receives high-quality, structured input while reducing dimensionality and computational overhead. The specific preprocessing steps may be adjusted based on the target domain and analysis objectives.This preprocessing step establishes the dataset in a way that facilitates training and testing. The tweets are further categorized and labeled with either a positive (1) or negative (0) label, thus forming vector features suitable for word level sentiment classification.

Fig. 2: Word Cloud

C. Developing and Fine-tuning The Model

Vector tags are used in training the model among several algorithms, in order to assess which is a better form of classification for sentiment analysis. This helps with evaluation and comparisons of performance based on accuracy, precision, and overall performance and efficacy.

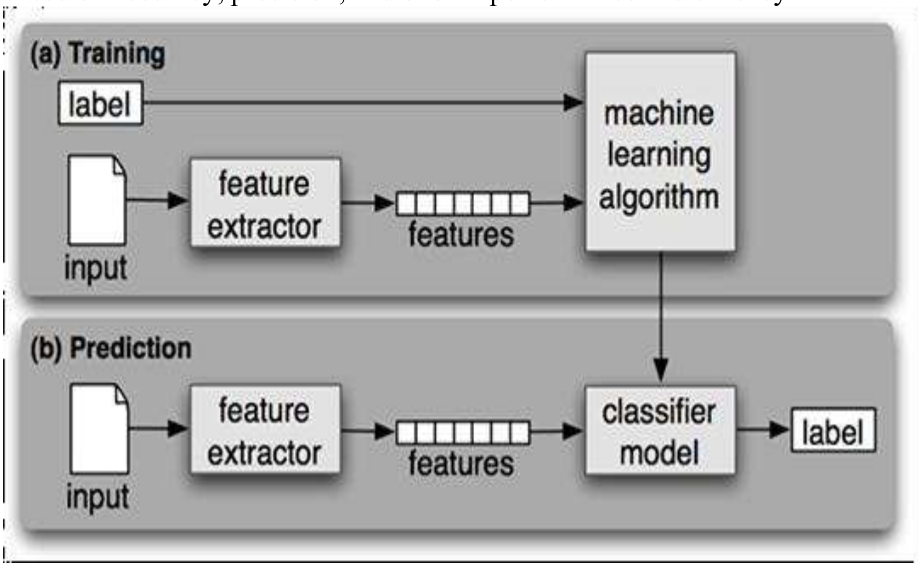


Fig. 3 Algorithm Flow

D. Creating API's For the Model

After training and evaluating various classifiers, the best-performing model is chosen. A Python-based Flask API is then developed to deliver sentiment classification results for any input tweet. When text is provided as a parameter, the trained model analyzes it and determines the sentiment as either positive or negative.

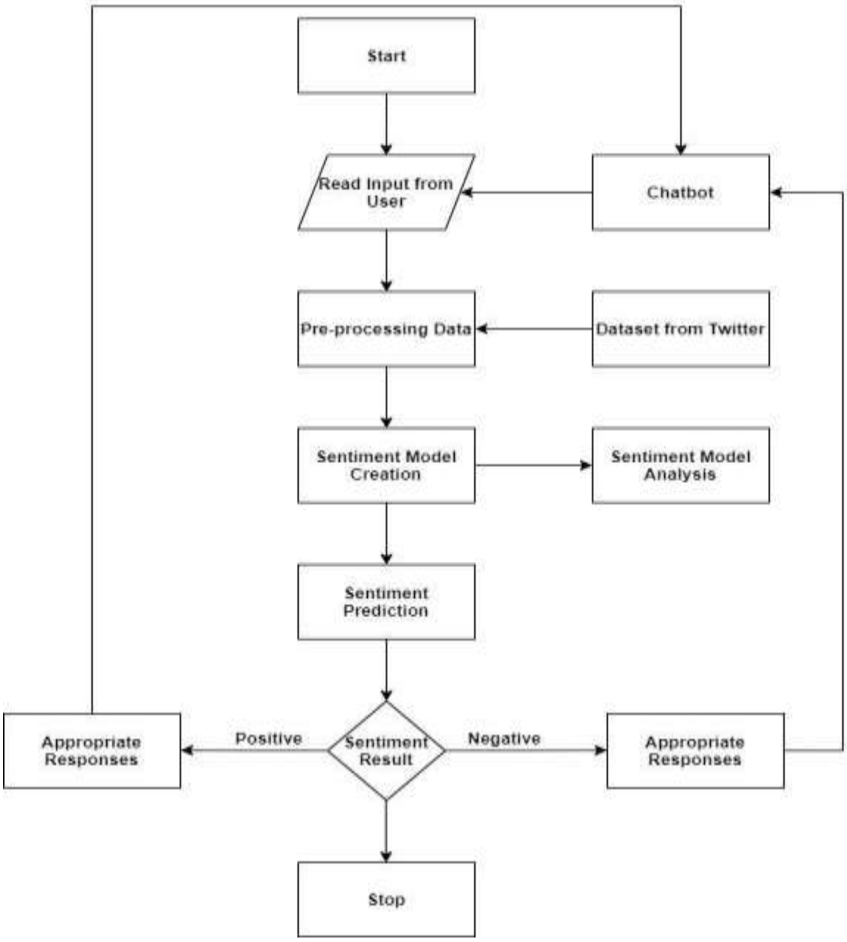
E. Developing The User Interface

We will create an intuitive user interface (UI) enabling users to interact with the model via the backend API. Users can input text for analysis, and the chatbot will generate a suitable response based on the detected sentiment.

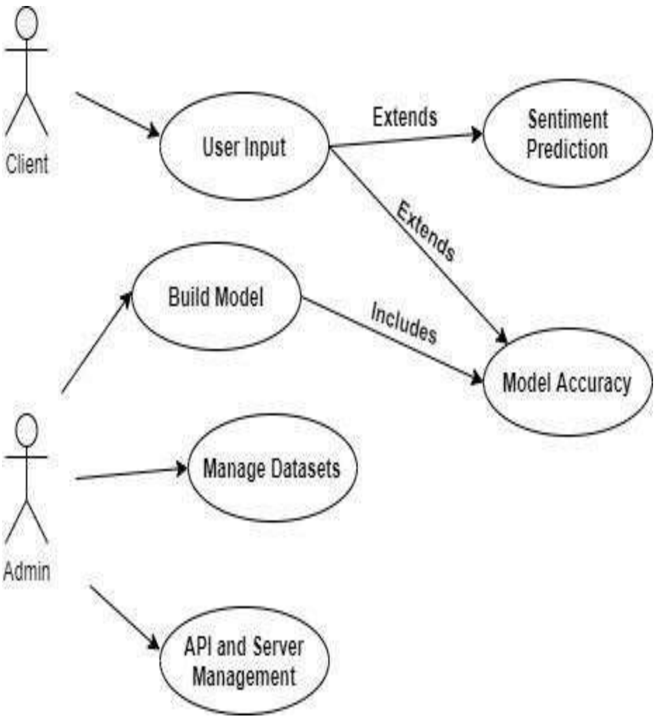
Fig. 4: Chat-bot UI

F. Diagrams

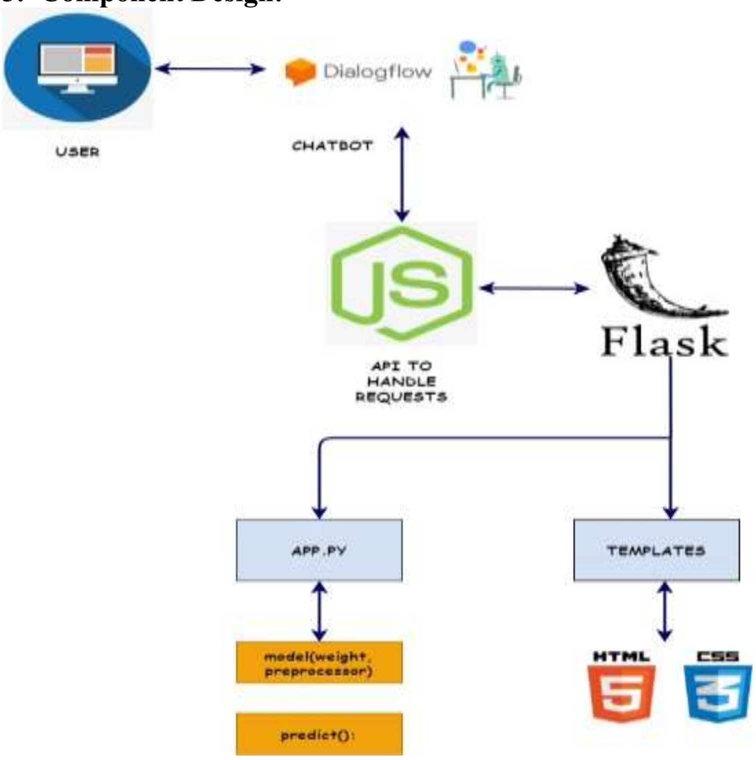
1. Flow Diagram:



2. Use-case Diagram:



3. Component Design:



V. SYSTEM IMPLEMENTATION

1. BERT Classifier

BERT is a powerful Transformer-based architecture that has achieved remarkable success across various NLP (Natural Language Processing) tasks. It generates vector-space representations of natural language, making it highly effective for deep learning applications. The Transformer encoder architecture of BERT models utilizes the Transformer encoder architecture, processing each token in relation to all preceding and succeeding tokens, thus the term bidirectional. Typically, BERT models undergo pre-training on a vast text corpus before being fined for NLP applications.

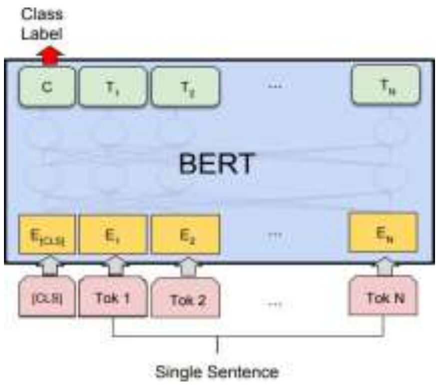


Fig. 5: BERT Transformers

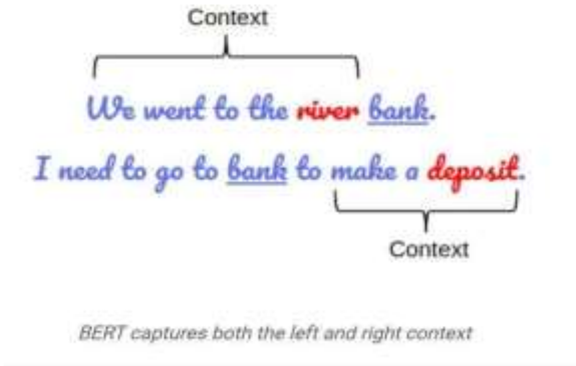


Fig. 6: BERT Sentiment Reading

For starters, every input embedding is a combination of 3 embeddings:

1. Position Embeddings: BERT utilizes positional embeddings to represent the position of words within a sentence. These embeddings help to overcome the limitations of Transformers, which, unlike RNNs, cannot accurately capture the sequential or ordered structure of text.

2. Embeddings: BERT can process sentence pairs as input, which is suitable for tasks such as question-answering**.** To distinguish between the two sentences, it acquires unique embeddings for each. In this manner, tokens from the initial sentence are assigned a specific embedding (EA), while tokens from the second sentence receive a different embedding (EB). This distinction enhances the model's understanding of the relationships between sentences.

3. Token Embeddings: These embeddings are utilized for each particular token from the WordPiece token vocabulary, enabling BERT to represent subword units and handle out-of-vocabulary words effectively.

VI. RESULT AND DISCUSSION

The final outcome enables users to engage with the chatbot, which responds appropriately based on their detected sentiment—whether positive or negative.

Dataset Showing Tweets, Subjectivity, Polarity, and Analysis

	tweets	Subjectivity	Polarity	Analysis
56054	getting a puppy or dog during the quarantine? ...	0.611111	0.477778	Positive
35610	10 launched fearnotthereisgod twitter campaign...	0.266667	-0.025000	Negative
47391	we met with our clients to discuss their fears...	0.625000	0.083333	Positive
39311	with funding from nsws is now able to offer up...	0.485000	0.260000	Positive
56154	if normals panic its cuz of the pandemic; if m...	1.000000	-0.500000	Negative
...	...	...	...	...
39520	anxiety over coronavirus can manifest in myria...	0.200000	-0.100000	Negative
32260	a thread about my anxiety on reopening back in...	0.450000	0.200000	Positive
16404	of course it's high the state was shut down. t...	0.476296	0.001481	Positive
955	take the positive step to make a change now. t...	0.415152	0.209091	Positive
71648	respected madame looking at crazy volatility a...	0.390972	-0.220139	Negative

Fig. 7: Dataset

Training Process

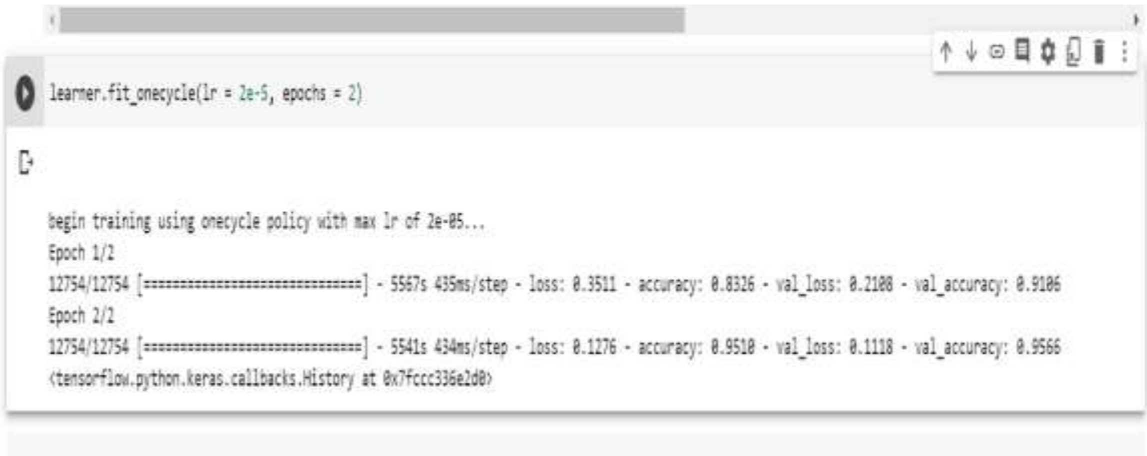


Fig. 8: Training the Model

Model Evaluation

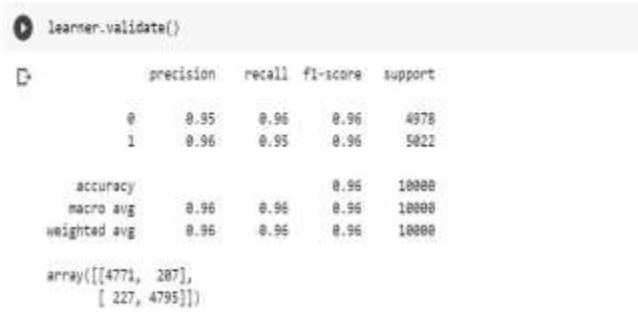


Fig. 9: Model Evaluation

Chat-bot User Interface

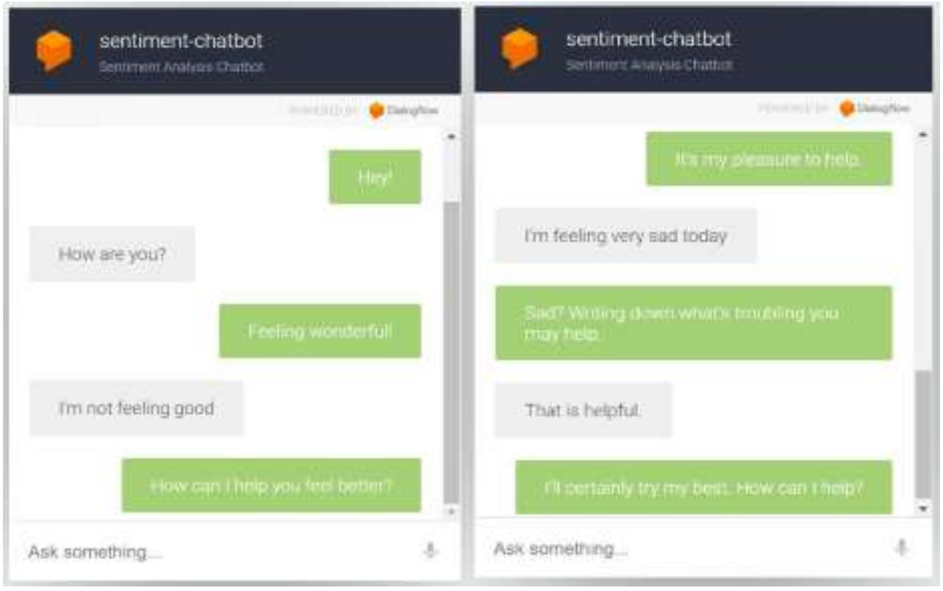


Fig. 9: Chat-bot UI

VII. CONCLUSION

Building upon established research linking linguistic patterns to depression, this study aims to advance social media-based mental health assessment by developing a BERT-based classifier capable of detecting text-based depressive indicators. By leveraging self-reported depressive markers in tweets, the model identifies at-risk individuals earlier than traditional diagnostic methods, enabling proactive intervention. Early Detection System: Analyzes linguistic cues (e.g., negative self-references, emotional polarity) in social media posts to flag potential depression. Provides actionable insights to users, caregivers, and clinicians through interpretable predictions. Deployment Framework: Predictions are served via a Flask API, enabling seamless integration with web/mobile platforms. Designed for scalability to accommodate high-volume social media data streams. Future Integration: Extensible to real-time chat platforms (e.g., Slack, Facebook Messenger) for contextual mental health monitoring. Potential to couple with chatbot interfaces for immediate support or crisis resource recommendations. This approach bridges the gap between computational linguistics and clinical psychology, offering a scalable, low-cost tool for early mental health screening. By transforming social media into a passive assessment medium, it reduces barriers to help-seeking while preserving user privacy.

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