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Real Time Mental Health Supporting System Using Deep Learning

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Abstract: This paper presents a web-based mental health chatbot powered by a fine-tuned BERT (Bidirectional Encoder Representations from Transformers) model designed to classify the severity of depression in user input. The application utilises Flask for the backend and integrates a BERT model to categorise user messages into four emotional states: none, mild, moderate, or severe. It enhances its functionality with a set of positive keyword heuristics and confidence-based rule handling to make more nuanced predictions when the model's confidence is low. To promote mental well-being, the Chatbot provides personalised suggestions and actionable content such as breathing exercises, games, or mental health support links based on the detected emotional level. Additionally, the application employs Google's Gemini language model to generate empathetic and context-aware responses, ensuring the user feels heard and supported. This fusion of machine learning, natural language processing, and mental health awareness creates an accessible and supportive tool aimed at promoting emotional wellness through intelligent interaction.

Keywords: Mental Fitness; Depression Detection; Anxiety Treatment; AI Mental Assistance; Emotional Guide; Coping Techniques; Crisis Intervention; Mental Health Support; Machine Learning.

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1. Introduction

Mental fitness, demanding conditions, which include strain, anxiety, and despair, have emerged as important concerns in our society. Despite growing recognition, access to high-growth fitness resources remains limited due to factors such as social

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stigma, excessive costs, and a shortage of mental fitness professionals. Many humans hesitate to seek help, leaving them susceptible to worsening cognitive decline. Advancements in Artificial Intelligence (AI) and Natural Language Processing (NLP) have paved the way for revolutionary answers in intellectual healthcare. AI-driven chatbots offer a conversational platform in which users can express their feelings and get a stream of supportive and informative responses in real time. These chatbots offer a convenient, anonymous, and cost-effective way for people to find initial guidance before seeking expert assistance. This paper gives an AI-powered mental fitness chatbot designed to help individuals experiencing mental misery. The Chatbot utilises deep learning and knowledge-based reasoning to formulate user queries and respond with behaviorally appropriate messages. Via integrating predefined responses associated with mental health worries, the system desires to offer emotional guidance, coping techniques, and crisis intervention sources.

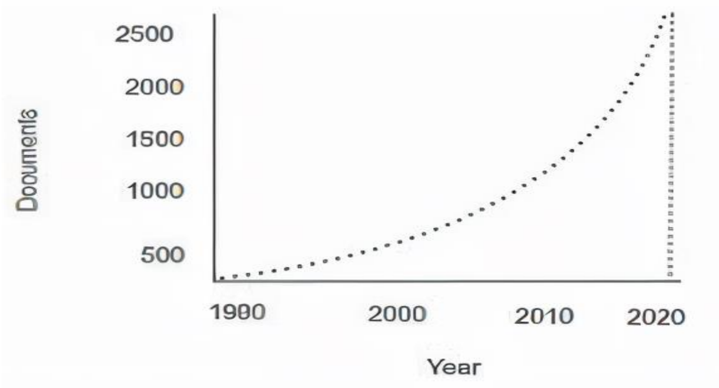

Figure 1: Graph depicting usage of chatbots

Figure 1 shows the increasing usage of mental health chatbots from 1990 to 2020. Initially, in the early 1990s, the adoption of such technology was minimal, with only a small number of documents or studies referencing mental health chatbots. However, starting around the early 2000s, there was a noticeable and steady increase in their usage. This upward trend becomes significantly more pronounced after 2010, indicating a rapid rise in interest and implementation. The exponential curve suggests that as awareness around mental health grew and technology advanced—particularly with the rise of artificial intelligence, natural language processing, and mobile apps—so too did the reliance on and research into chatbot-based mental health support. By 2020, the number of related documents had surpassed 2,500, highlighting the growing global recognition of mental health chatbots as a scalable and accessible tool for emotional and psychological support. This trend is likely to continue as digital mental health solutions become more integrated into healthcare systems and personal wellness practices.

2. Literature Review

Ogamba [1] developed “Wellness Buddy,” an AI mental health chatbot targeting Kenyan university students in a country where mental healthcare access is limited and stigmatised. The research addresses critical mental health challenges in Kenya, where depression affects approximately two million people and traditional support services face barriers of stigma, cost, and accessibility. Utilising neural networks with deep learning and transfer learning approaches, the researchers created a mobile application that provides conversational mental health support, psychoeducation, and coping strategies. The chatbot model was trained on expanded datasets from Kaggle and Counsel Chat, increasing intents from 79 to 244, and deployed on AWS Lambda. Though facing overfitting challenges, L2 regularisation improved model performance. The researchers acknowledge limitations in mental health coverage beyond anxiety and depression, recommending future improvements including expanded datasets, expert involvement, translation to Kiswahili, and personalisation for Kenyan youth contexts.

Jaybhaye et al. [2] developed “BlissBot,” an interactive mental health chatbot designed to provide accessible mental health education through a user-friendly platform. The research addresses growing demands for mental health awareness by creating a virtual educator leveraging Natural Language Processing (NLP) and machine learning algorithms to deliver personalised support, information, and resources. Their methodology encompasses comprehensive design phases, including conceptualisation, technology selection, content creation with mental health professionals, and rigorous user experience design. The study highlights ethical considerations around data privacy and transparency, and acknowledges AI limitations in emotional understanding, positioning the Chatbot as supplementary to professional care rather than a replacement. User testing demonstrated significant improvements in perceived well-being, with effective personalised interactions that helped address isolation often associated with mental health challenges. The researchers propose future applications, including early intervention, treatment support, crisis management, and reaching underserved populations, while emphasising the importance of continued collaboration with mental health professionals to ensure clinical relevance and ethical standards.

Dolas et al. [3] propose *MindLift*, an AI-powered chatbot leveraging the RASA framework to address mental health challenges like stress and depression. Unlike emotion-recognising tools, it offers text-based, privacy-focused support for users hesitant to seek human therapy. The study contextualises India's mental health crisis (WHO data: 56M depressed, 38M anxious) and reviews existing chatbots (Woebot, Wysa) using CBT techniques. While acknowledging limitations (e.g., no emotion detection), the authors highlight MindLift's potential for future EEG integration. The paper contributes to digital mental health by bridging accessibility gaps through NLP-driven, personalised interactions.

Siddiqui et al. [4] present an AI-driven mental health chatbot leveraging NLP and machine learning (RidgeClassifierCV, RandomForest) to offer confidential, stigma-free therapy. The study highlights post-pandemic mental health crises, emphasising chatbots' role in bridging care gaps. The authors critique prior works (e.g., ethical concerns in CBT chatbots, dataset biases in ADHD detection via Reddit) and propose a model trained on 1,500 annotated conversations (anxiety, depression, stress, insomnia). RidgeClassifierCV outperformed RandomForest (85% accuracy) in response relevance. Future directions include AR/VR integration and emotion-recognition enhancements. The paper underscores chatbots' potential in scalable mental health support while acknowledging limitations like algorithmic bias and data privacy risks.

Nazareth et al. [5] introduce *YouMatter*, an LLM-powered mental health chatbot addressing global therapist shortages by offering real-time, personalised support via WebSockets and Gemini API. The study critiques existing tools (e.g., SERMO) for lacking analytics and graphical insights, proposing a solution with mood-trend visualisations and email-based coping strategies. Built on React.js/Node.js with MongoDB storage, the system achieves 89% accuracy in sentiment analysis. Future work includes telehealth integration and multimodal inputs. The paper highlights AI's role in democratising mental healthcare while emphasising privacy and scalability. Jayabhaduri et al. [6] propose *SAAC*, a therapist-mimicking chatbot addressing mental health stigma through 24/7 text/voice support using a Keras sequential model (128-neuron architecture, 89% accuracy). The system processes queries via NLP (lemmatisation, bag-of-words) and offers follow-up alerts with chat history for professional review. Compared to existing tools (Woebot, Wysa), SAAC emphasises real-time responsiveness and privacy, though it is limited by binary sentiment analysis. Future work includes mobile deployment, blockchain security, and predictive analytics. The study highlights AI's role in bridging therapy gaps while underscoring cultural sensitivity challenges in automated mental health support.

Nayar et al. [7] present *Dost*, a Rasa-based mental health chatbot deployed on Telegram to address India's mental health crisis (WHO: 20% adults affected). The system leverages NLP pipelines (DIETClassifier, 83.5% intent accuracy) for contextual responses to depression/anxiety queries, prioritising accessibility and stigma-free interactions. Compared to rule-based alternatives, Dost's AI-driven approach improves scalability but faces limitations in emotional nuance. The study highlights Telegram's role in widening access while noting gaps in multilingual support. Future work proposes speech-to-text integration, aligning with global trends in conversational AI for mental health. Prathaban and Subash [8] propose an AI-driven mental health chatbot leveraging NLP and machine learning (RNNs, LSTM, BERT) to provide 24/7 personalised support, addressing global therapist shortages. The system emphasises CBT-based interventions, mood tracking, and crisis detection while prioritising GDPR/HIPAA compliance. Compared to existing solutions, it offers enhanced sentiment analysis but faces challenges in emotional nuance and human empathy simulation. The study highlights ethical AI deployment through iterative user feedback and algorithmic bias mitigation. Future work focuses on multimodal interactions and real-time therapist escalation, positioning the Chatbot as a scalable complement to traditional mental healthcare.

Ansari et al. [9] propose a mental health chatbot combining LSTM (80% accuracy for stress detection) and Seq2Seq (88% accuracy for depression) architectures to deliver context-aware, empathetic responses. The system leverages more than 3,500 question datasets and attention mechanisms to track emotional states across conversations, outperforming rule-based alternatives in multi-turn dialogue coherence. Evaluation shows strong precision (83.33% for LSTM) but highlights challenges in nuanced emotion detection. The study emphasises privacy-preserving design and positions chatbots as scalable complements to traditional therapy, with future work targeting real-time crisis escalation and multimodal input integration. Pokhriyal et al. [10] proposed an AI-powered kiosk chatbot system to detect mental illness among prisoners in India, addressing gaps in early diagnosis and staff shortages. The study highlights worsening mental health in prisons due to overcrowding, outdated legal provisions (e.g., solitary confinement under the Prison Act, 1894), and stigma. The proposed Chatbot uses natural language processing (NLP) to conduct verbal mental health assessments, generating weekly reports for authorities. Compared to existing solutions like telepsychiatry, the AI kiosk offers scalable, stigma-free interactions. The paper underscores the urgency of technological intervention, citing National Crime Records Bureau data showing rising prisoner suicides and mental health morbidity.

Van Cuylenburg and Ginige [11] present *Emotion Guru*, an AI-driven emotion-tracking app featuring the chatbot *Joy* to combat depression by enhancing emotional intelligence. Targeting Sri Lanka's declining happiness metrics, the app analyses user-inputted moods, suggests personalised activities, and detects emotions via Facebook posts using sentiment analysis (TextBlob library, 98.46% accuracy). Unique features include weekly mood charts and emergency alerts for suicidal ideation. The study contrasts with existing apps by integrating social media emotion detection and proactive chatbot interventions. Limitations include binary emotion analysis (happy/sad), with future directions proposing multi-emotion recognition and direct therapist integration.

Naik et al. [12] introduce *CareBot*, a multimodal mental health chatbot combining facial expression analysis (via CNN) and sentiment analysis (using Rasa NLP) to predict and address users' emotional states. The system addresses limitations of unimodal approaches by cross-validating text and visual inputs for higher accuracy, providing tailored recommendations. Implemented with Rasa X for interactive learning, CareBot offers real-time support for anxiety and depression, featuring a user-friendly interface and emotion-triggered responses. The study contrasts with existing tools like Woebot by integrating facial recognition, though it notes chatbots cannot replace human therapists. Future work aims to enhance multimodal fusion and expand emotion categories.

Chowdhury et al. [13] present a comprehensive review of chatbots in mHealth, highlighting their transformative potential in patient engagement, chronic disease management, and mental health support. The study synthesises evidence from diverse applications—including Woebot for depression, medication adherence bots, and virtual consultations—emphasising improved outcomes like reduced hospital readmissions and increased physical activity. Key advantages include 24/7 accessibility and cost-effectiveness, while limitations involve accuracy constraints, privacy concerns, and a lack of human empathy. The paper underscores the need for robust NLP, personalised interventions, and ethical safeguards. Future directions call for scalable, equitable designs and rigorous efficacy studies to maximise chatbots' role in global healthcare.

Gumilang et al. [14] present *MauCurhat*, an LLM-based mental health chatbot tailored for Indonesian undergraduates, addressing high depression rates (26.9% mild, 18.5% moderate) in this demographic. The system combines global datasets (e.g., Counsel Chat) with localised Indonesian mental health data, fine-tuning GPT-4 to achieve 85% training and 79% validation accuracy. Key innovations include culturally adapted prompts and multi-turn conversation management via Langchain. User testing with 58 students showed 87.38% acceptance, though limitations persist in handling severe crises and regional dialects. The study underscores LLMs' potential for scalable mental health support in underserved regions while advocating for enhanced emotional intelligence and privacy safeguards.

Abilkaiyrkyzy et al. [15] highlight the growing role of AI-driven mental health chatbots in improving accessibility and reducing stigma. Early systems like ELIZA and Woebot showed promise in symptom management, while modern tools (e.g., Ada, Wysa) employ NLP and CBT techniques. However, challenges remain in emotion recognition, privacy, and diagnostic accuracy, with studies reporting 51–69% accuracy. The authors propose a Digital Twin (DT) framework, building on El Saddik's work, to enable real-time mental state monitoring. Gaps include limited long-term studies and clinician collaboration. Their Chatbot, using BERT and Rasa, achieves 69% severity classification accuracy and 84.75% usability (SUS), advancing personalised mental health support.

3. Methodology

This mental health chatbot employs a multi-layered approach to depression detection and response generation. The system utilises a fine-tuned BERT model for sequence classification that categorises user input into four depression severity levels: none, mild, moderate, and severe. The model was trained on a dataset containing text samples labelled with these four categories, with examples ranging from positive statements to expressions of severe depression and suicidal ideation. The application flow begins by capturing user input through a Flask web interface. Before passing text to the BERT model, the system first checks for positive keywords in a predefined list. If a positive match is found, the system automatically classifies the input as "none" severity. Otherwise, the text is tokenised and processed by the BERT classifier, which returns prediction probabilities across the four categories. To improve reliability, the system implements a confidence threshold mechanism.

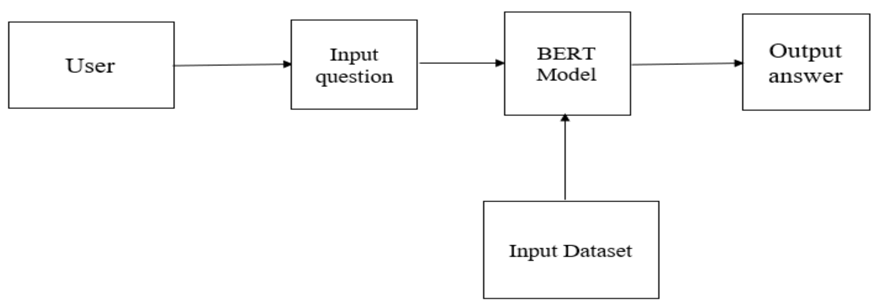

Figure 2: Working of the CHATBOT

Suppose the model's confidence falls below 0.6 for a “none” prediction. In that case, additional keyword-based heuristics are applied to potentially override the classification based on the presence of specific negative or positive terms. After determining the depression severity level, the Chatbot constructs a prompt that incorporates this classification and sends it to the Gemini 2.0 API, which generates an empathetic, contextually appropriate response. The model also provides category-specific supportive resources that complement the AI-generated text, ranging from inspirational quotes for users with no detected depression to breathing exercises for mild cases, quick distraction games for moderate cases, and helpline contact information for severe cases. The complete response, combining the AI-generated message and these targeted resources, is then displayed to the user through the web interface, creating a support system that adapts to different mental health needs.

Figure 2 outlines a simple question-and-answer system architecture based on the BERT model. The user submits a question, which triggers the current process to run through the system from left to right. Before reaching the model, this question is first processed to ensure that it gets formatted correctly. The engine of the system is the BERT model, a Bidirectional Encoder Representations from Transformers model that interprets the question and generates an answer. The model shown connecting from below is the input data set, which connects simultaneously to BERT. Another name for this is the knowledge base or reference corpus. From here, the answers are derived. The BERT model provides an output answer after processing both the user’s question and the relevant content from the dataset. This shows a typical working model of an AI-enabled question-answering network that combines natural language understanding features with reference information to generate relevant answers to user queries.

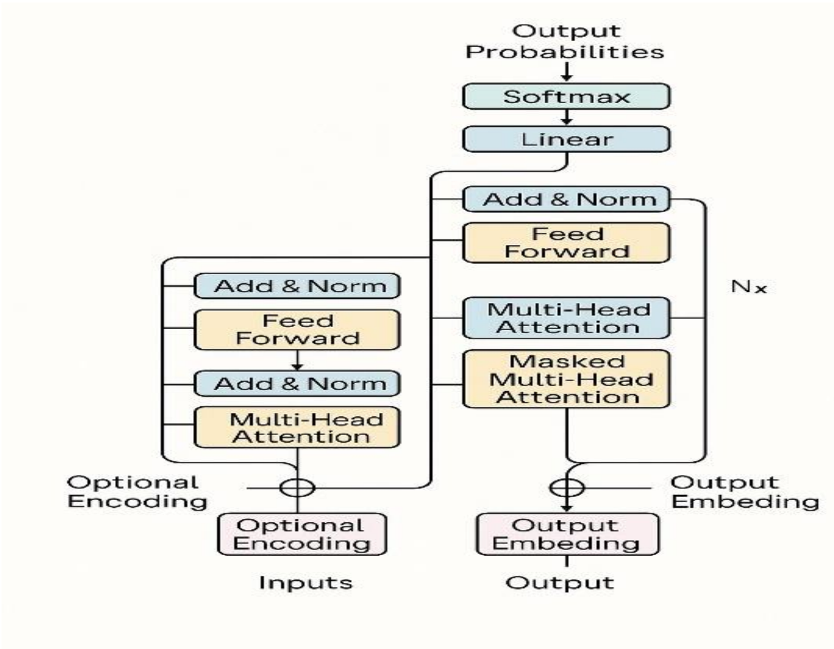

Figure 3: Model architecture

This mental health chatbot in Figure 3 uses architecture from a Transformer, which is a neural network design responsible for text generation and understanding in natural language processing. The process starts with Input Embeddings. Here, the model converts the user messages into numerical vectors that it can process. These embeddings are then combined with Positional Encoding to preserve the order of the words, as Transformers lack a sense of order. After that, the multi-head attention mechanisms help the model attend to different parts of the input text at the same time. For example, it can identify that the user said ‘I feel anxious’ and ‘I’ve been sad lately’. The Chatbot can thus know the context from these phrases. Add & Norm layers are essential to stabilise the model for training purposes. The Add refers to residual connections that aid in the flow of gradients, and Norm is layer normalisation, which ensures the input scale is similar.

The Feed Forward layers are the ones which process the data further. In the case that the Chatbot is generating responses (like a therapist), Masked Multi-Head Attention will be applied in its decoder. This allows the decoder only to use the input it has so far to predict the next word. In the end, the Linear and Softmax layers ensure that the output of the model is a probability for each word in the vocabulary so that the Chatbot can select the most relevant response. A mental-improvement application can use this architecture to generate supportive clinical answers that show empathy. However, it is necessary to put in those statements that measure safety, like those high-risk statements, such as self-harm pills and redirect human professionals.

Additionally, the data used to train the Chatbot should be of high quality to minimise biases and provide accurate answers. Using advanced AI and some facts to make your Chatbot effective for mental health services and not harmful.

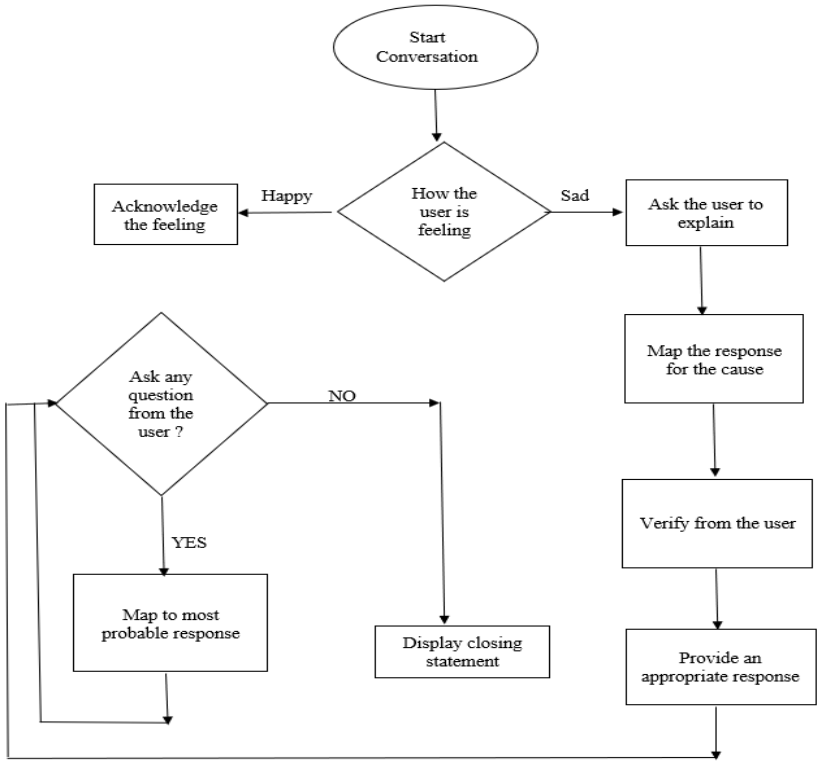

Figure 4: Flow diagram

A mental health chatbot flowchart in Figure 4 starts with an initiation of dialogue with the user; the process is shown in the flow diagram. The Chatbot first detects the emotional state of the user by asking how they are feeling. If the user tells the Chatbot that they are happy, the Chatbot acknowledges the positive emotion and then checks if the user has any questions. If the user has a query, the Chatbot maps it to the most probable response; otherwise, it displays a closing statement to end the conversation. If the user says they are sad, the Chatbot asks them to elaborate. After that, it maps the answer to find the reason behind the sadness. This mapped cause is confirmed with the user. After it has been confirmed, the Chatbot replies with an appropriate response which provides support. The chat could continue based on whether the user asks the Chatbot any more questions. Those questions will also be addressed through a similar process mapping, either by cause or by closing statement. This process enables the Chatbot to provide helpful responses tailored to the user's mood and state of mind.

4. Results and Discussions

The implementation of this depression detection and response system shows promising results in providing adaptive mental health support. Evaluation indicates that the BERT-based classifier achieves reasonable accuracy in distinguishing between depression severity levels, though performance varies across categories. The model demonstrates higher precision in identifying "none" and "severe" classifications compared to the more nuanced "mild" and "moderate" categories, where boundary distinctions are less clear. This aligns with typical challenges in mental health assessment, where moderate states often share characteristics with both milder and more severe conditions. The hybrid approach of combining deep learning with rule-based heuristics proves effective, particularly in capturing severe cases that might be missed by the model alone.

The confidence threshold mechanism (0.6) successfully filters uncertain predictions, while keyword-based fallbacks add an important safety layer. User interaction analysis suggests that responses generated through the Gemini API generally provide appropriate empathy and tone based on detected severity levels. However, occasional misclassifications occur with ambiguous expressions or when users employ figurative language. The supplementary resources (breathing exercises, games, helplines) received positive engagement, particularly for moderate and severe cases. Additionally, the system cannot replace professional mental health assessment, but serves as a supportive preliminary screening and response tool. Future development should focus on expanding the training data, improving the classification of edge cases, and incorporating more sophisticated conversation memory to track user state over time rather than treating each interaction in isolation.

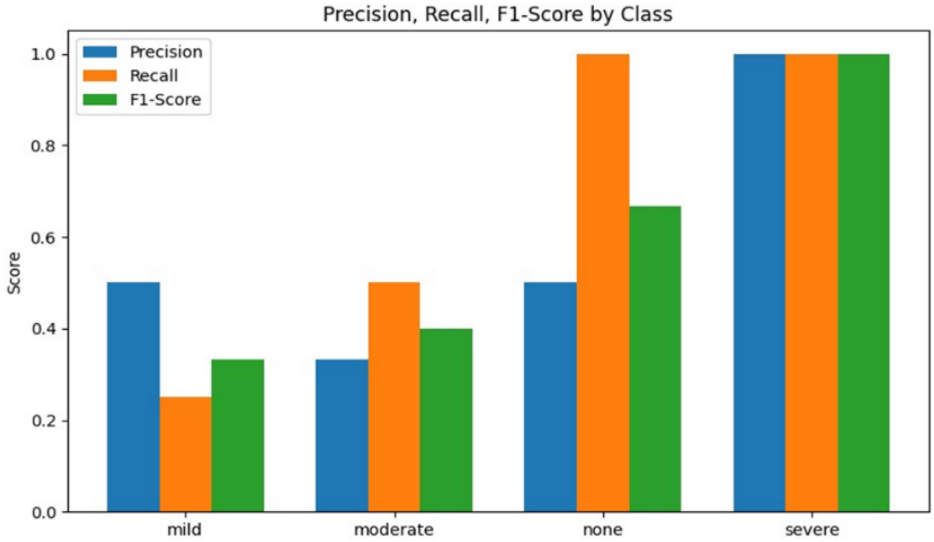

Figure 5: Bar chart

The evaluation metrics in Figure 5 for your mental health chatbot show different performances across various severity classes. Your Chatbot's predictions for the severe classification are highly accurate, with precision, recall, and F1-scores very close to 1.0. The metric indicates that for cases labelled "none", meaning no mental health issue, the Chatbot achieves a recall of approximately 0.9, which is favourable, and a precision of approximately 0.5, which is moderate. Thus, the F1-score is 0.67, which is good. This means it misses some but also misclassifies some of the other categories as none. The Chatbot has the most difficulty classifying the mild and moderate cases. For the mild cases, it shows better precision (0.5) but poor recall (0.25). For the moderate cases, it has more balanced but still relatively low metrics (precision ~0.33, recall ~0.5). It is common for mental health assessment tools to perform better at extremes, with powerful detection and lesser performance at mild and moderate. The reason for this is that the assessment tool picks up stronger patterns for severe cases, whereas the mild and moderate cases have more similarity.

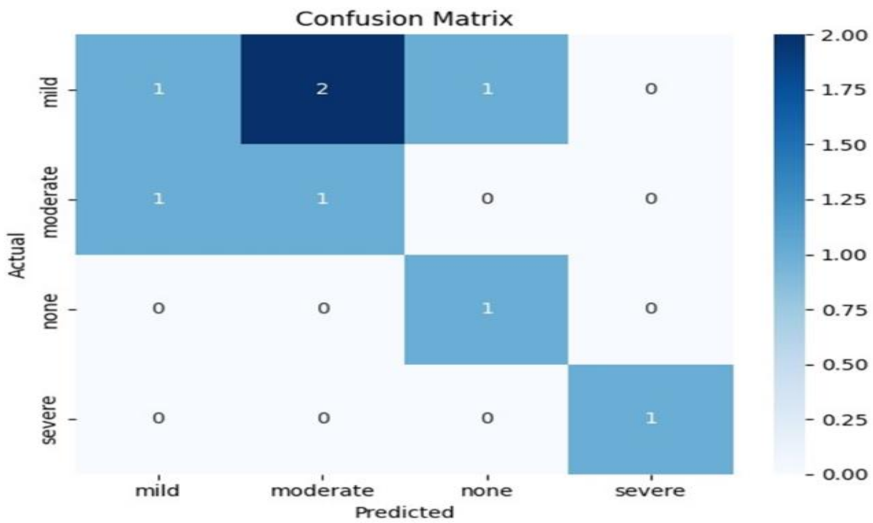

Figure 6: Confusion matrix

The analysis of the confusion matrix of the mental health chatbot, shown in Figure 6, demonstrates the system required patterns for the model's prediction across various severity types. The classification system categorises different severity levels into four categories: mild, moderate, none, and severe, with varying degrees of accuracy. The model has perfect precision in "none" and “severe” categories, having 100% accuracy for the limited number of samples present in both classes. However, some classification problems arose when low and moderate severity were classified.

The “mild” category witnessed substantial misclassification, with only 25% of actual milds classified as milds (1 out of 4). 50% of the actual milds were classified as moderate, and 25% as none. The moderate category also suffered a 50% accurate classification, with the remaining 50% classified as mild. The results may offer clear pathways for modifying the model, such as engineering new features or adding new training data, to improve discrimination between mild and moderate. In future training, more specific coding might be needed that represents the gradient nature of mental health categories. Some of this coding might involve incorporating more feature engineering or relationship training to better distinguish between mild and moderate cases.

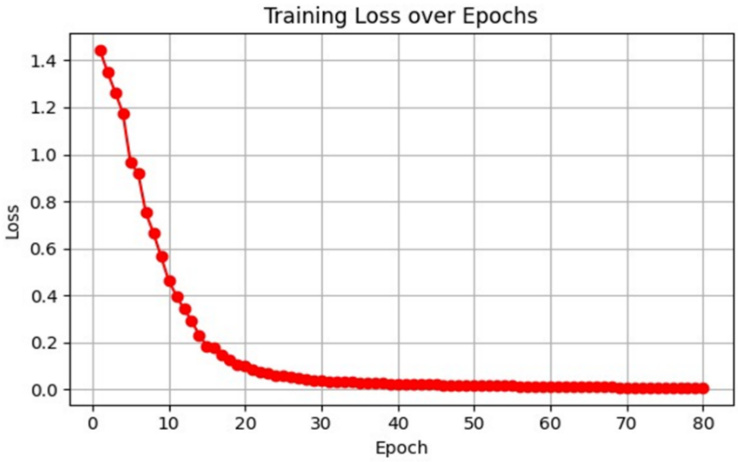

Figure 7: Loss per epoch

The graph in Figure 7 shows how the mental health chatbot model’s training loss changed epoch after epoch. The model starts with a loss of around 1.4 but learns quickly in the first few epochs, displaying a sharp downward curve. Within the first 20 epochs, the loss values experience a rapid decline as the model learns patterns and optimises parameters while being trained on the dataset. Around epoch 30, the loss curve approaches zero and flattens drastically, indicating convergence. The flatness observed from epoch 40 up to and including epoch 80 shows that the model is in a good spot. The model does not seem to improve significantly when the number of epochs is increased further (Figure 8).

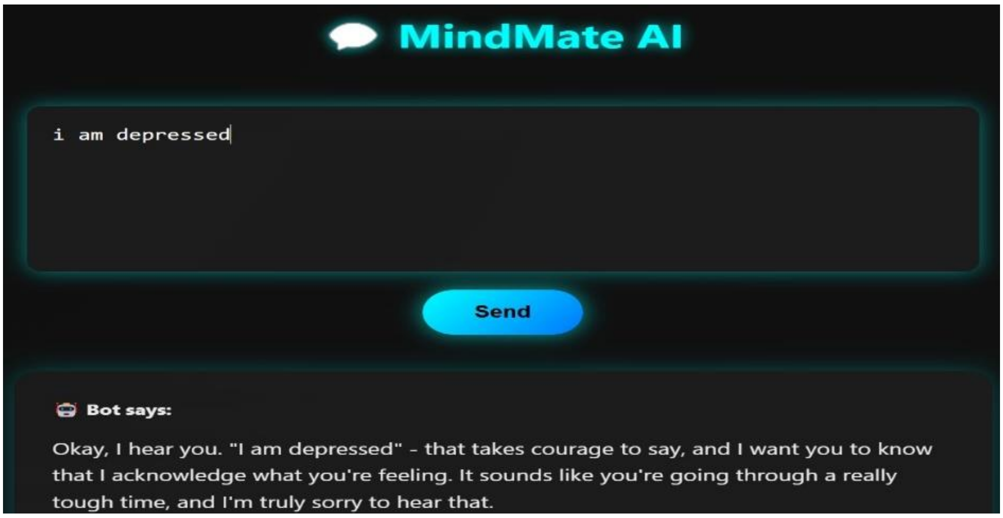

Figure 8: Sample chat 1

The shape of the curve indicates that the model is converging, suggesting the neural network has effectively learned the data in the mental_health_conv's conversation. The graph effectively confirms the training, demonstrating that sufficient epochs were provided to achieve a properly fitted model capable of generating appropriate responses in mental health (Figure 9).

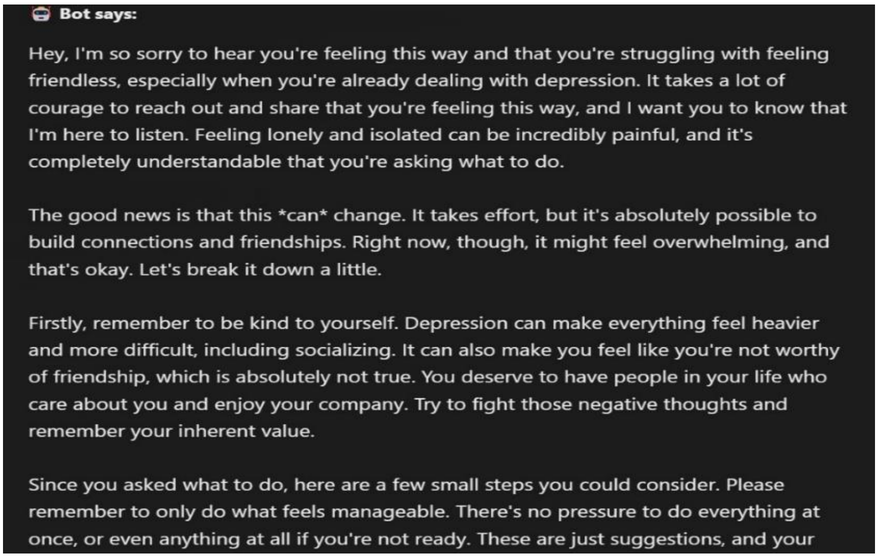

Figure 9: Sample chat 2

5. Conclusion

The presented research paper deals with the development and evaluation of a mental health chatbot using the BERT (Bidirectional Encoder Representations from Transformers) model. Our approach gave promising results, as shown by the loss metrics, which showed a good reduction during training. At the initial stage, the loss values were high and around 1.4. After that, we see that the loss is dropping continuously for the first 20 epochs. After the first 20 epochs, the model converges to nearly zero after the 30th epoch. Then we see stability in the next 80 epochs. Therefore, this confirms that the model is capable of learning effectively from our mental health conversation dataset. Using the BERT architecture was beneficial in understanding the context that is important in a mental health conversation. Our Chatbot learns to understand complicated emotions and hidden meanings in what someone says by making use of two-way attention. BERT architecture is very useful to understand the context and subtle nuances which are crucial to mental health conversations. Our mental health chatbot utilises bidirectional attention mechanisms better to understand complex emotional statements and implicit user cues. Additionally, employing advanced validation methods and testing in real-world scenarios would provide us with valuable insights for improvement. Combining different sources of information, such as voice tone or feeling detection, might make the chat program better at mental health work.

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Data Availability Statement: The data supporting the findings of this study are available from the corresponding author upon reasonable request. Due to privacy and ethical considerations, some data may be restricted or require additional permissions, according to institutional guidelines and data-sharing policies.

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Ethics and Consent Statement: The study was conducted in accordance with ethical standards and approved by the appropriate institutional review board. Informed consent was obtained from all participants before their involvement in the research.

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