Cognitive Insights: Machine Learning for Emotion Detection, Mental Health Analysis, and Suicide Prediction

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***Abstract*—Mental health chatbots have presented themselves as an efficient way to fill the big demand of cheap and easy mental availability on support. AI-based virtual assistants using NLP and Machine Learning offer therapeutic conversations and mental wellness support. This paper reviews research trends, benefits, challenges, and how chatbots improve mental healthcare accessibility, focusing on stress, anxiety, and depression management. Finally, we consider chatbot responses involving sentiment analysis, emotion recognition and cognitive-behavioural therapy (CBT). Although they offer benefits, mental health chatbots struggle with ethical implications data privacy, AI biases and the inability to provide a degree of empathy like a human. In this paper we touch on the restrictions of modern models and how hybrid AI-human can bring higher emotional intelligence. We also identify advancements in the future like chatbot effectiveness through real-time wearables insights and personal AI interventions. We seek to open up a discussion on the possibility of chatbots aiding as a supportive tool in mental healthcare for mental health and the necessity of ongoing development to offer users safe, ethical and efficient support.**

***Index Terms*—Mental health chatbots, Artificial Intelligence (AI), Natural Language Processing (NLP), Sentiment analysis, Emotion recognition, Cognitive Behavioral Therapy (CBT), Conversational AI, Mental healthcare, AI ethics, Digital mental health.**

I. Introduction

Mental health conditions are increasingly recognized as a global health concern that immensely impacts hundreds of millions of people around the world of all age groups and phenotypes. The upsurge of anxiety, depression and stress-related diseases has increased the demand for mental health care that is more widely available at a lower cost. Traditional therapy often remains costly, with long waiting lists and social stigma preventing access. Therefore, technology-driven solutions like mental health chatbots have emerged as a promising alternative to bridge this gap. [1].

Mental health chatbots are a new class of AI voice and chat powered virtual assistant which can deliver counselling help via conversation. Chatbots use Natural Language Understanding (NLU), sentiment analysis and a suite of algorithms to read user data inputs and produce individual responses. A lot of chatbots are using cognitive behavioural therapy (CBT) tips, self-help guided tools for use and mood tracking to facilitate users on taking care of their mental health. AI-powered systems led to take it all away (from privacy point of view) ongoing 24/7 availability and non-disclosable assistance in reducing access barriers for mental health support [2].

Though they have the potential, mental health chatbots come with a lot of restraints from ethical questions based on privacy to AI never truly being able to understand human emotions. Human therapists are better at nitty gritty emotional nuances and less straightforward emotional responses that chatbots by comparison may not be able to handle. AI bias and wrong responses also harm user trust, as does using chatbots for interventions. These are the challenges that should be addressed in order for responsible and ethical mental health chatbots to be deployed. The mental health chatbots are evolving as quickly as AI and digital health technology is advancing [3].

Overall, as AI and mental health technology research develops, forthcoming inventions may help chatbots do better with emotional intelligence, real-feel monitoring and hybrid AI-human support top models. Combining chatbot with wearable devices, mental health applications allow for more personalized and data-based support of users at another end. In addition, deep learning and NLP might lead chatbots to understand human language in a more conversational, organic fashion, and could potentially make them better psychological helpers. The AI driven tools have the potential to augment traditional therapy and offer real time help, reduce help seeking stigma chronic through increase access to usually hard to reach populations [4].

The paper will present mental health chatbots research, from the development and its consequences on modern psychological treatment to challenges in this field. We will dissect their merit, ethical issues, and future to supervise the understanding of how the digital mental healthcare can employ this to complement other support options related to their full capacity. By understanding the current trends, our study aims to visualize, mental health chatbots can be a useful adjunct in battling the escalating mental health crisis providing to implement them ethically [5].

II. Background and Related Work

The need for readily available, affordable psychological support is increased number of mental disorders making demand on accessible and affordable mental health consultation. Conventional mental health services are burdened with rising costs, rationing for lack of workforce and social stigma which prevent people from accessing it. One such novel solution to tackle this is the AI-powered mental health chatbots which give immediate feedback and advice to users in conversational channels. These chatbots leverage NLP, machine learning, and CBT concepts to support users with stress, anxiety and depression[6].

The AI-driven mental health chatbots Woebot, Wysa and Replika use NLP and sentiment analysis to facilitate users in an ongoing therapeutic conversation, provide subtle emotional support as well self-help advice. Research suggests that chatbots can be effective in enhancing users' emotional well-being through the structured intervention, mood tracking and behavioral exercises delivered to users on daily basis. Nevertheless, even if chatbots have clear benefits of anonymity, anytime anywhere availability, and scaling, they basically struggle with deciphering the nuances of deep emotions in order to give comprehensive therapy.

Previous studies in the domain of digital health have shown effectiveness of mental health Chatbots. Studies show that chatbots based on AI can alleviate symptoms of depression and anxiety, particularly when paired with psychological therapy interventions based in evidence. Still, there are multiple ethics, data privacy and AI bias concerns on top of that. Users have little confidence in the privacy of their personal data and this is further exacerbated by biases in training the AI, so it could be providing less accurate, or inappropriate responses which makes these chatbots appear less trustworthy. On the other hand, personalization that only chatbot interactions could provide is not empathy and understanding provided by professional human therapists so it must be used carefully as standalone mental solutions.

Apart from chatbot oriented solutions researchers have looked at hybrid models to marry AI aid with a human hand. Chatbots are used in these models not as an isolated solution, but instead conjunction chatbot guided self-help and human moderation at regular intervals that users will get in case the AI limitations kick in. AI and NLP keep advancing thereby the mental health chatbots are evolving rapidly on emotional intelligence, real-time tracking as well personalized responses. Research will continue to ensure the ability, but also any challenges in implementing ethical AI for improved capabilities should be tackled as this would determine their place in a modern-day mental healthcare. Building upon existing work, this study examines the what is happening with mental health chatbots, the implications going forward and possible future directions in light of AI psychological support systems discourse [7].

Elsayed et al. designed a deep learning model to detect suicidal ideation in digital text, particularly within chatbot interactions. They used a GRU (Gated Recurrent Unit) architecture, which efficiently learns sequential context and avoids the vanishing gradient problem common in RNNs. Their model enables early intervention by automatically flagging high-risk text inputs for further analysis. [8].

Wang et al. proposed an emotion analysis system for psychological crisis hotlines. Their approach combines pitch acoustic features with deep learning to distinguish subtle emotional variations in voice calls. The model achieved a strong F1-score of 79.13% for negative emotion classification, demonstrating its practical use for real-time emotional monitoring in mental health services. [9].

Qiu et al. developed PsyGUARD, an intelligent system for suicide ideation detection and risk assessment in psychological counselling. It integrates machine learning with a structured taxonomy to categorize different levels and signs of suicidal tendencies. This fine-grained risk framework allows clinicians to make quicker and more informed decisions when managing at-risk individuals. [10].

A study published in Scientific Reports highlights how AI and machine learning can strengthen suicide prevention. By leveraging diverse data types such as text, voice, and behavioural patterns, their models reach detection accuracies up to 90%. The research outlines best practices for deploying AI tools in crisis detection and timely interventions. [11].

Leveraging massive datasets that mix several kinds of information, these AI models are able to make predictions with clinical applicability in terms of significance that could revolutionize clinical and counseling practice however much faster as well as reliably leaving the gold standard assessment methods.in the dust for identifying people at-risk and intervening at earlier times [12].

To conclude suicide prevention represents an important advancement within this space that will yield better predictive abilities as well the promise of timely and accurate interventions. Studies such as Qiu et al., and findings in scientific reports support the value of big data approaches with complex algorithms in identifying suicide ideation and risk assessment. Yet future studies are needed to overcome present limitations of these systems including bridging the gap between emotion detection models and chatbot interventions.

III. Methodology

This section outlines the detailed methodology followed to develop and integrate advanced machine learning models into a mental health chatbot. The approach encompasses the handling, preprocessing, and analysis of three distinct datasets:

emotion detection, suicide rate prediction, and mental health issue classification. Each of these datasets plays a crucial role in providing the necessary insights for creating a system capable of detecting emotions, predicting suicide risks, and addressing mental health concerns in a comprehensive manner.

A. Datasets Used:

GoEmotions: An open-source dataset containing 211,225 Reddit comments annotated with 28 distinct emotion labels and a neutral category. Each comment can have multiple emotion labels, providing a rich resource for multi-label emotion detection tasks. Suicide Rates Overview 1985–2016: This dataset compiles suicide rates along with demographic and economic variables such as age, sex, country, GDP, and generation across over 30 years. The dataset is valuable for exploring correlations and building predictive models for suicide rates at a population level. Mental Health Reddit Dataset: A labeled collection of Reddit posts from mental health-related forums. Each entry is tagged with one or more mental health conditions (e.g., anxiety, depression, bipolar disorder), making it suitable for multi-class classification of user mental health status.

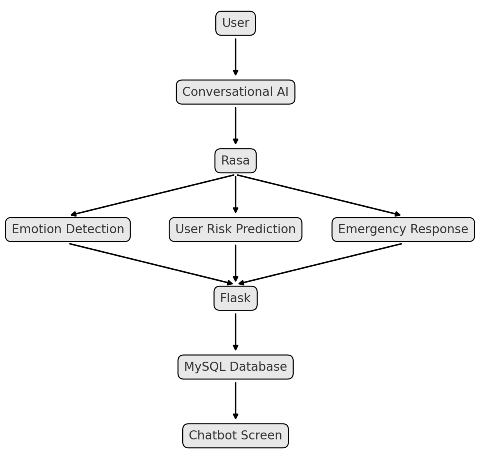

Fig. 1. **System Architecture Flowchart**

Fig. 1 represents the overall system architecture of the mental health chatbot developed in this study. User input is captured by conversational AI using Rasa and simultaneously routed through three key modules: Emotion Detection, User Risk Prediction, and Emergency Response. Results from these modules are integrated via Flask and stored in a MySQL database before being displayed on the chatbot screen.

B. Emotion Detection

We used GoEmotions dataset (211,225 Reddit comments in one-year window, with 28 emotions and neutral on multi-label annotations) for our emotion detection model. The labels were aggregated for single-label classification as the annotations were frequent multi-labels one could say that it simply took the most dominant emotion per comment. The text data was cleaned by removing irrelevant fields, duplicates, and standard NLP preprocessing (lowercasing, tokenization, stopwords removal, lemmatization). Features were vectorized using TF-IDF with unigrams and bigrams.[13].

The step of preparing the dataset for modeling that was the most difficult to resolve was dealing with class imbalance. After that we created with SMOTE i.e. Synthetic Minority Over-sampling Technique to synthesize samples for minority classes and RandomUnderSampler for dominating class which got more distribution (31k samples of each emotion excluding neutral). As such, the very first model Random Forest gave us an accuracy of less than or around 43.5% as a baseline. But it was overtaken by LightGBM almost immediately after, hitting an accuracy of 48.8%. Further to improve performance, we switched out for a transformer model pre-finetuned on Hugging Face (the "j-hartmann/emotion-english-distilroberta-base", model). This transformer-based technique gave us impressive accuracy where an individual emotion resulted in 99% for fear and 98% for joy, making it highly accurate emotion detection system.

C. Suicide Rate Prediction

Suicide Rates Overview 1985–2016 Dataset, containing demographics, economic indicators (Graphics to be updated with demographics and economic variables it overall predicts suicide rates across different countries were used for predicting the suicide rates. Demographic and economic data were cleaned, missing values imputed with medians, categorical variables one-hot encoded, and duplicates removed to ensure consistency for model training

We performed Exploratory Data Analysis (EDA) to understand the relationship between variables. Upon visual and statistical analyses, (correlation heatmaps, Chi-square tests for categorical variables, ANOVA test for numeric variables) we found some strong predictors that were significant like GDP, age group and gender predicting the suicide rate. We further looked into various regression models such as Random Forest, LightGBM, Xgboost and CatBoost through the model training phase. From these selected, XGBoost was the best model with an R^2 score of 0.9963, MAE of 0.50 and RMSE of 1.13, hence it is selected for deployment. The last and finnaly trained XGBoost model was pickled into a file (.pkl) to be used in real-time suicide rate prediction by the mental health chatbot [14].

D. Mental Health Issue Classification

Mental Health Issue Classification We used the Mental Health Reddit dataset — labelled with various mental health conditions such as anxiety, depression, bipolar disorder etc. That dataset was the basis of training the model to classify user inputs into mental health categories accurately which is very important to the chatbot so that it can give proper and time-based response on the users' reported symptoms or query.

Data preprocessing was needed to conduct somehow the text data clean part and it needed many steps of preprocessing steps. First, we deleted stop words and symbols with BERT tokenizer that is specifically crafted for this use case as it aims to make the natural language processing as optimized by breaking text into smaller tokens that the model could handle. This was to clean and standardize the dataset for the next part of model training, this step was helping a lot. Next, the data was annotated to stop the chatbot from mislabeling user inputs (which were a free-form of text) wherever they may feed into mental health categories [15].

In the model development/training phase, we experimented with different LSTM models one at first and increased the number of LSTM layers and also training epochs in order to entangle the long-range dependencies over text data .The models reached up to a max accuracy of 70.50%, average is not bad but sometimes they will just be fine-tuned from scratch… So we added a Bidirectional LSTM (BiLSTM)! Where it only slightly improved accuracy to 68.89% Since we wanted higher performance than this, we went ahead and moved to a transformer-based BERT model, finetuning the pre-trained BERT-base-uncased for the mental health dataset. The performance was significantly improved with this fine-tuning (up to 81%E accuracy) to eventually take directly into the chat bot stream with real time classification of user inputs as mental health issues [16].

E. Integration into Mental Health Chatbot

Emotion Detection, Suicide Risk Prediction and Mental Health Classification models trained in python (FastAPI) for real time conversation were effortlessly embedded in the chat backend. Emotion Detection, which classifies the emotions of user in real-time so the chatbot can be empathetic and contextually relevant. The Suicide Risk Prediction model predicts how risky it is for users to commit suicide based on demographics and emotions detected. The Mental Health Classification model also takes user inputs and spot mental health conditions — thereby delivering personalized support with education related resources. Such holistic approach allows the chatbot respond adaptively up on user emotion and mental condition by providing empathetic, individualized and evidence-based responses. In the end the models left for embedding into chatbot were finely tuned to support real-time empathetic, accurate and empathic mental health support [17].

Although employing a single machine learning model across all tasks may appear simpler, the diverse nature of the tasks demands specialized approaches. Emotion detection involves complex natural language understanding, best addressed by transformer-based models like DistilRoBERTa due to their contextual language comprehension. Suicide rate prediction uses structured numeric and categorical demographic data, where ensemble regression methods such as XGBoost perform optimally. Mental health issue classification involves nuanced multi-class text classification, making fine-tuned BERT ideal because of its robust contextual language representation. Thus, selecting tailored models for each task ensures the highest accuracy and efficiency for each specific use case.

IV. Experiments and Results

This section describes the results obtained through systematic experimentation, including initial findings, subsequent improvements, and final optimized models for emotion detection, suicide rate prediction, and mental health issue classification.

Effective preprocessing significantly enhanced the performance across all machine learning tasks. For the emotion detection task, preprocessing involved duplicate removal, class balancing through SMOTE and RandomUnderSampler, and comprehensive text cleaning, greatly improving class representation and classification accuracy. In the suicide prediction task, careful handling of missing values via median imputation and categorical encoding resulted in substantial predictive accuracy improvements. For mental health classification, meticulous text preprocessing using BERT tokenizer standardized the data effectively, leading directly to improved accuracy in classifying mental health conditions. Overall, preprocessing was critical in addressing data quality issues, enabling models to achieve optimal performance.

A. Emotion Detection Results

Prior to the Emotion Detection model, which started with a baseline of 42.5% accuracy being hit by logistic regression. As we wanted better performance/accuracy, we migrated to LightGBM and were able to go up to 48.8%. However, class imbalance caused the model to predict more of those well-represented emotions (neutral) and (admiration), which made it difficult. Although this did help with the representation of classes, LightGBM had trouble in properly separating overlapping emotions and it needed another solution.

To overcome these limitations, we moved to transformer-based pre-trained model of ”j-hartmann/emotion-english-distilroberta-base”, which improved the accuracy largely in our system. In the wild, the model performed at 99% accuracy for fear, 98% accuracy for joy, and over 95% on sadness, anger and happiness. This transformer-based approach does not require much of manual effort(trivial text preprocessing) and drastically improves in real-time set compared to basic machine learning models, providing rapid solution for emotion detection in Chatbot [18].

B. Suicide Rate Prediction Results

First model evaluation process for Suicide Rate Prediction was to train Multiple regression algorithm (Random Forest, XGBoost, LightGBM and CatBoost) and thus select the best approach. Models wise among them, XGBoost had the best performance with the highest R^2 of 0.9963, least RMSE(1.13) and near equivalence MAE (0.50) that made it optimal for deployment.

While Random Forest gave best R^2 score of 0.9943, Random Forest was kind of underperformed with higher RMSE as opposed to that of XGBoost and LightGBM (RMSE: 1.41 &10.53 with the scores of Random 0.9907; .9820— for feature bagging models). These comparisons are summarized in Table I which highlights the relative strengths and weaknesses of each approach [19].

TABLE I
COMPARISON OF MODELS

Model	Score	MAE	RMSE
Random Forest	0.9943	0.3	1.41
XGBoost	0.9963	0.5	1.13
LightGBM	0.9907	0.62	1.80
CatBoost	0.9820	1.19	2.51

With respect to feature importance, feature population, GDP, age group (timevariant) and gender appeared to be the most predictive and therefore, proved the demographical/economic indicators significance in the mental health trends analysis. These observations also emphasize relationship between economic stability and demographic variables and suicide risks, emphasizing the necessity of data-based interventions in mental health. Second, the model provides predictive power to direct policy and resource allocation towards mental health support programs.

C. Mental Health Issue Classification Resutls

The first Mental Health Classification models were served from LSTM based models, but with little more to write here. LSTM baseline was 52.58% accuracy; it beat 69.34% (from 10 to 30 epochs and boosted again upto 70.50% further upto50 epochs increment in training. When trying different embedding methods (e.g. GloVe embeddings (100d), which slightly penalizes accuracy from 33.33% as the initial checkpoint due to vocab mismatch). Hyperparameter tuning was performed extensively, the accuracy recovered to 68.45%, but it was still short of desired performance. This was, however upgraded a little to 68.89% by implementing Bidirectional LSTM (BiLSTM)though still not satisfactory.

In order to address these shortcomings, we followed a transformer-based model with a considerably better performance as compared to LSTM (more than two orders of magnitude) as BERT-base-uncased. Fine-tuning BERT, initially at 80.21% accuracy followed by further three fine-tuning epochs lifted it up to 81.11%, which is the best performing model. To improve performance again, and for this the fine-tuned BERT would be finally integrated into chatbot to build mental health classification model with more accurate and context-based [20].

A summary of all model performances is presented in Table II.

In the end the models left for embedding into chatbot were finely tuned to support real-time empathetic, accurate and empathic mental health support. Having the Pre-trained DistilRoBERTa (j-hartmann) transformer model and it is among the best emotion detection models because it can recognize a large number of emotions. This was a XGBoost model for Suicide Rate Prediction (highest performance on regression among all the models, R^2 = 0.9963). The fine-tuned BERT model (81.11% accuracy) was chosen for Mental Health Classification as it showed significantly higher performance than LSTM-based approaches. Combined, these models enable the chatbot to show more empathetic, personalized and contextual support that produces the correct guidance to users with an emphasis on emotional state and health of mind.

TABLE II
MODEL PERFORMANCE COMPARISON

Task	Model	Accuracy/(R^2) Score
Emotion Detection	Logistic Regression	42%
	LightGBM	48%
	DistilRoBERTa	99%
Suicide Rate Prediction	CatBoost	98%
	LightGBM	99%
	XGBoost	99%
Mental Health Classification	LSTM	70%
	BiLSTM	68%
	BERT (Fine-tuned)	81%

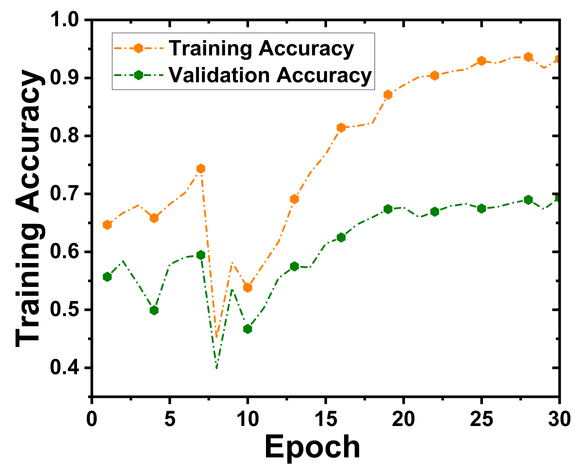

Fig. II. **Graph Showing LSTM Model Accuracy**

During the training phase, Fig. II shows training accuracy and validation accuracy over 30 epochs for the model. At the onset, both the accuracies are growing but sharply drops beginning from epoch no. 6 (for instance a learning rate issue or model instability). Training accuracy drops off a bit after this, then slowly increases to around 0.9 for final epoch whilst validation accuracy grows slower and eventually saturates at 0.7. The increasing gap between training and validation accuracy indicates that the network overfits, which means it catches training samples too much and generalizing power is low. This may be solved by using ways to train that helps improve generalization such as early stopping, dropout regularization or you could even decrease model complexity.

During the 30+ epochs of training, the Fig. III shows the training accuracy and validation accuracy. At the beginning, both plots are increasing pretty fast and steep and they are very close to each other until epoch 10. Beyond, training accuracy keep on improving and outperforms 0.7 while validation accuracy oscillates consistently around 0.65). There is not

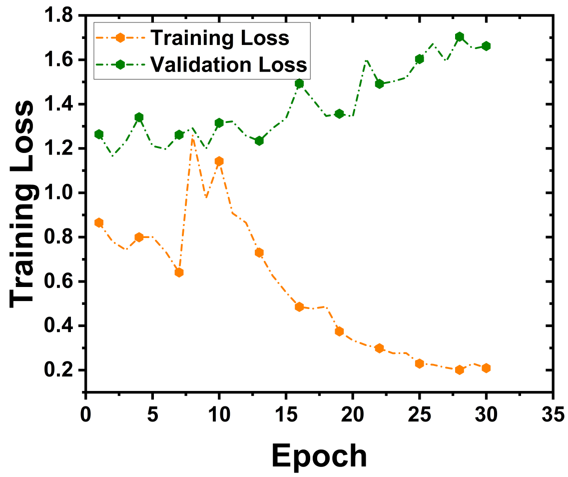

Fig. III. **Graph Showing LSTM Model Accuracy with GloVe**

a large gap between training and validation accuracy, which means the model is still not heavily overfitting but some slight variation in the validation accuracy shows that we may be underfitting due to noise and other disturbances.

V. Conclusion and Future Work

The project successfully implemented advanced machine learning models within a mental health chatbot to offer empathetic and real-time support to users. Utilizing DistilRoBERTa for emotion detection, XGBClassifier for suicide risk prediction, and a fine-tuned BERT model for mental health classification allowed the chatbot to accurately interpret user inputs in context. Integrating transformer-based models and regression techniques substantially improved prediction reliability and emotional nuance, enhancing the chatbot's ability to deliver timely, data-driven interventions. Moving forward, further advancements can be achieved by extending datasets, optimizing hyperparameters extensively to enhance model accuracy and universality, and integrating multimodal inputs such as voice recognition, facial expression analysis, and visual analytics for deeper emotional insights. Additionally, deploying the chatbot on scalable cloud infrastructure would increase accessibility, reliability, and seamless integration with existing mental health services. Ensuring rigorous ethical standards, privacy, data protection, and regulatory compliance will remain paramount. Longitudinal monitoring of mental health through the chatbot could facilitate preventive interventions and contribute positively to long-term mental well-being. Emphasis on context-aware interactions, multilingual support, real-time crisis management, adaptive learning, AI-driven mood detection, and collaboration with mental health professionals will significantly enhance user engagement and satisfaction, ultimately making the chatbot a powerful tool in public health and individual mental wellbeing.

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