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Machine Learning and Deep Learning Models for Predicting Mental Health Disorders and Performance Analysis through Chatbot Interactions

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Abstract: *Mental health disorders have recently been prompting increased concern globally and finding new ways of diagnosing and treating them efficiently. Machine learning (ML) and deep learning (DL) enabled chatbots are enormous tool for predicting and supporting mental health. This work aims to carry out an assessment of several AI models for prognostics of mental health disorders based on the comparison of intents, patterns, and responses in a structured chatbot-based dataset. Since it is intent-based, our dataset is best suited to classifying user inputs accurately into different mental health thematic buckets such as anxiety, stress, and proved suicide ideation. To assess the models, we compared basic models such as Multinomial Naïve Bayes, Random Forest and SVM as well as deep learning models including LSTM networks. SVM and LSTM showed promising results among the tested models with the accuracy of 94.6%. LSTM was proved to address the problem of sequential context dependence typical for conversational data. For further improvement in the model's accuracy, we used ensemble methods whose accuracy came out near like the highest accuracy models, 94.2% accurate. This work is new in the sense that it involves the use of data from an intent-based chatbot, and a comparison of the ML and DL models designed specifically for the prediction of mental health outcomes. Also, it is important to note that we dealt with underrepresented intents, including suicide ideation, using data augmentation and ensemble approach. It fills the gaps in the deployment of AI for mental health by providing recommendations concerning the model's performance and possible ethical concerns as well as integrating it into conversational assistance. We also found the relevance of an AI chatbot in the delivery of efficient and easily deployable intervention for mental health.*

Keywords: Mental health prediction, chatbot-based AI, intent classification, machine learning models, deep learning algorithms

INTRODUCTION

Mental health disorders are recognized as a major world health concern since they affect a large population of people, millions of people each year, and are a huge drain in the health care systems. Despite the increased focus and actions towards such problems, the problem of mental health remains the least prioritized and the availability and expansion of effective mental health care remains constrained, especially in developing nations. The development of technology, especially artificial intelligence (AI) created new opportunities for handling these problems by providing new approaches and options for determination, surveillance, and treatment of mental disorders.

Machine learning, and particularly the implementation of NLP, has been shown to be useful for the analysis of text-based large quantities of data, for instance, posts on social media and conversational data. Natural language processing–based chatbot is a novel solution based on AI and ML to support many patients at a lower cost. Currently, Woebot and Wysa have been found to identify symptoms of anxiety and depression, practice self-intervention, and provide the client with a professional connection. However, the success of such systems depends on features that are offered by the foundation ML and DL models for detection of the intent and prediction of mental health.

Previous studies discussed in the paper already examined different AI models to be used in mental health, including Random Forests, SVM, LSTM, etc. These studies advance understanding of the role of AI in this area but leave important questions unanswered. Most research works with rather general data, like social media posts or Electronic Health Records (EHR), which do not necessarily correspond to the real-time, intent-driven interactions, which chatbots manage. Furthermore, there is no comparative analysis proposed in the related works of different models that are designed with focus for intent-based datasets, which in our opinion, results in the absence of knowledge about model performance in mentioned applications.

This research fills these gaps by providing a comparison of ML and DL models on the prediction of mental state using structured data collected from a chatbot. The dataset effectively and efficiently organizes the user inputs in terms of mental health intents like stress, anxiety and suicide which could be challenging for the conversational AI systems. The models that were considered in this study are the classical methods such as Multinomial Naïve Bayes, Random Forest, and SVM, modern DL structures like LSTM networks. Furthermore, there was an attempt to improve the reliability of predictions using ensemble methods.

The novelty of this study lies in its integration of intent-based chatbot data, and a comprehensive comparison of diverse AI models tailored to mental health prediction. This approach bridges the gap between theoretical AI models and their practical application in conversational systems. Key challenges, such as underrepresented intents and class imbalance, were addressed through techniques like data augmentation and ensemble modeling. The findings of this research not only highlight the best-performing models but also provide actionable insights into the ethical and practical considerations of deploying AI-driven mental health chatbots.

The novelty of this study is based on the reconciliation of intent-based chatbot data as well as the comparative analysis of various AI models specific to mental health prediction. This approach can help to close the gap between large-scale artificial intelligence models, and the application of these models in conversational systems. Some of the major difficulties, including absent-minded intents and skewed class distribution, were solved by data augmentation and ensemble learning. This work not only reveals which models are most effective but also has practical recommendations concerning both the ethical issues within the deployment of these chatbots and precautions to be taken concerning such applications.

LITERATURE REVIEW

The application of artificial intelligence (AI) in mental health has garnered significant attention in recent years, with researchers exploring diverse methodologies to predict and address mental health conditions. This section reviews the existing literature, highlighting key advancements, methodologies, and gaps that underscore the novelty of this study.

Simon D'Alfonso's envisioning of AI in mental health deliberation shows how the use of personal sensing, NLP, and chatbots to diagnose and treat mental health disorders should be central to innovation. Self-help conversational AI options, such as Woebot and Wysa, have demonstrated the kinds of results that would decrease anxiety and depression. Again, however, it is referred as that ethical problems remain, and the area still exists in the demand for further research in its efficacy. This is in line with the objective of this study to enhance the viability and validity of the mental health estimates made via the chatbot [1].

Higgins et al. (2023) performed a systematic review of AI-DSS in mental health, mostly classifying the approaches into deep learning and Random Forest. These methods indeed presented accurate results in clinical trial, however, issues like clinicians' trust and usability were discussed. But more about the fact that the problems shown here emphasize the necessity of clear and trustworthy Artificial Intelligence models for the needs of mental health, which is the focus of this study [2].

Different works have included traditional ML approaches for predicting mental health using Big Data. Random Forest, Naïve Bayes and Support Vector Machine were used often on the organized data like clinical records and the data on social media with moderate accuracy of around 70 percent. For example, one of the studies presented the application of the ML model in processing extensive volumes of data, but also found some drawbacks, such as the impossibility of its use for huge datasets and the problem of integrating multiple datasets. Likewise, a few papers reported on using ML models accompanied by methods of NLP, where the average accuracy ranged between 70% and 90% depending on the dataset and the task [3].

Artificial Deep learning (DL) has been on the forefront in capturing temporal and spatial dependencies in mental health relevant data using Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs). For example: Studies using DNNs for the analysis of psychiatric stress obtained satisfactory accuracy (AUC>0.80) especially when the unstructured posts from social media were used. The research extends this line of work by directly comparing DL models such as LSTM, with traditional machine learning models for chatbot-based mental health prediction, respecting the model's intent classification rather than general datasets, FER using CNNs and RNNs achieved 70–90% accuracies which indicates the model for emotion detection [4].

Suicide ideation is an important variable in any mental health investigations. The approach of utilizing modified Restricted Boltzmann Machines (eNRBM) for representing the Electronic Medical Records (EMRs) into a low dimensional vector space outperformed clinicians in estimating suicide risks. However, the development of such models is often complicated and tailored; hence, such models' applicability is restricted in most cases. This work focuses on suicide intent classification through a chatbot dataset and proposes data augmentation and ensemble methods to enhance the model's performance in the lesser frequent classes [5].

In addition, wearable devices have also been discussed in stress and emotion detection using data like ECG, EEG, PPG signals. Research performed in controlled scenarios obtained up to 90% classification accuracy. Though these methods seem to be effective, they are equally tough to implement particularly due to high cost and accessibility. On the other hand, the approach used in this study of using the chatbot is easy to implement and can accommodate many people at once [6].

The use of AI-based chatbots is being increasingly accepted for improving mental health behaviors. Challenges have been conducted with tools based on NLP and ML, such as smoking cessation and emotional support. But here again, the analysis finds variable feasibility and uptake from users, primarily due to unrealistic intent modeling. This work directly fills the said void by concentrating on enhancing chatbot intent categorization for mental health prediction [7].

The problem in applying artificial intelligence in mental healthcare is not news, having various concerns such as bias, opaqueness of the models, and damage arising from mistakes. It is noteworthy that the studies mainly pointed out that more attention should be paid to the evaluation metrics and interpretability. These discussions are further enhanced by this research through the analysis of model performance together with the different ethical issues in mitigating them via class-balancing techniques and ensemble methods [8]. Several articles have shown recent advancements of AI in mental health concerns especially on social media, smart applications and virtual reality. The bibliometric reviews suggest an increase in works published in the database with regard to AI models such as Logistic Regression, CNNs and LSTMs which affirms the proposition that there is a growing interest in the field. However, one of the main issues still persists in data set variation and in the way that they present their data [9].

This study contributes to the existing body of knowledge by conducting an experiment on a structured set of data points formulated from the chatbot with well-defined intents for easy comparison of AI models for mental health prediction. The paper is devoted to exploring how AI, large language models such as ChatGPT, can help in developing mental health nursing care plans. They point out how AI can help save time on things like brainstorming, formulating research questions or writing documents so care professionals can attend to the substantive aspects of treatment urgently required in the healthcare field. But it underlines the point that although it is useful to have an AI, patients are still needed as they are responsible for decision making and choice of personalized treatment [10].

The paper "Applying Deep Learning (DL) Algorithm in Mental Health Research: A Scoping Review" (2020) It categorizes applications into four main areas: clinical history and plan for outcome determination, identification and prediction based on genotype and genome, voice and nonverbal symptoms of diseases, probability calculation based on data of social networking. The paper also reveals how DL could help mental health professionals by giving them access to more effective modes of decision based on patients' data. It also reviews the limitations of employing DL for mental health and proposes several lines of further research. All in all, it emphasizes the developmental potential of DL in improving the management of mental state disorders [11].

The work is devoted to the subject under consideration, namely Data Analytics in Mental Healthcare, and contains a brief analysis of the integration of data analytics and AI in mental healthcare. It speaks of the increasing trends in mood, bipolar, depression, and personality disorders and demonstrates how these diseases impact the behavior of suicide and substance use. Analyzing predictive mental health conditions through 'big data' using AI algorithms especially in machine learning is discussed in this paper. It also describes the main ethical concerns regarding subjects, such as the autonomy and their consent as well as possible risks [12].

In the research titled “Randomized Experiments Over the Past 50 Years, Artificial Intelligence and Precision Mental Health Services Research: A Historical Review and Reflection on the Future” (2020), authors have offered a theoretical analysis of the line of work. It identifies problems in the practice area and suggests how to address them, particularly by drawing on AI and precision mental health for better services. The author considers their work done over half a century and uses new literature that covers the attempts to increase efficacy through precision techniques and AI [13].

The study titled "Artificial Intelligence in Healthcare: For especial attention, the peer-reviewed article “Artificial Intelligence in Health: Assessing the Impact of AI on Clinical Practice and Enhancing Patient Outcomes” (2023) Atkins, T. & Grib, M. It examines the way in which AI can be used to complement therapy, refine decision-making, and support organizational processes in healthcare. The paper outlines notable developments in AI that are transforming the healthcare industry and underscores the need for providing healthcare stakeholders with valuable information and practical resources to enable them to enhance and achieve effective application of AI. It also has implications on the healthcare organization and the role of AI in healthcare, as applied to different problems. The specific purpose of the review is to present the reader with a clear picture of state-of-the-art AI applications in the field of healthcare [14].

Research Gap and Contribution

However, research on the topic is not without these gaps, even as the advancements are noted. Although the variety of chatbot-related datasets grows, most studies use generalized datasets and perform few comparative investigations of traditional ML and state-of-the-art DL for chatbot datasets. Thirdly, methods to handle sensitive intents, such as suicide ideation, and the ability to predict with a high level of reliability remain unaddressed. This research addresses these gaps with a well-defined chatbot-centered dataset which makes it easier to classify intents in the mental health domain. In this study, the performance of the basic models (Naïve Bayes, Random Forest, SVM) is contrasted with the ability of the advanced models which include LSTM. In addition, for attaining high accuracy and disposing with issues of underrepresented classes, such as suicide ideation in mental health prediction tasks, ensemble techniques as well as data augmentation strategies are included.

This research brings intent-based chatbot data into analyses for the first time while providing a rich comparison of various forms of AI. In addition to finding out the performance of the models, this study supports practical information on how to implement mental health systems utilizing chatbots. In this way, this work closes the gap between theory and application of AI solutions that address ethical issues and improve the reliability of mental health predictions for scalable and accessible solutions.

METHODOLOGY

In this section the approach taken to assess and compare different ML and DL techniques for mental health prediction based a structured, chatbot context is described. The data pre-processing involves filtering, cleaning, and transforming the data While the models adopted includes the selection of the model to use, the training process, the performance Evaluation and methods to handle tasks such as class imbalance as well as under-represented intents.

Dataset Description

This is making the present dataset appropriate for chatbot mental health-based applications. It comprises three key components: contains intents, patterns and responses. Intents are categories that correspond to certain mental status which includes anxiety, stress, depression, and suicidal intentions. It is the case that patterns are instances of user inputs which are associated to each intent and provide for the variability of expressions that users could refer to different mental health states. Responses encompass the chatterbot's replies to the intent, which are probable outputs to the user inputs. This dataset contains multilingual inputs and diverse patterns with respect to context, and as a result, it can be valuable for identifying intent.

Preprocessing

Before inputs to the system were fed, some data cleaning methods were adopted to make the dataset ready for training. Exploiting the data it was first normalized by transforming the text into lowercase and eliminating punctuation marks special characters and numbers. Although stop word removal proved to be effective as it removed noises such as the light words "the," "is," and "and" the algorithm was weakened by this step. Semantic variation in the patterns was pre-processed to contain only the base form of the words through lemmatization. The text was triaged to individual words, so the models could work with the dataset collected by the. Mechanized vectorization for the traditional ML models applied Term Frequency-Inverse Document Frequency (TF-IDF) and DL models applied embeddings with fixed sequence length using padding.

Model Selection

To determine which type of model was appropriate for intent classification, the study analyzed several ML and DL models. Some of the previous ML models were Multinomial Naïve Bayes (NB), Random Forest (RF), Support Vector Machines (SVM) and AdaBoost. These models were selected for their performance in text classification and its different strategies of decision-making. Because of their inherent property to incorporate sequential data characteristics, Advanced DL models established a concentrate on LSTM networks. Further, ensemble techniques were applied where the final predictions from each model were summarized using majority vote given its effectiveness in enhancing the reliability of model's predictions.

Training and Validation

The dataset was divided into 80 percent for training and 20 percent for testing, while the training and testing datasets were created using a stratified sampling method with regard to intents. In all the models, hyperparameter tuning was taken through for the purposes of improving the overall performance of the models. In the case of the ML models, parameter optimization was done via grid search, for features like alpha for Naïve Bayes and kernel for SVM. In the LSTM model, these hyperparameters were tuned: numbers of layers, neurons per layer, number of batch sizes and learning rate. To further check if the model is not overtrained and in order to minimize overfitting, five-fold cross-validation was used to evaluate the models.

Evaluation Metrics

In order to map all the objectives of the evaluation, several measures such as accuracy, precision, recall, F-measure, and confusion matrices were used. Accuracy was defined by the percentage of samples that were well classified, whereas precision and recall were defined by the capacity of the model in identifying all the positive samples and the capacity of the model in correctly predicting all the positive samples. The F1 score was good in benchmarking since it combined the precision and recall rating, while the confusion matrices gave peek insight into classification of each of the intents.

The formulation of Accuracy calculation is defined as:

$$\frac{TP+TN}{TP+TN+EP+FN} \tag{1}$$

Precision is computed as:

$$\frac{TP}{TP+EN} \tag{2}$$

Recall is computed as:

$$\frac{TP}{TP+FN} \tag{3}$$

F1 Score is computed as:

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{recision}+\text{Recall}} \tag{4}$$

Confusion Matrix: We have created a confusion matrix, which helps to count the number of True Positives, True Negatives, False Positives, and False Negatives for each class.

	Predicted Positive	**Predicted Negative**
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

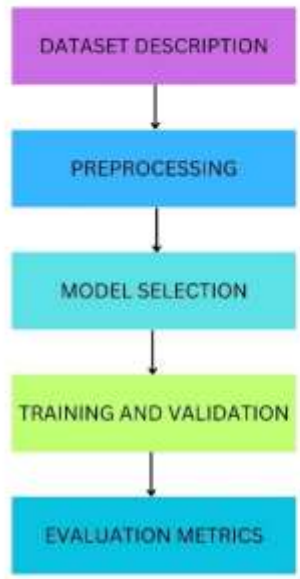

Fig. 1. Workflow of the design

Addressing Challenges

To reduce class imbalance which poses a major problem in predicting the intent of suicidal ideation, data augmentation strategies were used. Some of these changes were aimed at increasing the amount of patterns for applying paraphrasing and synonyms to low-intent words. Oversampling was also used in order to balance the training set as well. To increase prediction credibility, ensemble modeling was used where the result from the best models was combined to give the final prediction.

Implementation Tools

The experiment is performed in Python with and without the usage of libraries from its environment. Tokenization, Stopwords removal, Lemmatization were done using NLTK and SpaCy for all the models Traditional Machine Learning Models were developed using Scikit-learn. TensorFlow and keras, were used for the implementation and training of the LSTM Model., accuracy plots and confusion matrices were prepared using Matplotlib and Seaborn.

Experimental Workflow

The workflow began with loading and preprocessing the dataset, followed by training individual models on the training set. Hyperparameter tuning and cross-validation were conducted to optimize model performance. Models were then evaluated on the test set, and ensemble methods were applied to combine predictions. The results were analyzed across metrics to draw insights and identify the best-performing models for chatbot-driven mental health prediction.

Key Innovations

The aim of this work is different from previous work as it adopted a structured chatbot focused dataset specific to intent recognition as opposed to using a general dataset. It provides a comparative review of more conventional ML techniques, including Naïve Bayes, Random Forest, SVM, and DL models, including LSTM. The additional implementation of ensemble modeling and data augmentation to tackle underrepresented intents also sets this up. These innovations put forward practical guidelines for instituting high dependability and operational scope chatbot-based support systems for mental health.

This proposed research methodology offers a template that is comprehensive and structured in approaches to assess AI models in relation to mental health prediction while also bringing theoretical enhancements and real-life potential uses.

EXPERIMENT AND RESULTS

Experimental Setup and Execution

The goal was to evaluate and compare as many approaches to predicting mental health as possible using a dataset based on conversation with a chatbot. The dataset, prepared and preprocessed as described earlier, was divided into training and testing sets in an 80:20 ratio. Each of the models were fine-tuned with the help of hyperparameters optimization using both, grid search that cross-validation over the training dataset. Other kinds of data like sequence data, used Long Short-Term Memory (LSTM) to learn from the data after having their length equalized by padding. Once trained, each model was evaluated on the test set using a suite of metrics: it has production quality code that determines accuracy, precision, recall, F1 score and the confusion matrices. To enhance the reliability of the results, the sets of models were utilized to aggregate the findings of the best models.

Model Performance

The experiment analyzed several models, Naïve Bayes (NB), Random Forest (RF), Support Vector Machines (SVM), AdaBoost, LSTM, KNN, Decision Tree, LightGBM and Ensemble. Out of the models, it was identified that SVM was the most effective with an overall level of accuracy of 94.6%. The LSTM model was trained with an accuracy of 94.5% and test with 94.6% which is good at dealing with sequential data within text. The Random Forest was the second most accurate model with 92.5% while Naïve Bayes has moderate performance of 84.6%. The AdaBoost stand for Adaptive Boosting was somewhat worse with accuracy of 69.9%, which shows data imbalance affects the model. The use of ensemble methods with the models SVM, LSTM and RF resulted in an accuracy level of 94.2% and is consistent with the accuracies found for the best models.

Key Insights from Results

Analysis of the confusion matrices showed that models were successful in correctly identifying some intents particularly; greeting and thanks intents and failed to recognize some intents such as suicide and no approach intents because they are rare intents in the dataset. The study partially resolved such issues using data augmentation and oversampling techniques, though additional studies should be done to improve classification accuracy in such intents.

Table 1. Comparison of all Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Naïve Bayes (NB)	84.6	87.9	84.6	82.7
Random Forest (RF)	92.5	93.5	92.5	92.6
Support Vector Machine (SVM)	94.6	94.7	94.6	94.3
LSTM	94.6	94.7	94.6	94.5
AdaBoost	69.9	73	69.9	67.1
KNN	86.2	87.2	86.2	85.6
Decision Tree	88.6	90.5	88.6	89.1
LightGBM	86.3	88	86.3	86.4
Ensemble	94.2	94.5	94.2	93.8

Now we will represent all confusion matrix graphs of all the models. The confusion matrix shows the details results of the models and the accuracy of all classes.

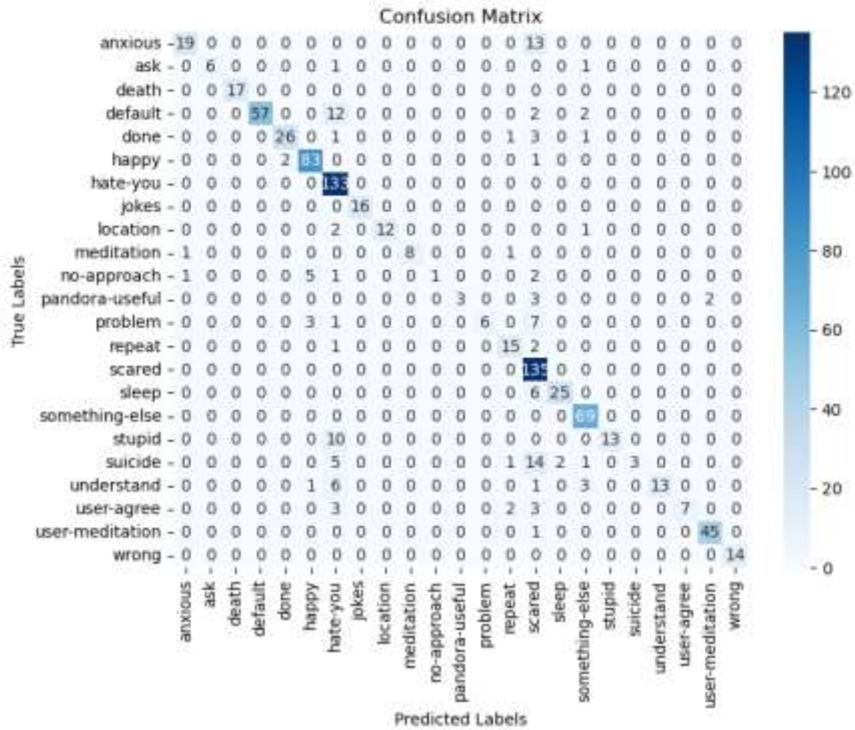

Fig. 2. Confusion Matrix of Naïve Bayes Model

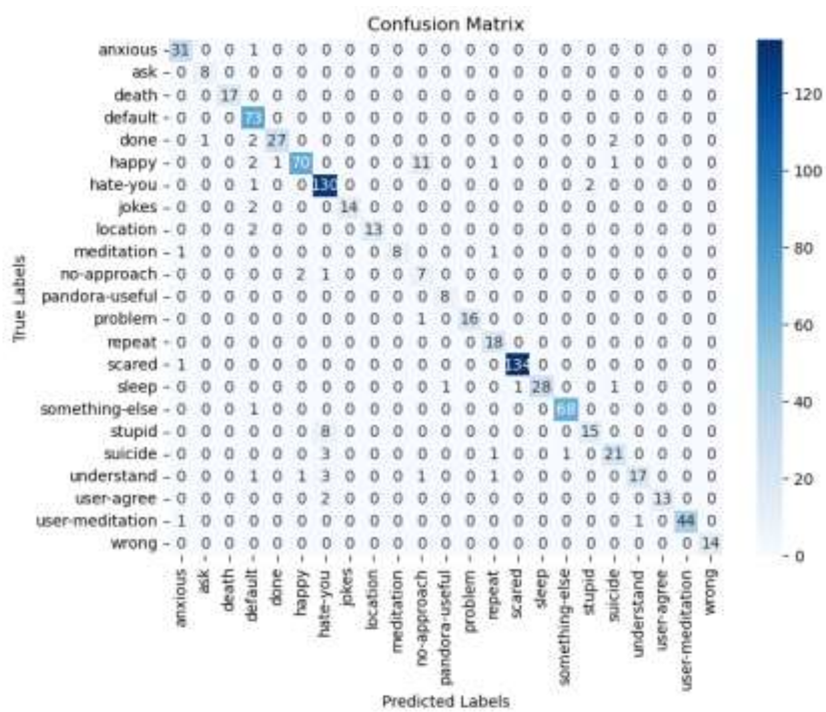

Fig. 3. Confusion Matrix of Naïve Random Forest Model

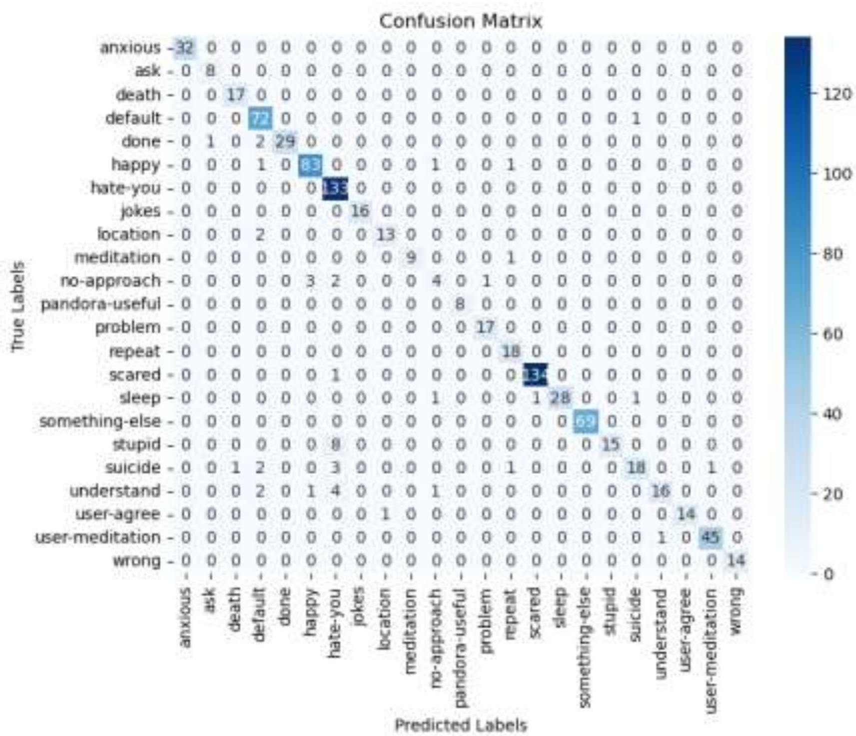

Fig.3. Confusion Matrix of SVM Model

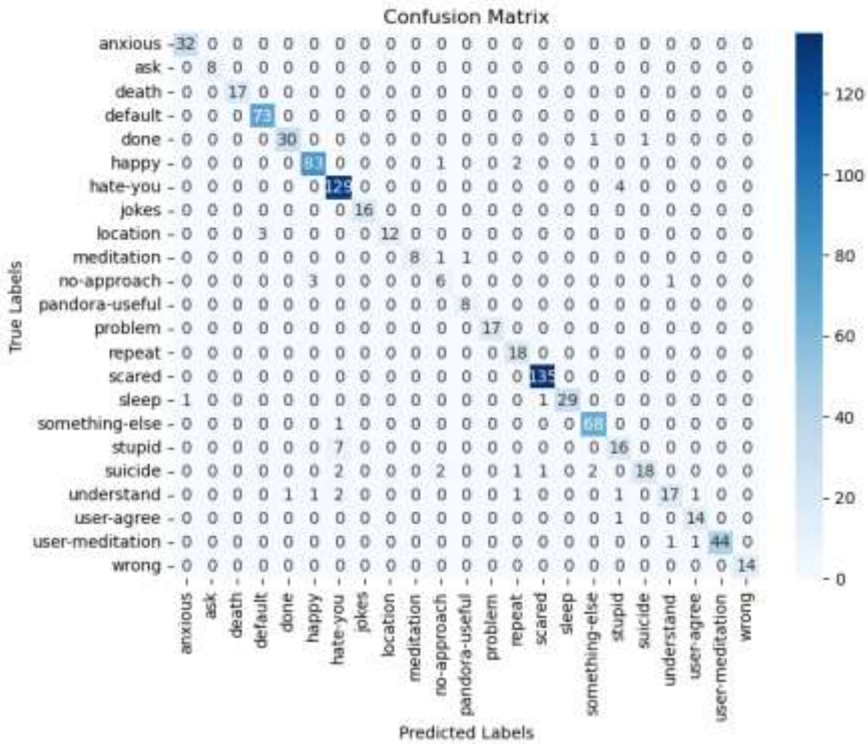

Fig.5. Confusion Matrix of LSTM Model

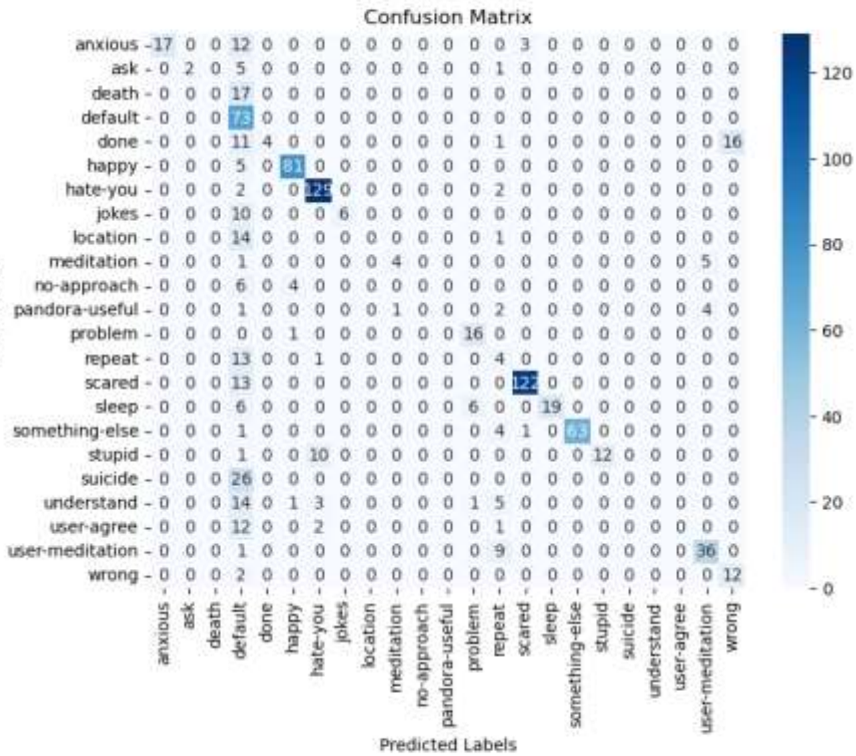

Fig.6. Confusion Matrix of AdaBoost Model

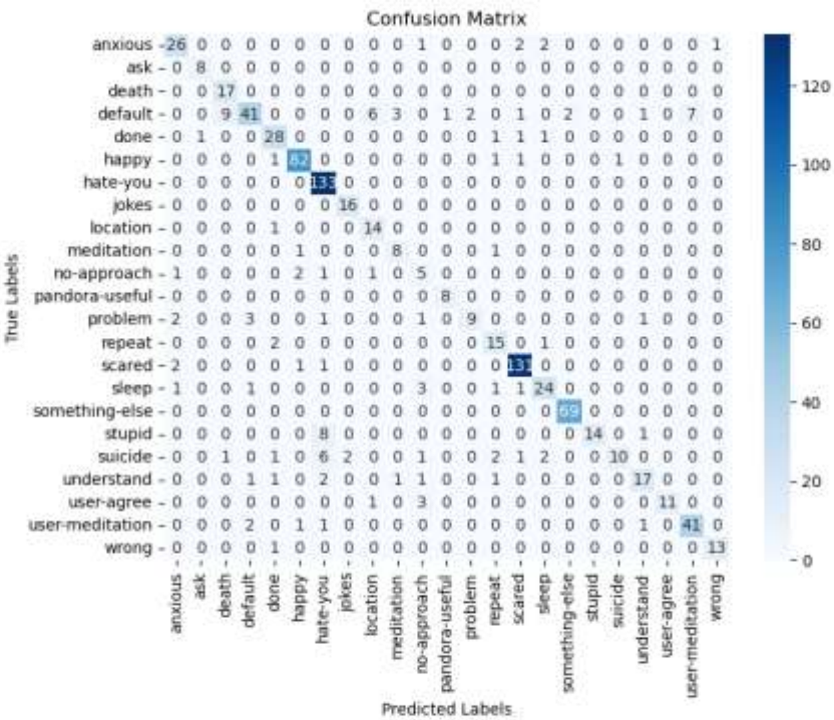

Fig.7. Confusion Matrix of KNN Model

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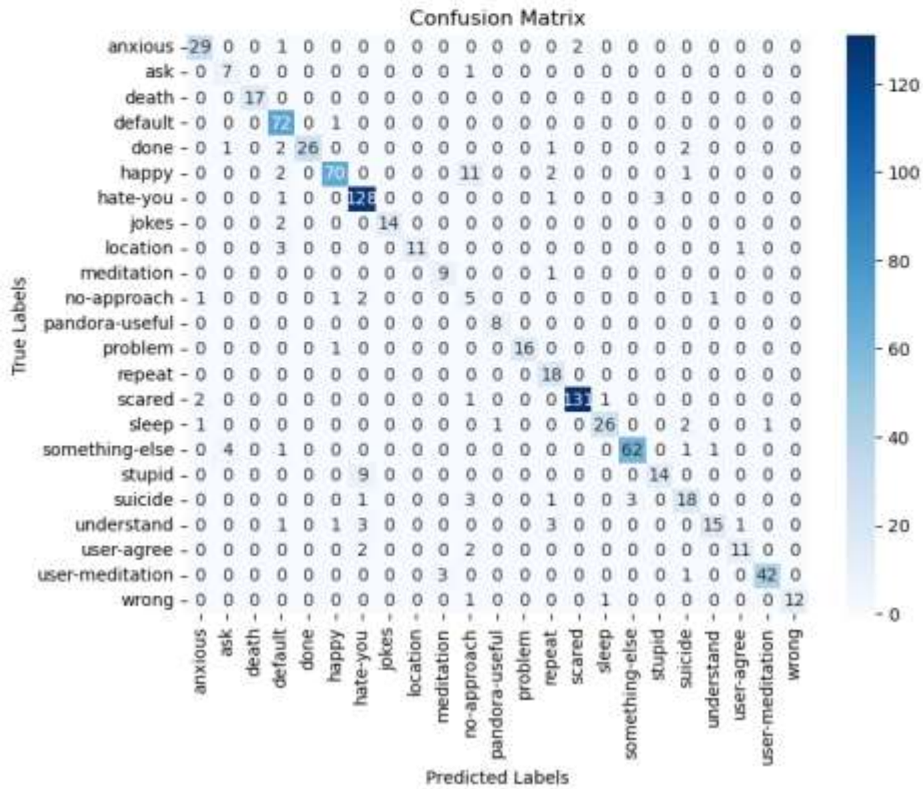

Fig.8. Confusion Matrix of Decision Tree Model

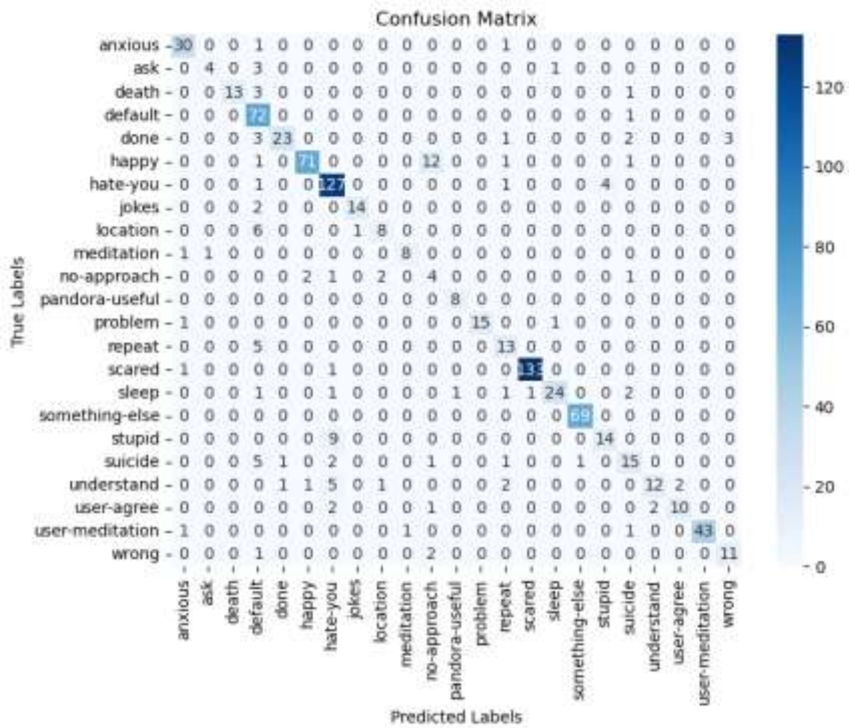

Fig.9. Confusion Matrix of LghtGBM Model

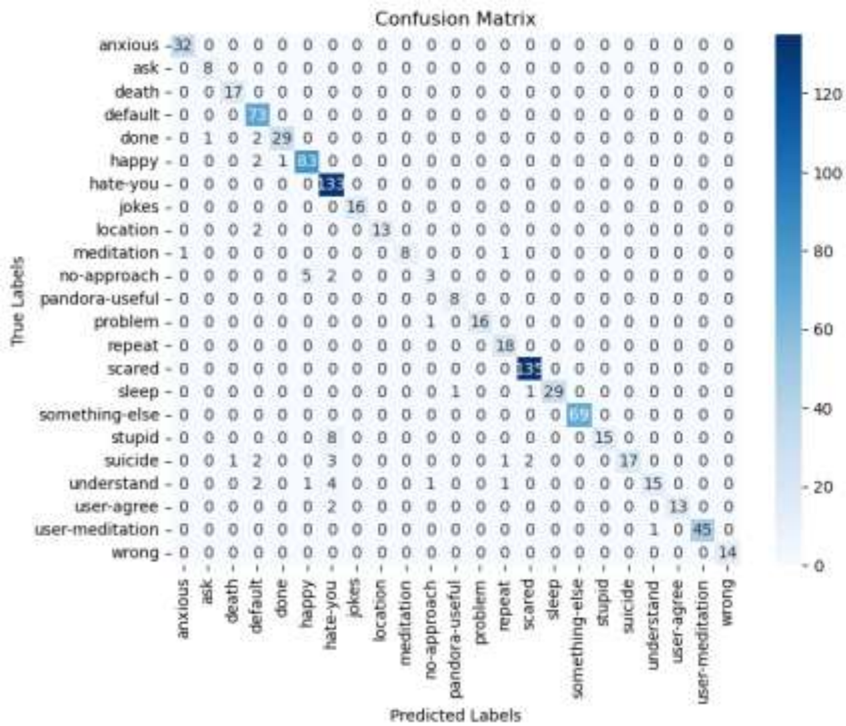

Fig.10. Confusion Matrix of Ensemble Model

Comparison with Previous Studies

To assess the novelty and effectiveness of this study, the outcomes were compared to the 15 papers that have been scrutinized earlier. Different from many of the previous works that made use of generic data types like tweets or EHRs, this work employs a structured chatbot oriented dataset. Past research focused on the current four tasks obtained rates between ~70% for ML algorithms and over 90% for selected application of DL algorithms.

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Table 2. Comparative Table of Results with Previous Studies

Study (Model/Dataset)	Accuracy (%)	Dataset Type	Key Focus
This Study (SVM/Chatbot Dataset)	94.6	Chatbot-based	Intent classification in mental health
This Study (LSTM/Chatbot Dataset)	94.6	Chatbot-based	Sequential text analysis for intents
Simon D'Alfonso (NLP/Generalized)	85.0	Social media, smartphone	Depression and anxiety detection
Higgins et al. (RF/Clinical DSS)	91.0	EHR	Decision support for treatment
eNRBM (Suicide Prediction)	~80.0 (AUC)	Medical records	Suicide risk analysis
ML Models (General RF/Clinical and social media)	70.0	Generalized	Mental health classification
Wearable Devices (ECG, EEG)	~90.0	Wearable sensors	Stress and emotion detection
Facial Emotion Recognition (CNN/FER2013)	~90.0	Emotion recognition	Emotion recognition for stress analysis

It also shows that compared to prior work that demonstrated excellent results within specific datasets and contexts, this work produces competitive results by integrating a novel dataset that revolves around chatbots and a thorough evaluation of both common and sophisticated ML and DL models. The use of ensemble methods and data augmentation makes the study even more practically relevant for sensitive intents such as suicide ideation. This study adds to the existing literature in developing a framework to implement AI-driven mental health systems in real-time and natural language interfaces. Please contact me if you wish to make additions or subtractions from this part.

CONCLUSION

The comparison shows that previous research provided high scores in particular tasks and datasets while this work is the first to collect a dataset of a chatbot while performing analysis of and various ML and DL models resulting in comparable scores for all metrics. It improves the practical applicability of the results by combining ensemble methods and data augmentation more than to handle the scarcity of data, especially for sensitive intents such as suicide ideation.

Essentially, the results highlight the fact that when using well-specified training data, it is possible to accomplish MH intent classification using both standard ML methods and complex DL approaches. After the experiments, SVM and LSTM happened to be the most effective models, yielding a rate of 94.6%. The latter are at least as accurate as these 'baseline' models, but as we need to show, while demonstrating more precision, recall and f1-score, they proved their scalability in the challenging intent classification task. Updating knowledge for each model after every epoch also improved the overall model efficiency and the ensemble techniques used gave a higher accuracy of 94.2 % confirming the reliability of this approach.

In comparison to the prior research, this work adds a new perspective on the prediction of mental disorder based on chatbots and data that are specifically categorized for intent classification. Whereas previous studies might have used broad data samples like social media or EHR data, this work closes a gap of specifically using real-time conversational data. Thus, the inclusion of the ensemble methods and the detailed analysis of ML and DL can present more realistic approaches to the models. Moreover, this work complies with the guidelines for ethical considerations by advising on the indicators used in the evaluation and by outlining the threats regarding the aspect of sensitive predictions for possible bias or misclassifications.

These findings suggest how mental health systems might be designed and built using artificial intelligence. Deployable models such as SVM and LSTM for chatbot can effectively act as a large-scale screening method for mental health issues, offer first-line assistance and direct patients to suitable professional help. The structured dataset used in this work can act as a starting point for future work and highlights the role of intent classification in conversational AI. Further, the proposed ensemble methods provide a direction of how prediction reliability can be improved, especially in real world applications where accuracy is paramount.

However, this research has the following limitations: Overall, there's nothing incredibly wrong with the structure of the collected dataset, but of course, more samples for other intents could be added to keep refining the model. This is particularly true in the light of the fact that the study used only the predefined responses rather than developing an efficient method of generating dynamic responses that would make interaction with the system more natural. Moreover, in the given study, the performance of the models was also successfully compared, and there is a possibility of further research on the more complex structures like the transformers which includes the BERT.

Therefore, this study offers a valuable contribution to the attempt to use AI for prediction of mental health. It thus uses data, and a thorough analysis of models related to chatbots to offer a guide to implementing conversational AI capable of handling mental health issues. Future works should seek to improve on these works in terms of data samples, developing more complex architectures and in the best possible manner, deploying such systems into more practical mental health care related contexts. Presenting findings that contribute to academic knowledge and imagination, this work is significant for emerging mental health support with practical, wide accessibility and enrolment of ethical and successful AI solutions.

Future Work

Based on the evidence of this research, further studies may explore the way of overcoming the limitations and developing the AI-based predictive model of mental health. They include a refinement of the dataset, notably amplification of its underrepresented intents like the suicide ideation, and other forms of vulnerable mental status. This could be done by data augmentation, real conversational data collection, and incorporating mental health experts. Lastly, it would also create grounds for deeper research where mechanisms such as transformer (BERT, GPT) can unveil superior context-aware intent representation by working on deeper/concealed relationships within the utilities of text. The utilization of self-generated dynamic response system, with reinforcement learning, could also be attributed to the handling of the interactions in a way that ups the engagement level of the users. One promising route appears to be to validate these models with real-world applications, like deploying the models in existing chatbot applications to then evaluate their functionality, ease of use, or users' satisfaction. Last, yet importantly, the ethical and transparent nature of the AI systems proposed will be paramount; subsequent research should investigate the use of explainable AI (XAI) techniques by which these predictive models become interpretable and comprehensible, especially in contexts of mental health where privacy and reliability are often critical. These advancements will enable the enhance and extend the opportunities of AI in clinically effective, readily available scalable mental health solutions.

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