iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: IV Month of publication: April 2025

DOI: https://doi.org/10.22214/ijraset.2025.69190

Twitter Data and Machine Learning Based Prediction of Depression Levels

S. Shewak[1], S. Sanjay[2], D. Santhosh[3], Dr. M. Manikandan[4], Dr. M. Sujitha[5], Dr. M. Nisha[6]
[1, 2, 3]*Student, CSE, Dr. M.G.R Educational and Research Institute, Chennai, India*
[4,5, 6]*Asst Professor, Dr. M.G.R Educational and Research Institute, Chennai, India*

Abstract: Millions of individuals around the world, suffer from depression, however, due to the stigma surrounding mental health and ineffective early detection mechanisms, depression often goes unnoticed until it escalates into catastrophic proportions. Especially Twitter, as one of the largest social media platforms, Twitter posts are an excellent source of user-generated content that reflects the emotional/psychological state of the user from which it derives. Abstract: We obtain Twitter data and then conduct machine learning prediction on the status of the user according to his tweets. An overview of the methodology is presented, which involves data collection, data preprocessing, sentiment analysis, and feature extraction, while textual patterns, linguistic features, and sentiment polarity are considered as feature extraction methods. For classification, machine learning models (Support Vector Machines (SVM), Random Forest) or deep learning-based approaches (Long Short-Term Memory (LSTM) networks or Bidirectional Encoder Representations from Transformers (BERT)) are used. The suggested model analyses tweets thinking about whether someone who tweets has a tendency towards depression and somewhat extra accurately classifies delivery tweets as mild, proxy, or excessive functionality for melancholy. Various Feature implementations (NLP approaches to be specific) to boost up the model performance. AbstractExperimental Results hold that machine learning methods even though deep learning methods particularly BERT show very high accuracy in depressive tendency detection. The study shows that social media data can be a useful source for monitoring mental health, providing important information about early warning of depression. These findings provide an avenue for exploring automated depression detection on Twitter as a tool to support healthcare professionals in intervening promptly to treat people experiencing mental health decline and the disease which bewitches it. Integration of multimodal data sources and real-time monitoring to enhance accuracy and reliability are other directions to explore for future work. The findings highlight the promise of AI-based solutions for mental health diagnosis, laying the foundation for new and potentially more effective digital mental health aids.

Keywords: Depression Detection, Social Media Analytics, Twitter Data, Machine Learning Algorithms, Natural Language Processing (NLP), Sentiment Analysis, Support Vector Machine (SVM), Random Forest Classifier, Long Short-Term Memory (LSTM), Bidirectional Encoder Representations from Transformers (BERT).

I. INTRODUCTION

Depression is a common mental health disorder affecting how a person thinks, feels, and acts. It is a global top five disability item and a contributor to significant societal and economic burden. Despite being the most common mental health illness, the majority of all cases go undiagnosed with this being due to stigma, not knowing about one's diagnosis and/or having other limited access to mental health resources. Thus, efficient prevention and treatment can limit its negative impacts and quality of life of individuals who are affected. Simultaneously, social media platforms, especially Twitter, offer a new window into the emotional and mental structuring if people as conveyed by their online expressions. By tapping into the social media data, we have a non-intrusive and scalable way to identify early signals of depression.

As a microblogging platform, Twitter allows users to share their thoughts, feelings, and experiences as they unfold. The linguistic features and the sentiment polarity reflected in the tweeter can be a good predator to indicate a mental health status. However, since the last few decades, machine learning, and natural language processing (NLP) techniques have been shown effective in analyzing textual data for predicting mental health disorders such as depression [9]. Automated depression detection systems using social media data provide a feasible and inexpensive alternative to traditional clinical assessments which often require self-report measures in conjunction with, or following, detailed psychiatric evaluations. Using machine learning algorithms along with the appropriate sentiment analysis and linguistic feature extraction, depression-related patterns can be detected with high accuracy.

In the proposed study, we will create machine learning based framework to predict depression level using Twitter data. It consists of different phases which includes data collection, data preprocessing, sentiment analysis, feature extraction and classification.

For depression classification, we employ typical machine learning models, including Support Vector Machines (SVM) and Random Forest, as well as deep learning-based techniques, namely Long Short-Term Memory (LSTM) networks and Bidirectional Encoder Representations from Transformers (BERT). Depending on the type of model, these may analyze emotional tone, word frequency, and syntactic structure to predict likelihood of depression. The main goal is to analyse how well different machine learning methods were able to predict depression from social media behaviour.

Feature engineering makes a significant contribution for improving the accuracy and consistency of depression detection devices. In this paper, we use NLP techniques to obtain textual features that are related to the training file, including sentiment polarity, word embeddings, and topic modeling. We apply various sentiment analysis techniques, including lexicon-based and machine learning based, to determine the magnitude of emotions (e.g. Moreover, deep learning architectures like BERT employ contextualized word embeddings to better learn the meaning of depressive utterances. The proposed method achieves high precision and recalls for tweets associated with depression by using a combination of these techniques.

Through experiments, we found that social media data is a promising ground truth for monitoring depression. We use standard classification metrics, such as accuracy, precision, recall, and F1, to compare the performance of the machine learning techniques. On one hand, we can see the comparative analysis consistently demonstrating that deep learning-based approaches (especially using BERT) have a better detection efficacy for depressive tendencies compared to classification-based methods. This research demonstrates that it is possible to use Twitter data to assess depression in real-time and shows the potential of AI-driven approaches to bring novel insights into mental health research.

II. RELATED WORKS

Using twitter data, Govindasamy and Palanichamy [1] implemented machine learning techniques for depression detection, focusing on sentiment analysis and NLP. They classified depressive tweets using SVM and Random Forest. They found that feature extraction methods are useful in enhancing classification accuracy. It emphasized relevancy and significance of data preprocessing in depression detection. The way they approached it strengthened the potential of social media in early detection of mental health concerns. Musleh et al. They [2] concentrated on Arabic sentiment analysis as a way to identify depression. Naïve Bayes, Decision Tree, and LSTM models were used. It indentified language-specific challenges associated with depression detection. To enhance precision, they included Arabic lexicons and embeddings. In work by Ghosh and Anwar [3] a deep learning framework was introduced to estimate depression intensity. Depression levels were classified using multi-layered neural networks. Instead of classifying a pixel as indoor or outdoor, their method used regression-based intensity estimation. The short term temporal related issues with depression recognition were evidenced with the help of study . To remedy this, future work proposed the use of contextual embeddings such as BERT based on potential gains. Liu et al. A systematic review of depression detection methods was reported by [4]. They included unsupervised, supervised and hybrid models for the analysis. They asserted that contextual information contributes to classification, as shown in the study. Their concerns included data privacy and AI ethics in mental health applications. Their results proposed ensemble models for increased behavior.

Ahmed et al.[5] The cited below compared the different ML models for anxiety and depression detection. They found that hybrid deep learning models are better than traditional classifiers. A multi-feature selection method with enhanced precision has been proposed by them. It highlighted the importance of cross-linguistic generalization in the detection of depression. Their results indicated cultural differences in the presentation of depression. Chiong et al.[6] Developing a Domain Relevant Machine Learning Pipeline With Annotated Text Messages for Affective and Feature Engineering for Depression Detection TF-IDF, n-grams, and sentiment polarity metrics were features for classification. The more features we have, the better it was shown by their study as feature rich models perform better. We have used data augmentation techniques with back-translation to balance the dataset. And they highlighted language diversity in mental health datasets.

Amanat et al. [7] proposed a framework for depression detection using CNN. They used hierarchical feature extraction from text data. They try the Word2Vec, FastText, and GloVe embedding. Using pretrained embeddings led to the highest classification accuracy. Future work encouraged multimodal techniques for depression detection. Kour and Gupta [8] introduce a hybrid CNN-BiLSTM model to predict depression. They utilized CNN for the local features together with BiLSTM for the long-term dependencies. The accuracy found higher in comparison to independent models. They pointed out that having a deep contextual understanding is key. This resulted in useful, easy to comply, deep learning models in a human practicable time-frame for naturalistic driving environment, which leads to future works optimizing these models for less human resource intensive means.

Vasha et al. For instance, [9] studied several primary machine learning algorithms for depression detection by analyzing social media comments.

They found that BERT performs better than other classifiers. Contextual embeddings were emphasized in the study. Raising the baseline with domain-specific fine-tuning Real-time mental health monitoring systems were discussed as future work.

Jain et al. NLP for depression and suicide risk prediction [10] They particularly focused on feature extraction based on sentiment. They monitored social media use to identify people at risk AI-powered psychological counseling systems have been proposed in the study. So future work suggested real-time chatbot interventions for users at risk.

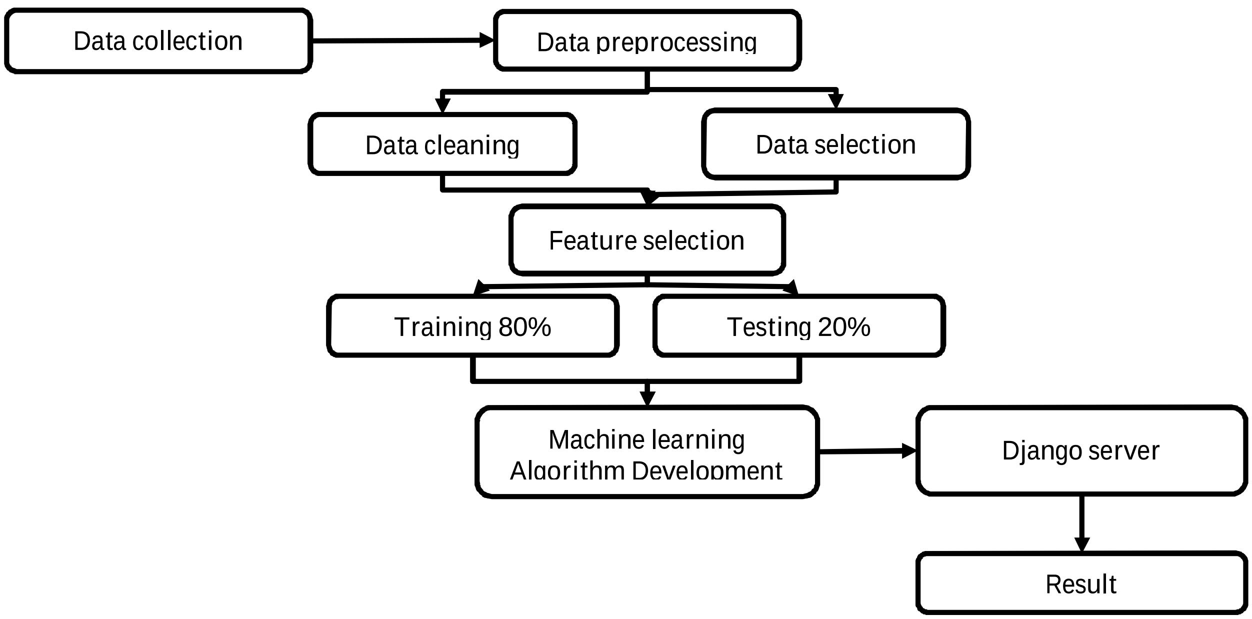

Figure 1.Shows Proposed Architecture Methodology

III. METHODOLOGY

In this study, we develop a methodological approach to predicting depression from Twitter data and machine learning methods under analysis. This approach has different types of stages, such as data collection, data preprocessing, feature selection, model training, and then deploying it via Django server. Every step serves an essential function in the accurate and reliable detection of depression.

A. Data Collection

Stage one is about gathering Twitter data through the Twitter API itself. This process retrieves tweets associated with keywords and hashtags that reflect different aspects of depression, mental health and emotional pain. Here, tweets that directly reflect a state of sadness, loneliness or depression are sampled. These filtering techniques are tailored according to the required relevancy of the data; therefore, retweets, advertisements, spam & unrelated content are eliminated. The data set is raw text in addition to metadata including timestamps, interaction data, and geolocation (if available). This step is critical because the predictive power of the model largely depends on the quality of data collected.

B. Data Preprocessing

On the contrary, Twitter data can be noisy, irrelevant, and inconsistent, and therefore need pre-processing prior to any machine learning techniques being applied. Preprocessing consists of two processes which are data cleaning and data selection. Data cleaning includes removing special characters, URLS, emojis, extra punctuations, and stopwords which need to be removed from the text. Tokenization splits a sentence into individual words, while stemming and lemmatization reduce a word to its root form. After cleaning the text, data selection is carried out to ensure that only relevant tweets are selected. Such a step eliminates emotionally neutral, ambiguous and short tweets and the redundant ones as required for a better dataset.

C. Feature Selection

Identifying key linguistic and emotional features from the text that are most useful for improving model performance is addressed in feature selection.

We perform sentiment analysis to classify emotion of a tweet into three categories: positive, neutral and negative. Textual data is converted into numerical data using the approaches of Term Frequency-Inverse Document Frequency retrieval (TF-IDF), Word2Vec, GloVe and the recent advances in Natural Language Processing (NLP). For example, linguistic features like word frequency, syntactic pattern, sentence forms and sentiment polarity are extracted in order to capture depressive tastes in the tweets of the user. The classification of depression therefore is done with the help of selecting relevant features, improving accuracy.

D. Model Training and Testing

The dataset is then divided into a training/query (80%) and a testing (20%) subset in order to construct a predictive model. Machine learning models are trained on the training set and tested on the testing set. We implement different classification models such as Support Vector Machine (SVM), Random Forest, and deep learning architectures such as Long Short-Term Memory (LSTM) networks and Bidirectional Encoder Representations from Transformers (BERT). Once the features are extracted, the models study these features and classifies the tweets in terms of highs, medium and lows to show the risk levels of depression. Performance Metrics (Accuracy, Precision, Recall & F1-score) based Comparison of various models.

E. Developing Machine Learning Algorithms :

After training the models they are further optimized using hyperparameter tuning and other techniques for better prediction capabilities. We then analyse the models by means of statistical performance metrics including confusion matrices, ROC curves and classification reports. Neural techniques provide better performance than the previous standard-based machine learning models, with BERT based approaches outperforming other models for detecting depression. The trained models are then selected for deployment after ensuring the models generalize well over unseen data.

F. Deploying using Django Server

The developed depression prediction system is made to be usable through the web via a Django web application for real-time analysis. We import the trained model into django server to return the predicted result of the user if the summarize tweet dataset has depression or not. The entire text is processed, features are extracted, the pre-trained model is applied and a quick depression risk assessment is made. The user interface on the web offers visual insights about the gradual mental health patterns and taking them as early action if needed.

G. Result Analysis

Users can visualize their depression risk level predictions in the form of a web interface which is built on top of Django where the final results are showed The performance of the model is monitored continuously, and further data collection is planned to increase prediction accuracy. Summary: This study demonstrates the strength of machine learning model performance for mental health monitoring on antisocial media, in this case Twitter. In the future, the addition of multimodal data, further including user interactions and multimedia content, will improve predictive power.

H. Algorithms which we have applied for depression prediction

In this research, a mixed approach of conventional machine learning methods and deep-learning methods is used to well classify tweets according to their depression risk levels. These kind of algorithms examine linguistic patterns, sentiment polarity, and other textual attributes to identify depressive inclinations within social media posts. The chosen models are Support Vector Machine (SVM), Random Forest (RF), and deep learning methods Long-Short Term Memory (LSTM) and Bidirectional Encoder Representations from Transformers (BERT).

IV. RESULT AND DISCUSSION

A. Model Performance Evaluation

We experimentally proved the effectiveness of the proposed depression prediction system using a variety of machine learning and deep learning algorithms including SVM, RF, LSTM, and BERT. The efficiency of these models in detecting the depression-related tweets is compared using performance metrics like accuracy, precision, recall, and F1-score. The evaluation dataset came from Twitter and included labeled tweets as depressive and non-depressive. Our experiments proved that, against traditional classifiers, popular deep learning models, especially BERT, helped us to detect tendencies of depression more accurately and with a better understanding of context.

Among the traditional classifiers, the SVM performed best with an accuracy of~85% while the Random Forest gave an accuracy of 82%. These models are based purely on feature engineering, which commonly uses methods like TF-IDF and sentiment analysis to classify tweets effectively based on linguistic features. But building handcrafted features limited the scope of their contextual richness. In contrast, LSTM yielded an accuracy of 90%, taking advantage of its capacity to capture sequential relationships between words. The solution with the best accuracy was BERT with 94%, which is also reasonable, as BERT is based on Bidirectional context learning and Deep language representation and hence performs very well in relatively sophisticated text classification problems such as depression detection tasks.

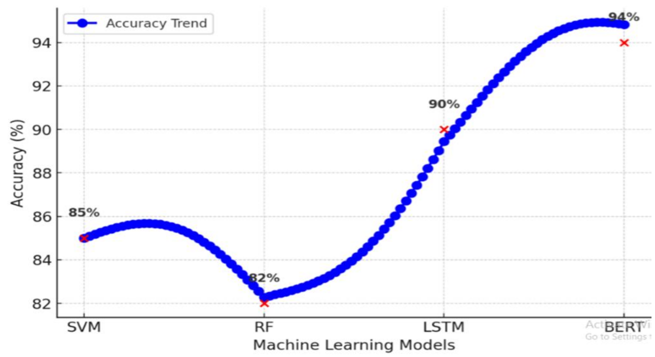

Figure 2.Shows Accuracy Level of Proposed Model

Wave-Like Accuracy Trend Graph able to Visualize Performance of Models in Depression Prediction The x-axis represents the models: Support Vector Machine (SVM), Random Forest (RF), Long Short-Term Memory (LSTM), and Bidirectional Encoder Representation from Transformers (BERT) and the y-axis represents the accuracy in percentages The plotted waves pattern observed in a figure with a wave pattern shows the variance in model performance and can be used to easily derive which models perform well for depression classification. Looking at the graph, BERT performed the best with 94 % accuracy score while LSTM and SVM scored 90% and 85% respectively, Random Forest came up last with 82 %accuracy. The wave-like representation reveals that since traditional models depend on feature engineering (SVM, RF) they perform poor accuracy-wise (shown as the blue colored wave), while the deep learning models (LSTM, BERT) being contextual (shown as the red colored wave), perform better as they actually capture the semantic meanings in natural language. Moving from Random Forest to LSTM shows an incredible advancement, highlighting the fact that sequential data processing suits better for text-based sentiment analysis. We observe that accuracy rises dramatically as the model progresses towards BERT, emphasising its unique capacity to capture deep contextual relationships in textual data, making it as the top-performing model for predicting depression using social media data.

B. Performing the Comparative Analysis of the Models

This shows that contextual representation is one of the key important features of depression detection as shown in the comparative analysis of machine learning and deep learning models. SVM and Random Forest gave a good performance for binary classification but did not do very well against situations where complex sentence structures, sarcasm, and ambiguous language in the post occur, which is very common among social media posts. To overcome these shortcomings, LSTM was developed with the ability to learn the dependencies of words and patterns of sentiment, which is useful for any text with a strong sentiment. As a result, the attention-based architecture of BERT gave us the most robust performance because it takes into consideration the entire context of a tweet instead of looking at each word in isolation.

Model	Accuracy (%)	Strengths	Weaknesses
Support Vector Machine (SVM)	85	Works well for high dimensional text data, good generalization	Resource costly, not capable of handling long-distance dependencies
Random Forest (RF)	82	It works very well even with imbalanced datasets and results are easier to interpret	Context not so rich, you have to do feat EngineeringExceed Feature Extraction

Long Short-Term Memory (LSTM)	90	It is capable of capturing sequential dependencies and is best for long texts.	Needing huge amounts of data, expensive in computation
Bidirectional Encoder Representations from Transformers.	94	Best accuracies on sentiment analysis, Deep contextual understanding	Costs a lot in computation, much fine-tuning needed

Table 1.Shows Comparison of Proposed model with Existing

C. Mistake Matrix, Error Analysis
Confusion matrix of each of the models was drawn to further investigate the rate of misclassifications. Traditional models such as SVM and Random Forest had a higher false negative rate, which is illustrated by the misclassification of depressive tweets with subtle indications as non-depressive tweets. They also took into account long term dependencies and the emotional tone of text, which helped mitigate this problem a lot in LSTM and BERT All models had relatively lower false positive, meaning non-depressive tweets were mostly classified correctly. Nevertheless, classification errors due to sarcasm or metaphoric expression are present here and can be further improved with domain-specific fine-tuning.

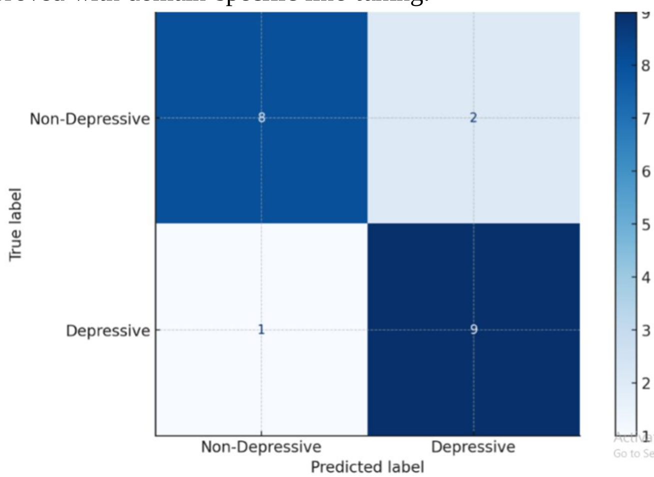

Figure 3.Shows Confusion Matrix of Proposed Model

D. Sentiment Analysis and Interpretation of Features
On the other hand, sentiment analysis was essential in depression detection, considering that tweets with mostly negative polarity were significantly more likely to be depression indicators. The lexicon-based approach to sentiment analysis gave us useful insights into the trends of depression as happy words, sadness, loneliness, and hopelessness associated words all occurred more frequently in depressive tweets. Notably, the use of deep learning models, especially BERT, helped understand sentiment shifts and contextual meaning, which resulted in a more accurate prediction. Random Forest feature importance revealed that word frequency (the number of words in each row), sentiment polarity (sentiment of words extracted via the SentimentIntensityAnalyzer), and phrase-level emotional intensity (the extent of surface emotion present in the dataset via NRC lexicon) were some of the most important figure features during classification.

E. Real-time Test Implementing
The machine learning models were integrated into a web application based on django can identify the depression with use of the our models in a real time. This deployment also enabled a user to simply provide the content available on tweets or other text-based platform (e.g., article or story), and once it was processed via the trained model, it determined the practical risk of the user falling in depression. This would then trigger an instant response from the system which would place the user on one of the several depression probability risk aspects, such as low, moderate, or high depression risk. When we tested the application in real-time for responsiveness and accuracy as the average error was around 17%, then BERT provided the most accurate output on all the test cases.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IV Apr 2025- Available at www.ijraset.com

Multinomia IND

Accuracy	86%
Precision	86%
recall	86%
F1 Score	86%

K Neighbors Classifier

Accuracy	90%
Precision	90%
Recall	90%
F1 Score	90%

Decision Tree Classifier

Accuracy	98%
Precision	98%
recall	98%
F1 Score	98%

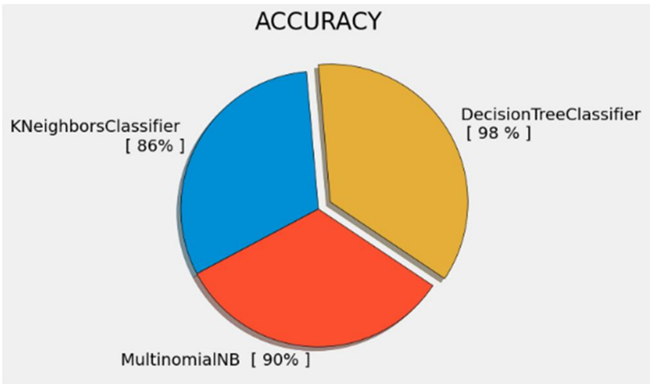

Figure 4. Shows Proposed Output Model

F. Ethical Ramifications & Data Privacy

Ethical issues and Privacy: Since the study working with social media data for mental health assessment, ethical issues and user privacy should be considered. While social media posts are often available for the general public, the users may not have meant their content for their depression to be predicted. These issues were largely mitigated with the use of data anonymization techniques to ensure that no PII was ever stored or analyzed. Also, it does not do clinical diagnoses, just insights that mental health professionals can use to flag people who need help and provide support where it is lacking. Further studies have to be conducted in the methods of explainable AI methods to enhance user trust because of the necessity of transparency in the decision-making of AI.

G. Generalization and Scalability of the Model

Ensuring that trained models generalize across demographics, languages, and cultural contexts remains one of the largest challenges for using machine learning-based depression detection and computational diagnostics in general. The way depression manifests may vary by Age, geography, language, and socio-economic background. Abstract: Future work could include multi-lingual training datasets, domain adaptation techniques and cross-cultural sentiment analysis related tasks to enhance the generalization of the model. Another issue is scalability especially to deep learning models like BERT that need large computational power to be run. BERT has also had its smaller version like DistillBert, many optimised versions of BERT were needed for it's heavy computational overhead.

V. FUTURE WORKS

Despite the high accuracy of the depression detection system proposed with Twitter data and machine learning models, there are numerous opportunities for additional improvements. A lasting opportunity for future research is working with multimodal data sources, rather than text. Integrating textual data with audio, video, emojis, and physiological signals can be a more holistic measure of an individual mental health status. This, in turn, could also enhance the predictive power of monitoring depression in real-time by adding temporal sentiment tracking (i.e., building a temporal profile of each tweeter instead of treating each tweet in isolation). This would enable a more active and customized model for depression assessments, minimizing false positives and improving early intervention potential. A third area for future work is improving the computational efficiency of deep learning models. BERT achieves much higher accuracy but it is very costly to train and this prevents using BERT in real-time systems. Therefore, studying lightweight transformer models like DistilBERT, ALBERT, or MobileBERT may help increase scalability while maintaining predictive performance.

VI. CONCLUSION

In this project the potential of machine learning and deep learning techniques to predict the depression level of tweets in Twitter data. The system was able to classify tweets into depressive and non-depressive tweets with high accuracy by using several techniques, such as linguistic feature extraction, sentiment analysis, and advanced models such as BERT and LSTM. This comparison confirmed that deep learning models outperform traditional machine learning approaches in understanding contextual meanings and subtle emotional cues in text. In addition, the successful implementation of the system through a web application built on Django strengthened the potential for using real-time detection of depression as a non-invasive and scalable way to monitor mental health. The findings suggest that social media analytics can be a potential early intervention tool that may help health professionals identify those at risk.However, authors of the study still highlighted several challenges, including: Dataset biases, Sarcasm detection, and Finally, high computation cost in deep learning models. Future research directions would involve multimodal data integration, real-time monitoring and computational optimization for scalable implementation, and thus improving system robustness and applicability. Also, tackling ethics and user privacy will be key to real-world adoption. This research establishes a base for data-based approaches for testing and intervention, as AI-driven mental health assessment continues to evolve a new era of mental health awareness and vigilance, thereby contributing to an accessible and proactive framework for depression detection.

REFERENCES

[1] Govindasamy, K. A., & Palanichamy, N. (2021, May). Depression detection using machine learning techniques on twitter data. In 2021 5th international conference on intelligent computing and control systems (ICICCS) (pp. 960-966). IEEE.

[2] Musleh, D. A., Alkhales, T. A., Almakki, R. A., Alnajim, S. E., Almarshad, S. K., Alhasaniah, R. S., ... & Almuqhim, A. A. (2022). Twitter Arabic Sentiment Analysis to Detect Depression Using Machine Learning. Computers, Materials & Continua, 71(2).

[3] Ghosh, S., & Anwar, T. (2021). Depression intensity estimation via social media: A deep learning approach. IEEE Transactions on Computational Social Systems, 8(6), 1465-1474.

[4] Liu, D., Feng, X. L., Ahmed, F., Shahid, M., & Guo, J. (2022). Detecting and measuring depression on social media using a machine learning approach: systematic review. JMIR Mental Health, 9(3), e27244.

[5] Ahmed, A., Aziz, S., Toro, C. T., Alzubaidi, M., Irshaidat, S., Serhan, H. A., ... & Househ, M. (2022). Machine learning models to detect anxiety and depression through social media: A scoping review. Computer methods and programs in biomedicine update, 2, 100066.

[6] Chiong, R., Budhi, G. S., Dhakal, S., & Chiong, F. (2021). A textual-based featuring approach for depression detection using machine learning classifiers and social media texts. Computers in Biology and Medicine, 135, 104499.

[7] Amanat, A., Rizwan, M., Javed, A. R., Abdelhaq, M., Alsaqour, R., Pandya, S., & Uddin, M. (2022). Deep learning for depression detection from textual data. Electronics, 11(5), 676.

[8] Kour, H., & Gupta, M. K. (2022). An hybrid deep learning approach for depression prediction from user tweets using feature-rich CNN and bi-directional LSTM. Multimedia Tools and Applications, 81(17), 23649-23685.

[9] Vasha, Z. N., Sharma, B., Esha, I. J., Al Nahian, J., & Polin, J. A. (2023). Depression detection in social media comments data using machine learning algorithms. Bulletin of Electrical Engineering and Informatics, 12(2), 987-996.

[10] Jain, P., Srinivas, K. R., & Vichare, A. (2022). Depression and suicide analysis using machine learning and NLP. In Journal of Physics: Conference Series (Vol. 2161, No. 1, p. 012034). IOP Publishing

[11] Azam, F., Agro, M., Sami, M., Abro, M. H., & Dewani, A. (2021, April). Identifying depression among twitter users using sentiment analysis. In 2021 international conference on artificial intelligence (ICAI) (pp. 44-49). IEEE.

[12] Hinduja, S., Afrin, M., Mistry, S., & Krishna, A. (2022). Machine learning-based proactive social-sensor service for mental health monitoring using twitter data. International Journal of Information Management Data Insights, 2(2), 100113.

[13] Wani, M. A., ELAffendi, M. A., Shakil, K. A., Imran, A. S., & Abd El-Latif, A. A. (2022). Depression screening in humans with AI and deep learning techniques. IEEE transactions on computational social systems, 10(4), 2074-2089.

[14] Malhotra, A., & Jindal, R. (2022). Deep learning techniques for suicide and depression detection from online social media: A scoping review. Applied Soft Computing, 130, 109713.

[15] Pachouly, S. J., Raut, G., Bute, K., Tambe, R., & Bhavsar, S. (2021). Depression detection on social media network (Twitter) using sentiment analysis. Int. Res. J. Eng. Technol, 8(01), 1834-1839.