Learning Techniques for Depression Detection: A Comparative Studies

Arnab Das
Department of Computer Science and Engineering
National Institute of Technology Agartala
Agartala, Tripura, India
arnabdascs@gmail.com

Mrinal Kanti Debbarama
Department of Computer Science and Engineering
National Institute of Technology Agartala
Agartala, Tripura, India
mkdb06@gmail.com

Rabindra K. Barik
School of Computer Applications
Kalinga Institute of Industrial Technology
Bhubaneswar, India
rabindra.mnnit@gmail.com

2023 International Conference on Intelligent Systems, Advanced Computing and Communication (ISACC) | 979-8-3503-9938-7/23/$31.00 ©2023 IEEE | DOI: 10.1109/ISACC56298.2023.10083576

***Abstract*—Depression is a common mental problem that can fundamentally affect individuals' emotional wellness as well as their everyday lives. After COVID-19 other pandemics and subsequent social isolation this issue is more potent than ever. Numerous research works have been going on searching for methods that effectively recognize depression in order to detect depression. In this regard, a number of studies have been proposed. In this study, it examines a number of previous ones utilizing various Machine Learning (ML) and Artificial Intelligence (AI) methods for depression detection. In addition, various methods for determining an individual's mood and emotion are discussed. This study also discusses how facial expression, voice, gesture can be understood by chatbot and classified it as a depressed person or not. Addition to this, it reviews all the related research works and evaluates their methods to detect depression.**

***Index Terms*—depression, detection, machine learning, artificial intelligence, machine learning.**

I. Introduction

Depression can be of varying degrees of severity. Serious mental health issues can result from prolonged depression. It has a significant impact on a person's productivity and, at worst, may result in self-harm and suicide. 80,000+ people become a victim of suicide as a reason for depression alone each year. And it is the second leading reason of death by suicide among people between ages of 15 and 29 (World Health Organization, 2014). According to the most recent Word Health Statistics 2021, the rate of suicide in the United States has increased by 28% during this period. Anxiety, loneliness, self-doubt, mood swings, eating disorders, and a variety of other symptoms are among the signs. Different people have different symptoms. A person experiencing depression does not feel at ease discussing their problems with anyone.

Thankfully, research has demonstrated that depression can be treated. According to Hadjipavlou, Hernandez, and Ogrodniczuk (2015) [1], psychotherapy, also known as talk therapy (Picardil and Gaetano, 2014) [2], is one of the treatment options. In psychotherapy, practitioners talk to patients rather than administering medication. For early intervention, a depressive disorder must be diagnosed early [3]. The suffering and long-term effects of depression are significantly reduced with early diagnosis and treatment. Sadly, however, 70 percent of patients would not be sufficiently aware to consult a doctor at the early stage, making the problem even more serious. Additionally, individual medical examinations take a lot of time, are expensive, and are not typically accessible to all segments of society.

As a means of releasing one's thoughts and sharing social experiences digitally, people use different platforms of social media to express their thoughts. The use of these social networking platforms has resulted in the creation of an abundance of data that is categorized in a variety of ways.

A depressed individual may use social media. So it may be a great idea to find signs or characteristics of mental disorders utilizing one's posts and other information. Not only social-media text, but the advancement of science and technology especially in Artificial Intelligence is capable of detecting depression from various sources of multimedia data like video, images, facial expression, body language, voice, conversations, etc. The number of people who suffer from depression will unquestionably decrease if the cutting-edge science of depression detection uses this enormous amount of data without disclosing any personal information.

Machine Learning, Deep Learning, Data Mining, and Emotional AI were some of the methods that researchers used when utilizing social media and other sources of data to investigate the depression.

This paper has done a survey on different Artificial Intelligence and statistical methods for depression detection. Section II has discussed the different types of depression and their symptoms. The review of different approaches for detecting depression is illustrated in section III. Section IV listed all the research works and its result also did comparative study. At last, Section V has concluded.

II. BACKGROUND STUDIES

A. Types of depression and its symptoms

In general there are two types of depression- Major Depressions and Persistent depressive disorder or dysthymia. In major Depressions the symptoms are minimum 2 weeks long and one's capacity to work, study, sleep, and eat are often hampered. In the other hand which often includes less severe symptoms of depression that last much longer, typically for at least 2 years. Other forms of depressions are perinatal depression, seasonal affective disorder, depression with symptoms of psychosis [4] (fig:1). According to [4] the common symptoms of depressions are as follows:

978-1-XXXX-XXXX-X/23/$31.00 ©2023 IEEE

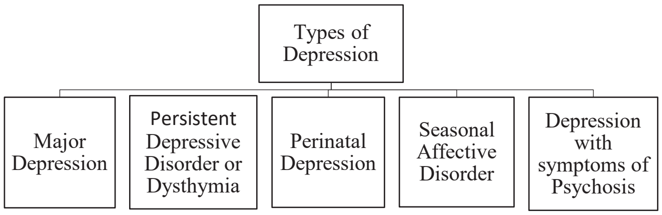

Fig. 1. Types of Depression

- Persistent sad, anxious, or "empty" mood.
- Feelings of hopelessness or pessimism Feelings of irritability, frustration or restlessness.
- Feelings of guilt, worthlessness, or helplessness.
- A decline in enjoyment or interest in hobbies or other activities.
- Difficulty concentrating, remembering, or making decisions.
- Difficulty sleeping, early morning awakening, or over-sleeping.
- Changes in appetite or unplanned weight changes.
- Aches or pains, headaches, cramps, or digestive problems without a clear physical cause and that do not ease even with treatment.
- Suicide attempts or thoughts of death or suicide.

B. Depression Symptoms for Teen

Children's and adolescents' symptoms of depression are similar to those of adults, but there may be some differences. Sadness, irritability, clinginess, worry, aches and pains, refusing to attend school, and being underweight are all signs of depression in younger children. Sadness, irritability, feeling worthless and negative, anger, poor school performance or attendance, feeling misunderstood and extremely sensitive, using recreational drugs or alcohol, eating or sleeping too much, self-harm, losing interest in normal activities, and avoiding social interaction are all symptoms that can occur in adolescents [5].

C. Depression Symptoms for Older Adults

Sorrow is definitely not an ordinary piece of becoming older, and it ought to never be messed with. Unfortunately, older adults may be reluctant to seek assistance because depression is frequently misdiagnosed and undertreated. Physical discomfort, exhaustion, loss of appetite, sleep issues, or a lack of desire in sex that is not brought on by a medical condition or medicine are just a few examples of the distinct or less evident indicators of depression that older people may display. Thoughts of suicide or feelings, especially in elderly males. Constantly desiring to stay home rather than venturing out and trying new stuff or socializing [5].

III. LEARNING TECHNIQUES

The conventional way of depression detection is proper medical treatment. One-to-one conversations with the doctor and their guidance surely help the victims of depression. But this method is so time-consuming and expensive. Fortunately, the advancement of Artificial Intelligence fixed this issue. Depression can be detected by various methods using various machine learning, deep learning, and statistical approaches.

A computational method for depression detection demands different types of user data like social media text, facial expressions, and voice-record, question-answers of a conversation or chats. Most of the techniques follow the genericsteps (fig: 2). There are various ML and DL models for this purpose. Linear Regression, Ridge Regression, Support Vector Machine, Naive Bayes, Decision Tree and Random Forest are some machine learning techniques. RNN, LSTM, Bi-LSTM, BERT and transformer are some deep learning methods for detecting depressions. A combination of ML and DL is also used as a hybrid model. There are also some lexicon based methods for this purpose (fig: 3).

IV. COMPARITIVE STUDIES

Several platforms of Social media like Facebook, Reedit, Twitter, and Instagram have the idea of social communication all over the world. People are more connected than ever and have developed a kind of online character through this social media. Social networking undoubtedly has some amazing perks, but there are also unquestionable drawbacks. It is shown that a huge amount of data is generated every moment through these platforms. Recent research has found a link between increased depression and frequent use of social media platforms. So most of the researchers focus to use social media data for detecting depression. By analyzing the data from social media posts, previous studies have discovered factors that demonstrate the characteristics of depressed individuals.

M. Nadeem [6] did experiments on 2.5M twitter posts. He used the bag-of-word strategy to vectorize the text and created 846,496-dimensional feature space as an input vector. In the implementation, count vectorizer with default settings from Scikit-learn was used to make vectors from text data. 1-gram and 2-gram both methods have been experimented and it was observed that the uni-gram method captured significantly more data present than the bi-gram technique. He also got a slight computational advantage in the uni-gram method. This paper focused on machine learning algorithms (SVM, Decision Tree, Ridge Classifier, Naive Bayes). All models were trained on the same processed data. The unigram-based Naive Bayes scored the best accuracy of 86% but failed to produce the best precision, recall, and f1 score. The other models performed better than the unigram-based Naive Bayes model regarding precision, recall, and f1. So author proposed a way to select the best model for a particular task. If prioritization is necessary then recall is a more crucial factor than precision. And hence Linear SVM is the best choice.

The deep learning LSTM-RNN model was used to identify depression in an unbalanced dataset of tweets from the Kaggle platform [7]. After cleaning and preprocessing the data PCA (Principle component analysis) was used for extracting the features from the dataset. After that, they applied LSTM-RNN and gained a very high accuracy of 99%. They also compared with various Machine Learning models like SVM and found that the LSTM-RNN model gave them the best result.

TABLE I: DIFFERENT TECHNIQUES FOR DETECTING DEPRESSION

S.N.	Paper References	Used Dataset	Techniques Used to Detect Depression	Accuracy	Precision	Recall	f1- score	Result
1.	Identifying depression on Twitter.[6]	2.5M Tweets	Decision Tree, SVM, Naïve Bayes, Logistic Regression, Ridge Classifier	Naïve Bayes 2-gram: 0.82 Naïve Bayes 1-gram: 0.86 Logistic Regression 0.82 Decision Tree: 0.67 Linear SVM: 0.82 Ridge classifier: 0.79	Naïve Bayes 2-gram: 0.82 Naïve Bayes 1-gram: 0.81 Logistic Regression 0.86 Decision Tree: 0.67 Linear SVM: 0.82 Ridge classifier: 0.81	Naïve Bayes 2-gram: 0.82 Naïve Bayes 1-gram: 0.82 Logistic Regression 0.82 Decision Tree: 0.68 Linear SVM: 0.83 Ridge classifier: 0.79	- Naïve Bayes 2-gram: 0.82 Naïve Bayes 1-gram: 0.81 Logistic Regression 0.84 Decision Tree: 0.75 Linear SVM: 0.83 Ridge classifier: 0.78	846,496 dimensional feature space is created using Bag-of-word method. Authors observed uni-gram method gave better result than bi-gram model. If accuracy is the priority then Naïve Bayes 1-gram with 86% accuracy is the best.
2.	Deep Learning for Depression Detection from Textual Data [7]	-		LSTM: 0.9966 SVM: 97.21 Naïve Bayes: 97.31	LSTM: 0.99	LSTM:0.98	LSTM: 0.99	Use PCA for feature extraction from a imbalanced dataset. Use LSTM-RNN deep learning method.
3.	Machine Learning-based Approach for Depression Detection in Twitter Using Content and Activity Features[8]	Tweets of different users. Each user contains maximum 3000 recent tweets	SVM, Naïve Bayes, Decision Tree	Linear SVM: 82.5 Naïve Bayes: 80.00	Liner SVM: 0.73913 Naïve Bayes: 00.6538	Linear SVM: 0.85 Naïve Bayes: 00.8095	Linear SVM: 0.790698 Naïve Bayes:00.723404	Used extensively feature engineering for extracting the patterns to detect depression. They applied different ML methods.
4.	Predicting depression via social media[10]	2M tweets-476 users(questionnaire)	SVM	70	74.00	0.62	-	Used different statistical measures for feature selections. They also observed various linguistic style. Use PCA for avoiding the overfitting.
5.	Forecasting the onset and course of mental illness with Twitter data [20]	105 depressed users out of 204	1200 –Random Forest		0.8666	.683		Use ML and got the best result.
6.	Depression Detection of Tweets and A Comparative Test[21]	Sentiment 140, tweet Scrap from Twitter and google word2vec	TF-IDF, Naïve Bayes, LSTM, Logistic Regression, SVM	LSTM:0.99525 Logistic Regression:0.98003 TF-IDF: 0.99265	LSTM:0.99585 Logistic Regression:0.98548 TF-IDF: 0.99595	LSTM:0.99544 Logistic Regression: 0.98876 TF-IDF: 0.99959	LSTM:0.99565 Logistic Regression: 0.98003 TF-IDF: 0.99731	Among various ML and DL model DL model i.e. LSTM outperforms all the models
7.	Detecting depression using a framework combining deep multimodal neural networks with a purpose-built automated evaluation.[12]	671 participants of an interview recorded by webcam and microphone	Multimodal Deep learning model	.6802	.6861	.6859	.6766 (F score)	Find a method to detect depression with minimal human intervention

8.	The Utility of Artificial Intelligence for Mood Analysis, Depression Detection, and Suicide Risk Management[11]		Combination of Optical Character Reader with AI for facial expression recognition	-	-	-	-	Proposed a combination of OCR and Artificial intelligence to detect human face and emotions
9.	Predicting Depression Levels Using Social Media Posts[13]	6773 Social Media posts from Twitter, Facebook, Livejournal	SVM, Naïve Bayes	SVM: 0.57 NB: 0.63	SVM:0.67 NB: 1.00	SVM:0.56 NB: 0.58	-	NB gives better result
10.	Mental Illness Classification on Social Media Texts using Deep [10] Learning and Transfer Learning[14]	16,930 Reddit post	Transfer Learning (BERT, RoBERTa,XLNet) , LSTM,Bi-LSTM,GRU,Bi-GRU,,CNN,Classical ML method	BERT: 0.78 RoBERTa: 0.83 XLNet:0.79 Bi-LSTM: 0.78 LSTM:0.76 CNN: 0.64 GRU:0.62 Bi-GRU:0.63	-	-	BERT: 0.80 RoBERTa: 0.83 XLNet0.80 Bi-LSTM: 0.79 LSTM:0.77 CNN: 0.65 GRU:0.64 Bi-GRU:0.65	Bi-LSTM is as good as BERT for multiclass classification. GRU and other ML model is not good as BERT and Bi-LSTM.
11.	Integration of Text and Graph-based Features for Detecting Mental Health Disorders from Voice[15]	The Distress Analysis Interview Corpus/Wizard-of-Oz set (DAIC-WOZ) dataset (Gratch et al., 2014; DeVault et al., 2014)	BERT-UNCASED, BERT-CASED, ALBERT, ROB ERTA, CLINICALBERT, DISTILBERT, BLUEBERT	BERT-UNCASED 0.82, BERT-CASED 0.75, ALBERT 0.63 , ROB ERTA 0.77, CLINICALBERT 0.73, DISTILBERT 0.75 , BLUEBERT 0.77	BERT-UNCASED 0.68, BERT-CASED:0.60, ALBERT:0.46, ROB ERTA:0.66, CLINICAL BERT;0.54, DISTILBERT:0.61, BLUEBERT :0.66	BERT-UNCASED :0.78, BERT-CASED:0.64, ALBERT:0 .49, ROB ERTA:0.42 , CLINICAL BERT:0.75 , DISTILBERT:0.57, BLUEBERT:0.57	BERT-UNCASED :0.72, BERT-CASE:0.62, ALBERT:0.47, ROB ERTA:0.52, CLINICAL BERT:0.63, DISTILBERT:0.59, BLUEBERT:0.61	The use of multimodal method (voice and text) and transformer gave a high accuracy. Also the graph based feature extraction from the audio signal increase the performance of the model a lot.
12.	Predicting Anxiety, Depression and Stress in Modern Life using Machine Learning Algorithms[16]	348 participants via Google forms aged between 20 and 60 years both male and female	Decision Tree, Random Forest Tree, Naïve Bayes, Support Vector Machine and KNN	DT: 0.778 RF: 0.798 NB: 0.855 SVM: 0.803 KNN: 0.721	DT:0.731 RF:0.202 NB:0.822 SVM: 0.820 KNN: 0.750	DT:0.714 RF:0.678 NB:0.850 SVM:0.716 KNN:0.634	DT:0.723 RF:0.766 NB:0.836 SVM:0.765 KNN:0.687	Method can find 5 different severity of stress, depression and anxiety. They found 'scared_without_any_good_reason', 'Life_was_meaningless' and 'Difficult_to_relax' for the scales of Anxiety, Depression and Stress, respectively
13.	Psychological Analysis for Depression Detection from Social Networking Sites[17]	Two twitter dataset. Sentiment_140 and Sentiment_tweets3	Decision Tree, Linear Regression, SVM, KNN, LSTM	(IMBALANCED) LR:0.71 SVM:0.52 KNN:0.65 LSTM:0.78 (SMOTE) DT:0.68 LR:0.76 SVM:0.62 KNN:0.71 LSTM:0.83	(IMBALANCED) DT: 0.73 LR: 0.75 SVM:0.67 KNN:0.75 LSTM:0.79 (SMOTE) DT:0.76 LR:0.77 SVM:0.79 KNN:0.69 LSTM:0.84	(IMBALANCED) DT:0.63 LR:0.68 SVM:0.67 KNN:0.56 LSTM:0.72 (SMOTE) DT:0.64 LR:0.72 SVM:0.69 KNN:0.59 LSTM:0.75	(IMBALANCED) DT:0.67 LR:0.71 SVM:0.71 KNN:0.61 LSTM: 0.74 (SMOTE) DT:0.69 LR:0.74 SVM:0.73 KNN:0.63 LSTM:0.79	The authors find a way to handle imbalanced dataset using two method SMOTE and RUS. Also the paper found that LSTM is the best model for depression detection

14.	Depression Detection and Analysis[4]	53 Volunteers	RBFN (Radial Basis function network)	0.714	-	-	-	Proposed chatbot platform that can recommend music or articles to the user based on their mental condition
15.	Review on Mood Detection using Image Processing and Chatbot using Artificial[3]	An image with 6000 features	Haar-cascade algorithm and Adaboost	-	Satisfactory	-	-	Proposed chatbot for detect facial expression using neural network and Haar Cascade algorithm. And recommend jocks, music etc.

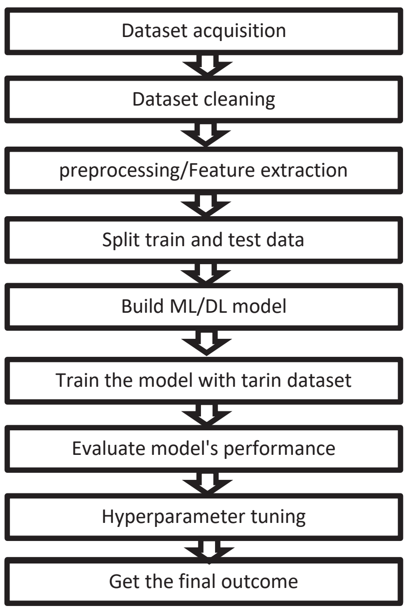

Fig. 2. Generic Steps of Depression Detection

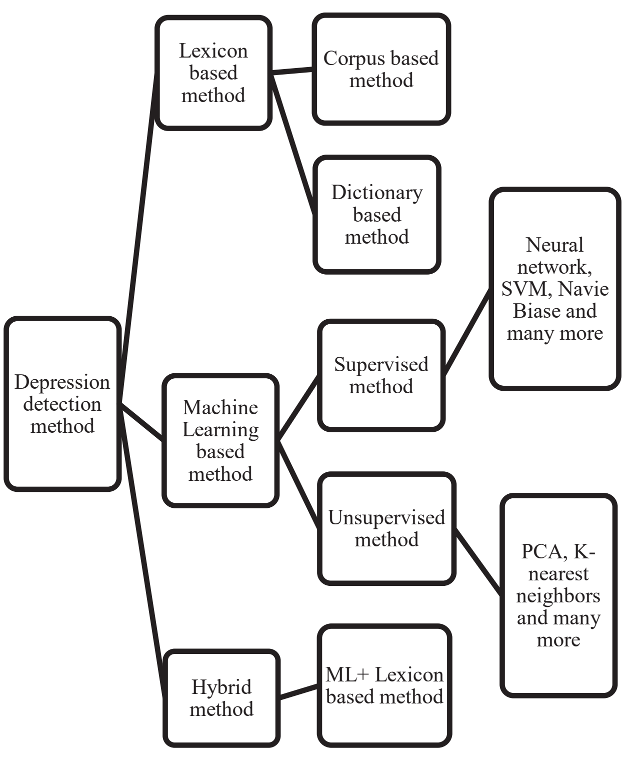

Fig. 3. Technique of Depression Detection

H. S. AlSagri and M. Ykhlef worked extensively on feature engineering [8]. The process of applying domain expertise of the data to produce features that machine learning algorithms may utilize to detect patterns is known as feature engineering [9]. After the feature engineering, data was divided it into two types of features- 'User Activity feature', and 'Tweets' feature'. The 'User Activity feature' was divided further into three categories and the 'Tweets' feature' was categorized into 6 types for example 'self-center', 'sentiment', 'TF-IDF', and so on. SVM and other ML models like Naive Bayes had been used for the detection of depression. In that research, they found that SVM gave the best result.

Some research works used different statistical measures for the selection of features [10]. They used the post as well as interactions of the other as raw materials of the features. They introduced a measure of the linguistic style using LIWC to classify 22 specific linguistic styles. They used PCA for avoiding the overfitting of the model. They got the best result using 10-fold cross-validation SVM with a Radial Bias Function (RBF).

B. Zohuri and S. Zadeh proposed an idea of integration of ML and DL with OCR (Optical Character Recognition) [11]. Here FER (facial expression recognition) and EM (emotion detection) were discussed. Those have the ability to detect human emotions with the help of ML and DL. The authors also discussed the different effects of this mental disorder based on gender and age.

Different ML and DL models were used for detecting depression [12],[13]. Naive Bayes model of Z. Jamil outperformed SVM [9]. Where some authors used AUC and ROC along with accuracy, precision, recall, and f1 score to evaluate their model [12].

A research work detected 5 common mental disorders: depression, anxiety, bipolar disorder, ADHD, and PTSD [14]. Their approach was classical ML, DL, and also Transfer Learning for detecting multiclass classification problems. In their experiment, Bi- LSTM overall gave the best result. It is interesting to observe that Bi-LSTM performed similarly to BERT. It indicates that the Bi-LSTM model performs equally well on multiclass classification.

N. Ghadiri, R. Samani, and F. Shahrokh experimented with multimodal hybrid architecture [15]. The authors used a combination of voice and text to detect depression. They introduced a graph-based feature extraction method that can extract features through the mapping of speech signal into a complex network. Transformer-based deep learning technique was used by the authors. As they used graph-based feature extraction from audio, multimodal method, and

BERT, the performance of the models are also very good.

To gather the data, the DASS-21 a standard questionnaire that measures typical symptoms of stress, depression, and anxiety was used [16]. This paper worked on five different severity levels of anxiety, depression, and stress. They found that the accuracy of Naive Bayes is the highest among all the models but Random forest is the best model. As the dataset was imbalanced they gave more weightage to the f1 score for evaluating the result. This paper also discussed some important variables like ‘scared without any good reason’, ‘Life was meaningless’, and ‘Difficult to relax’ for the scales of Anxiety, Depression, and Stress, respectively to detect psychological disorder.

Imbalanced data is a challenge to researchers. Imbalanced data produce a biased result. So it is a primary task to eliminate or reduce the biases of the imbalanced data. Authors proposed two approaches for class imbalanced dataset SMOTE, RUS. SMOTE balances the class distribution by finding the K-Nearest Neighbors and calculating the Euclidian distance between the minority class and other instances [17]. The RUS method just does undersampling the majority class. A subset of the majority class is combined with the minority class for the final dataset. After that, they found LSTM to be the best model for depression detection and SMOTE is a better approach than RUS. Even Imbalanced data set behaves slightlybetter than RUS dataset.

Internet-based cognitive behavioral therapy is a popular method for depression detection. Chatbots or interactive platforms can do various tasks based on AI and NLP and Vision. S. Oak proposed a chatbot that can interact with humans and suggest them music or article based on the mental status ofthe user [18]. The main 2 goals of the author were – (1) users shouldfeel comfortable to share their feelings on that platform. (2) And the final goal was to reach out to those people who are not capable of affording expensive medical treatment or are shy to express their problems to others. The author analyzed speech along with text for the detection of depression. The non- verbal features are extracted and the audio is transformed into text with the help of google API. The Radial Basis Function Network is applied to the data for the creation of the model. The user’s anonymity is kept here so that he/she can interact with the chatbot comfortably. After the detection of the mental conditions of a user, the platform recommends suitable text or music. The text and music are stored on a database category- wise.

Another research work detected one’s mood by Image processing and AI through a chatbot [3]. This paper used the Haar Cascade image processing Algorithm to detect the face. This algorithm is trained with lots of positive (images with face) and negative (images without face). Neural network is used to train the model along with AdaBoost. This platform interacts with a user and based on their expression on the face they recommend some music, articles, or jocks to lighten the mode of the user.

T. Yang experiments with different initialization method (Xaiver and Kaiming) of deep learning for detecting depression from a dataset [19].

V. CONCLUSION

This review paper observes the various implementation of early depression detection. The study started by collecting a number of papers and sorting 15 papers for discussion. The papers are sorted to maintain the versatility of the method, dataset and technology. Not only social media, but also we selected such papers that worked on the data collected by questioners, google form, and images.

Based on the above findings in this survey, it is found that the majority of authors used Machine learning technique. SVM, Naive Bayes is the most successful model in Machine Learning. Apart from these, Decision Tree, Random Forest, Linear Regression and KNN are also used by most of the authors. When ML model produces an average result then Neural Network completely outperforms it. LSTM, Bi-LSTM, BERT, and its various version based model are also discussed in this review paper. BERT and transformer are very powerful methods for depression detection.

Not only textual data but voice is also used to detect depression. A novel graph-based approach for extracting the features of audio is discussed here. An Interactive AI Platform is also discussed here. For example, a chatbot is used to detect mental conditions using facial expressions and chat and recommend songs, jokes, or articles based on the mood of the user. The main aim of this chatbot is to identify the mood of the user and try to make them happy and relaxed using emotional AI. To conclude depression can be identified through speech, text, facial expression and question-answer by different approaches of Machine learning, neural network, emotional AI, vision and Natural Language Processing.

VI. REFERENCES

[1] G. Hadjipavlou, C. A. S. Hernandez, and J. S. Ogrodniczuk, “Psychotherapy in contemporary psychiatric practice,” The Canadian Journal of Psychiatry, vol. 60, no. 6, pp. 294–300, 2015.

[2] A. Picardi and P. Gaetano, “Psychotherapy of mood disorders,” Clinical practice and epidemiology in mental health: CP & EMH, vol. 10, p. 140, 2014.

[3] D. Thosar, V. Gothe, P. Bhorkade, and V. Sanap, “Review on mood detection using image processing and chatbot using artificial intelligence,” life, vol. 5, no. 03, 2018.

[4] E. Stover, W. Fenton, A. Rosenfeld, and T. R. Insel, “Depression and comorbid medical illness: the national institute of mental health perspective,” Biological Psychiatry, vol. 54, no. 3, pp. 184–186, 2003.

[5] M. Craig Sawchuk, “Depression (major depressive disorder),” 2016.

[6] M. Nadeem, “Identifying depression on twitter,” arXiv preprint arXiv:1607.07384, 2016.

[7] A. Amanat, M. Rizwan, A. R. Javed, M. Abdelhaq, R. Alsaqour, S. Pandya, and M. Uddin, “Deep learning for depression detection from textual data,” Electronics, vol. 11, no. 5, p. 676, 2022.

[8] H. S. AlSagri and M. Ykhlef, “Machine learning-based approach for depression detection in twitter using content and activity features,” IEICE Transactions on Information and Systems, vol. 103, no. 8, pp. 1825–1832, 2020.

[9] Z. Jamil, Monitoring tweets for depression to detect at-risk users. PhD thesis, Universite d’Ottawa/University of Ottawa, 2017. ´

[10] M. De Choudhury, M. Gamon, S. Counts, and E. Horvitz, “Predicting depression via social media,” in Seventh international AAAI conference on weblogs and social media, 2013.

[11] B. Zohuri and S. Zadeh, “The utility of artificial intelligence for mood analysis, depression detection, and suicide risk management,” Journal of Health Science, vol. 8, pp. 67–73, 2020.

[12] E. Victor, Z. M. Aghajan, A. R. Sewart, and R. Christian, “Detecting depression using a framework combining deep multimodal neural networks with a purpose-built automated evaluation.,” Psychological assessment, vol. 31, no. 8, p. 1019, 2019.

[13] M. M. Aldarwish and H. F. Ahmad, “Predicting depression levels using social media posts,” in 2017 IEEE 13th international Symposium on Autonomous decentralized system (ISADS), pp. 277–280, IEEE, 2017.

[14] I. Ameer, M. Arif, G. Sidorov, H. Gomez-Adorno, and A. Gelbukh, ` “Mental illness classification on social media texts using deep learning and transfer learning,” arXiv preprint arXiv:2207.01012, 2022.

[15] N. Ghadiri, R. Samani, and F. Shahrokh, “Integration of text and graph-

based features for detecting mental health disorders from voice," arXiv preprint arXiv:2205.07006, 2022.
[16] A. Priya, S. Garg, and N. P. Tigga, "Predicting anxiety, depression and stress in modern life using machine learning algorithms," Procedia Computer Science, vol. 167, pp. 1258–1267, 2020.
[17] S. Gupta, L. Goel, A. Singh, A. Prasad, and M. A. Ullah, "Psychological analysis for depression detection from social networking sites," Computational Intelligence and Neuroscience, vol. 2022, 2022.
[18] S. Oak, "Depression detection and analysis," in 2017 AAAI spring symposium series, 2017.
[19] T. Yang, "Neural networks with different initialization methods for depression detection," arXiv preprint arXiv:2205.04792, 2022.
[20] A. G. Reece, A. J. Reagan, K. L. Lix, P. S. Dodds, C. M. Danforth, and E. J. Langer, "Forecasting the onset and course of mental illness with twitter data," Scientific reports, vol. 7, no. 1, pp. 1–11, 2017.
[21] P. Rajaraman and A. Nath, "Akshaya. pr, chatur bhuja. g depression detection of tweets and a comparative test," International Journal of Engineering Research & Technology (IJERT), vol. 9, no. 03, 2020