Artificial intelligence assisted tools for the detection of anxiety and depression leading to suicidal ideation in adolescents: a review

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Abstract
Epidemiological studies report high levels of anxiety and depression amongst adolescents. These psychiatric conditions and complex interplays of biological, social and environmental factors are important risk factors for suicidal behaviours and suicide, which show a peak in late adolescence and early adulthood. Although deaths by suicide have fallen globally in recent years, suicide deaths are increasing in some countries, such as the US. Suicide prevention is a challenging global public health problem. Currently, there aren’t any validated clinical biomarkers for suicidal diagnosis, and traditional methods exhibit limitations. Artificial intelligence (AI) is budding in many fields, including in the diagnosis of medical conditions. This review paper summarizes recent studies (past 8 years) that employed AI tools for the automated detection of depression and/or anxiety disorder and discusses the limitations and effects of some modalities. The studies assert that AI tools produce promising results and could overcome the limitations of traditional diagnostic methods. Although using AI tools for suicidal ideation exhibits limitations, these are outweighed by the advantages. Thus, this review article also proposes extracting a fusion of features such as facial images, speech signals, and visual and clinical history features from deep models for the automated detection of depression and/or anxiety disorder in individuals, for future work. This may pave the way for the identification of individuals with suicidal thoughts.

Keywords Artificial intelligence · Machine learning · Classifiers · Deep learning · Depression · Anxiety · Suicidal ideation

Introduction
Suicide is a major health burden: the World Health Organisation (WHO) reports ~ 785,000 suicides annually, equivalent to one person dying every 40 s, with an incidence of 10.6 per 100,000 population (Naghavi 2019). Epidemiological studies show huge variations in suicides between different geographical areas: although suicides have fallen in China (all people) and India (young people), they are growing in many countries, including the USA, Brazil, and South Korea. The risk of suicide is complex to predict. It is understood to be influenced by the interaction
of multiple factors. These include biological (for example, personality factors), clinical (psychiatric and physical health conditions), psychological and social, cultural, and environmental factors. For example, suicidal rates are correlated with economic recession, access to high lethality measures and media reporting of suicides.

The Centers for Disease Control and Prevention report that suicide is the third leading cause of death amongst teenagers and adolescents in the US (Health, United States 2004: with chartbook on trends in the health of Americans and updated tables 2005). Epidemiological studies further indicate that young adults between the ages of 15–21 represent the highest prevalence rates of mental illness at 39% (Eisenberg et al. 2007). Psychiatric conditions associated with suicidal ideation and behaviour include depression, anxiety, substance use disorders, and eating disorders (Brådvik 2018). Some indications of suicidal ideation include an earlier suicide attempt or intentional self-harm behaviour, just as cutting or burning oneself (Korczak et al. 2015). A recent review article reported that language barriers and separation from family were risk factors of suicide, as these factors can lead to a feeling of hopelessness, depression, and anxiety. Other risk factors for suicidality amongst adolescents are poor communication between adolescents and their parents, parental mental health conditions, and intra-family disputes (Korczak et al. 2015). A study by Izadinia et al. (2010) reported that while anxiety, depression, mental health, and everyday stresses were all correlated with suicidal ideations, depression, followed by anxiety, were the main contributors to suicidal ideation (Izadinia et al. 2010). Furthermore, Yeh et al. (2019) established that half of the people who died by suicide had at least one diagnosed mental health condition before the death. Therefore, screening for suicidal risks is a critical step in reducing suicides. This review article focuses on diagnosing depression and anxiety mental health disorders as part of screening for suicidal behaviours and suicide. “Introduction” section describes the background of suicidal ideation and its main contributors. “Traditional screening tools for suicide” section discusses the traditional screening methods used in clinical practice and their limitations. “Biological markers for suicide” section discusses biological markers. “Machine learning tools for diagnosis” section describes the possibility of employing machine learning methods to detect depression and/or anxiety disorder for suicidal ideation identification. In “Methodology for the study” section, the methodology of this review study is explained. In “Summarised studies” section, the summarised studies are described. In “Discussion” section, the findings of the review study are discussed. In “Future avenues for research” section, future avenues for research are proposed, and in “Conclusion” section, the study is concluded.

Traditional screening tools for suicide

Providing support to people who disclose their suicidal ideation is critical in suicide prevention. However, some individuals choose not to seek help for their suicidal ideation, which significantly impedes suicide prevention efforts (Brådvik 2018). For example, although suicidal ideation is generally higher in females (Nock et al. 2008), deaths by suicide are higher in males due to both choices of more lethal methods and reluctance to seek help (World Health Organization 2014). Studies have also shown that many individuals generally prefer consulting their primary care practitioners for emotional concerns than suicidal ideation, specifically due to the stigma associated with suicide (Calear and Batterham 2019). There are various screening tools such as the Columbia Suicide Screen, Risk of Suicide Questionnaire, Suicidal Ideation Questionnaire, Suicidal Ideation Questionnaire JR, Diagnostic Predictive Scales, Suicide Risk Screen and the Suicide Probability Scale (Joe and Bryant 2007) that are widely used by non-mental health professionals for suicide assessment. Additionally, screening programs are largely used in schools to assess suicide risks. For instance, in the first stage of the Teen Screen program, which is described as a model for early suicide prevention intervention, students are tasked to complete the Teen Screen screening questionnaire, after which those identified to be at a higher risk are further assessed through the use of the Diagnostic Interview Schedule for children. In the final stage, a clinician interviews the identified at-risk students (Calear and Batterham 2019). Hence, conventional diagnosis of suicide includes self-reports and clinical interviews.

Limitations of traditional screening methods

However, the afore-mentioned screening tools exhibit some limitations. Studies have shown that a lack of resources due to scarce funding for the assessment programs hinder the implementation of such programs in schools. Furthermore, as educators and school counselors are overwhelmed with the demands of each school day, they are reluctant to implement such risk assessment programs in schools (Mazza 1997). Additionally, several studies that were conducted on the effectiveness of school-based screenings reported a high incidence of false positives (Thompson and Eggert 1999). Also, since most of the suicide screening tools were developed using individuals who were identified as being of white ethnicity (Manetta and Ormand 2005), the tools may not be effective in identifying at-risk adolescents of different ethnicities.
Biological markers for suicide

There are no proven accurate biological markers of suicide that can be integrated into clinical practice. Some demographic and behavioural markers exist (Heeringen and Mann 2014). Forecasting and averting suicidal behaviour is still a budding research field, and several markers have been identified for future study (Nugent et al. 2019). For instance, Niculesu et al. (2017) reported that Apolipoprotein E and interleukin-6 were promising biomarkers for suicidal prediction. Kaminsky et al. (2015) reported epigenetic and genetic markers, including SKA2, as potential markers for suicidality, but further study replication was recommended. Many studies recognized changed sleep architecture to be a biomarker of suicidal thoughts and behaviour (Malik et al. 2014; Bernert et al. 2017; Ballard et al. 2016). The lack of an animal model for suicide (Gould et al. 2017) is a major constraint on basic scientific research, although developing such models is underway. An inadequate number of post-mortem brains available for research poses another challenge (Costanza et al. 2014).

Machine learning tools for diagnosis

The need for AI tools for the diagnosis of suicide risk

The limitations of clinical screening methods for suicide and the frequency of non-disclosure of suicidal ideation mean that 60–70% of individuals who commit suicide are not known to be at risk by their primary care practitioners (Ahmedani et al. 2014). Pourmand et al. (2018) reported in a recent review that adolescents often divulge risk factors for suicide on social media like Facebook and Twitter, even though they don’t disclose them to doctors. Of all the mental health-related tweets shared by large media outlets, around 30% had reference to suicide (Calear and Batterham 2019). Hence researchers have explored information from social media which overtly mentions suicidal thoughts or attempts. In another recent review by Franco et al. (2018), about 3.23% of studies exploring such data were related to machine learning algorithms, highlighting the potential of cutting-edge technological tools to predict suicide risk (Calear and Batterham 2019).

Traditional machine learning models

Machine learning is a sub-field of artificial intelligence (AI). Training of the machine learning model involves a sequence of steps; the input data is usually pre-processed to remove any noise, after which significant features are extracted and selected before the classification process. This workflow is presented in Fig. 1. In conventional machine learning, the system learns from its experience, wherein the system learns the pattern of the input data and responds from its learning, at the output (Voulodimos et al. 2018). At this juncture, the system becomes smarter as it learns the data automatically, without any human intervention (Voulodimos et al. 2018). However, machine learning works well with small data, but the extraction and selection of significant features are manual processes that require human intervention. Some examples of machine learning models commonly used for the classification of diseases include the support vector machine (Cristianini and Shawe-Taylor 2000), decision tree (Kingsford and Salzberg 2008), probabilistic neural networks (Specht 1990), k-nearest neighbour (Hu et al. 2016), and artificial neural networks (Grossi and Buscema 2007). Such conventional machine learning models have been fervently used in the classification of some mental illnesses such as schizophrenia (Sharma and Acharya 2021; Jahmunah et al. 2019), depression (Sharma et al. 2018a), Parkinson’s disease (Tuncer et al. 2020), and Alzheimer’s disease (Wei et al. 2020).

Advanced deep learning models

On the contrary, in more advanced machine learning, deep learning models with several layers between the input and output layers are used for classification purposes (Sharma et al. 2021a). Unlike conventional models, these models learn large input data before predicting a classification outcome. Furthermore, in contrast to traditional classifiers in deep models, the feature extraction and selection processes are automatically done by the model, without requiring human aid. Some examples of deep models commonly used for the classification of diseases include the convolutional neural network (CNN) (Sharma et al. 2018b), long short-term memory (LSTM) (Houdt et al. 2020), and autoencoders (Lopez Pinaya et al. 2019).
A CNN model comprises three main layers: convolution, pooling, and fully connected layers. The convolution and pooling layers aid in creating new feature maps in each succeeding layer, enabling the extraction of more complex features from the input data deeper into the network. The fully connected layers provide the output of the classification (Sharma et al. 2018b). Autoencoders comprise two main components known as the encoder, in which the model reduces the feature size and presents the input data into an encoded representation, and the decoder, wherein the model re-creates the data from the encoded version, such that it represents the original data very closely (Lopez Pinaya et al. 2019). The LSTM mainly comprises the input, forget, and output gates that control the information stored, read, and written on the cell, respectively, with the onset of input data. The model works by recollecting crucial information from previous states and building on them (Houdt et al. 2020). These models have been successfully employed in the automated detection of mental health conditions such as Parkinson’s disease (Oh et al. 2018), depression (Ay et al. 2019), and schizophrenia (Oh et al. 2020). Hence, machine learning techniques have also been employed efficaciously to detect mental health disorders. Figures 2a–c illustrate the architectures of the CNN, autoencoder, and LSTM deep models, respectively. The figures depict the workings of the models when the input data is fed to them.

Methodology for the study

This review study was conducted based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to select the most relevant studies on AI tools developed for depression and/or anxiety diagnosis. To analyze more recent articles, the search was...
conducted between the years 2013 and 2022. The appropriate journal articles were searched through the Institute of Electrical and Electronics Engineers (IEEE), Google Scholar, PubMed, Science Direct, and Springer Link scientific repositories. The Boolean search strings such as “Machine Learning”, “Deep Learning”, “Artificial intelligence tools”, “Depression”, “Anxiety disorders” and “Suicidal ideation” were used in various combinations as perceived in Table 1. Three key processes were involved in the retrieval of articles based on the PRISMA guidelines. Initially, a total of 48,407 articles were identified based on the Boolean search strings for depression and anxiety disorder detection, wherein, for depression detection, 119,17801, 8, 47771, and 3963 articles were retrieved from the IEEE, Google Scholar, PubMed, Science Direct and Springer link repositories respectively. For anxiety disorder detection, 16, 17,400, 3, 2211, and 2116 articles were retrieved from the aforementioned repositories. Then, articles were screened to eradicate duplicate and irrelevant articles, based on the inclusion and exclusion criteria, wherein articles on ‘mental health’, ‘stress’, ‘treatment’ or ‘treatment response’, ‘monitoring’, and ‘management’ were all excluded. Furthermore, theses, books, and abstracts were also omitted. The final number of articles relevant to this review were selected and set to 76, as seen in Tables 2, 3, 4 and 5. Figure 3 details how the PRISMA guideline was used to select the most relevant articles in this review.

The search was conducted between May to June 2021. Studies were included if they met the following criteria:

(i) They described the use of AI tools to diagnose depression and/or anxiety
(ii) They were published between the years 2013 and 2022, 
(iii) They were published in a peer-reviewed journal,
(iv) They were published in English. 

Studies were excluded if:

(i) They described the use of AI tools to diagnose depression and/or anxiety together with other conditions or disorders
(ii) The article was not published in English
(iii) The article was not published in a peer-reviewed journal
(iv) The article was published before 2013

### Summarised studies

Tables 2, 3, 4 and 5 summarize studies for detecting depression, anxiety disorder, suicidal ideation, and depression and anxiety disorder using AI tools, respectively. Comparing the tables, it can be deduced that most of the studies focus on detecting depression followed by depression and anxiety disorder as comorbid conditions. From the tables, it is also notable that most authors have successfully investigated audio and/or facial features for the detection of depression and/or anxiety disorder (Ooi et al. 2013; Zhou et al. 2015; Williamson et al. 2016; Pampouchidou et al. 2015; Pampouchidou et al. 2020; Yang et al. 2016, 2017; Dham et al. 2017; Alhanai et al. 2018; He and Cao 2018; Afshan et al. 2018; Zhu et al. 2018; Venkataraman 2018; Gavrilescu and Vizireanu 2019; Melo et al. 2019; Victor et al. 2019; Chlasta et al. 2019; Guntuku et al. 2019; Detecting Depression Using a Framework Combining Deep Multimodal Neural Networks with a Purpose-Built Automated Evaluation xxxx; Vázquez-Romero and Gallardo-Antolín 2020; Quatieri et al. 2020; Shinde et al. 2020; Zhang et al. Jul. 2020; Espinola et al. 2021; Matteo et al. 2021; Guo et al. 2021;

| Table 1 Results of the Boolean search string for the respective repositories |
|-------------------------------------|---------------------------------|-----------------|
| Database | Title | AND (Title/Abstract/Full text) | No. of articles |
| IEEE | “Detection of depression AND/OR anxiety disorder” | Depression: 119, Anxiety disorder: 16, Total: 135 |
| Google scholar | Machine learning, Neural networks, deep learning | Depression: 4771 Anxiety disorder: 2211, Total: 6982 |
| PubMed | “Detection of depression AND/OR anxiety disorder” | Depression: 17,801, Anxiety disorder: 17,400, Total: 35,201 |
| Science direct | Depression: 8, Anxiety disorder: 3, Total: 11 |
| Springer link | Depression: 4771 Anxiety disorder: 2211, Total: 6982 |
| Springer link | Depression: 3963, Anxiety disorder: 2116, Total: 6079 |
Table 2 Summary of studies for detecting depression using AI tools

| Author, year       | Features and methods                                                                 | Database/data collection and Participant information                                                                 | Findings/result (%)                          |
|--------------------|--------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------|----------------------------------------------|
| Ooi et al. (2013)  | Acoustic parameters (prosodic, glottal, Teager’s energy operator, spectral)          | ORYGEN-YH research centre                                                                                              | Ac: 73                                       |
|                    | Multichannel + weighted classification decision technique                             | At risk MDD: 15 patients                                                                                                |                                              |
|                    | 4 Gaussian mixture models                                                             | Not at risk MDD: 15 subjects                                                                                           |                                              |
| Kipli et al. (2013)| MRI images                                                                          | ELUDE database                                                                                                         | MRI-based detection methods have the potential to detect depression |
|                    | Feature extraction, selection                                                         | Depression: 284 patients                                                                                               |                                              |
|                    | Traditional classifier                                                                | N: 154 subjects                                                                                                        |                                              |
|                    |                                                                                        | MIRIAD databases                                                                                                       |                                              |
|                    |                                                                                        | D: 50 patients                                                                                                         |                                              |
|                    |                                                                                        | N: 50 subjects                                                                                                         |                                              |
| Faust et al. (2014)| EEG signals                                                                          | Data recorded from the Psychiatry Department of the Medical College, India                                             | PNN classifier Ac: 99                        |
|                    | Wavelet packet decomposition                                                         | Depression: 284 patients                                                                                               |                                              |
|                    | Nonlinear features                                                                   | N: 154 subjects                                                                                                        |                                              |
|                    | Traditional classifiers                                                              | MIRIAD databases                                                                                                       |                                              |
|                    |                                                                                        | D: 50 patients                                                                                                         |                                              |
|                    |                                                                                        | N: 50 subjects                                                                                                         |                                              |
| Zhou et al. (2015) | 12 multimodal time-series signals extracted during users’ online activities/webcam video tracking of head movement, heart rate, eye blink, pupillary response, facial expression, head movement tracking| Participants’ data recorded from developed system                                                                   | Signals extracted from negative and positive states are more discriminatory, with Ac values of 95 and 91, respectively |
|                    | Leave-one-subject-out validation                                                     | MDD: 5 patients                                                                                                        |                                              |
|                    |                                                                                        | N: 162 videos from 27 subjects                                                                                         |                                              |
| Acharya et al. (2015)| EEG signals                                                                           | Psychiatry Department Medical College, India (Depression dataset)                                                      | Ac: 98                                       |
|                    | Nonlinear features                                                                   | MDD: 15 patients                                                                                                        |                                              |
|                    | Support vector machine classifier                                                    | N: 15 subjects                                                                                                         |                                              |
| Williamson et al. (2016)| Combination of audio (loudness variation, spectral, lower vocal tract physiology), video, and semantic features (spoken content) | Audio/Visual Emotion Challenge and Workshop 2016 depression dataset(AVEC 2016)                                      | Proposed method yields a mean F1 score of 70, similar to the challenge baseline test results |
|                    | Gaussian staircase regression model                                                   | Training set                                                                                                           |                                              |
|                    | Patient Health Questionnaire(PHQ) score                                              | MDD: 21 patients, N: 86 subjects                                                                                        |                                              |
|                    |                                                                                        | Development set                                                                                                        |                                              |
|                    |                                                                                        | MDD: 7 patients, N: 28 subjects                                                                                       |                                              |
|                    |                                                                                        | Test set                                                                                                               |                                              |
|                    |                                                                                        | MDD: 9 patients, N: 38 subjects                                                                                       |                                              |
|                    |                                                                                        | I-vector system performs the best for audio features. Polynomial parameterization of facial landmarks coupled with geometrical features is the best video feature set |                                              |
| Pampouchidou et al. (2015)| Facial expression features (eye pair, geometry)                                       | AVEC Challenge dataset                                                                                                 | Proposed method could be used to assess depression severity (4-class) |
|                    | Local Gabor binary patterns from three orthogonal planes + curvelet transform         | 41 pseudo images                                                                                                       |                                              |
|                    | K-nearest neighbour classifier                                                        |                                                                                        |                                              |
| Nasir et al. (2016) | Various audio speech + facial video features                                         | Multimodal depression data set, Distress Analysis Interview Corpus—Wizard of Oz (DAIC-WOZ)                           |                                              |
|                    | Support vector machine, Gaussian Probabilistic Linear Discriminant Analysis classifiers |                                                                                        |                                              |
|                    | Feature fusion techniques                                                             |                                                                                        |                                              |
|                    | I-vector, polynomial parameterization techniques                                     |                                                                                        |                                              |
| Author, year | Features and methods | Database/data collection and Participant information | Findings/result (%) |
|--------------|----------------------|-----------------------------------------------------|---------------------|
| Yang et al. (2016) | Decision tree classifier built according to the multimodal prediction of PHQ-8 scores Text + audio (prosodic, voice quality features) + video features (eye gaze, head pose) | Multimodal depression data set, Distress Analysis Interview Corpus—Wizard of Oz (DAIC-WOZ) + AVEC 2016 Challenge dataset | F1 score for depression class: 57.1 F1 score for normal class: 87.7 |
| Bairy et al. (2016) | EEG signals Discrete wavelet transform Extraction of nonlinear features Student’s t-test SVM with radial basis kernel function classifier | Psychiatry department of Medical College, India D: 2400 data N: 2159 data | Ac: 88.9 |
| Yang et al. (2017) | Audio and visual recordings Deep convolutional neural network + PHQ-8 score | AVEC 2016 Challenge dataset Females MDD: 13 N: 13 Males MDD: 8 N: 55 | Proposed method is promising in depression diagnosis |
| Liao et al. (2017) | EEG signals Kernel eigen filter bank common spatial pattern Leave-one-participant-out technique SVM classifier | Data acquisition from National Taiwan University Hospital MDD: 12 patients N: 12 subjects | Ac: 81.23% |
| Haritha et al. (2017) | Anxiety detection Respiratory signals Extraction of time and frequency domain features SVM classifier with polynomial kernel | – | Ac: 69.23 |
| Khandoker et al. (2017) | Photo-plethysmogram (PPG) signals from fingertips + anthropometric parameters PPG features (systole peak, pulse wave velocity etc.) Multivariate logistic regression analysis Leave-one-out cross validation technique | MDD with suicidal ideation: 16 patients MDD without suicidal ideation: 16 N: 29 subjects | Ac: 96.7 |
| Dham et al. (2017) | Multimodal feature extraction (audio, text features) Gaussian Mixture Model clustering Fisher vector Support vector machine classifier, neural network | Distress Analysis and Interview—Corpus Wizard of Oz database | Results obtained were better than baseline results |
| Alhanai et al. (2018) | Audio + text features LSTM model Questions asked by virtual agent | Distress analysis and interview corpus database D: Audio + text transcriptions of 142 patients | Proposed method suggests that depression can be detected through sequential modelling of an interaction |
| Kim et al. (2018) | Electrodermal activity (measured in 5 phases) as input features Support vector machine recursive feature elimination for feature selection Decision tree classifier | Data recording done during 5 experimental phases MDD: 30 patients N: 37 subjects | Ac: 74 |
| Author, year | Features and methods | Database/data collection and Participant information | Findings/result (%) |
|-------------|----------------------|-----------------------------------------------|---------------------|
| Islam et al. (2018) | Facebook user’s comments captured using Ncapture tool, LIWC software for text analysis, Emotional variables (positive, negative, sad etc.), temporal categories (current focus, past focus etc.), nine linguistic dimensions (articles, prepositions, verbs etc.) | Raw data collected from Facebook, 7145 users’s comments | Decision tree, Ac (all features): 71.0 |
| Lech et al. (2018) | Spectral roll-off range features (19) mRMR filter to extract features, MIQ score to rank features, Support vector machine classifier | ORI-DB database, MDD: 29 patients, N: 34 subjects | Males: Ac: 97.5, Females: Ac: 92.3 |
| He et al. (2018) | Speech signals, Hand-crafted + deep learned features, Low level descriptors from raw audio files, median robust extended local binary patterns from audio spectrograms, Deep convolutional neural network | AVEC 2013 + 2014 depression datasets, Audio visual video from 292 depressive patients, Training, development, test sets: 100 recordings each | Proposed method is robust and effective for depression diagnosis as compared to current audio-based techniques |
| Zhu et al. (2018) | GoogleNet deep model, Dynamic deep convolutional neural network, Computation of optical flow between every 10 frames | Public face recognition database + AVEC 2014 depression database, 10,575 subjects, 494,414 facial images, Training set for videos: 100, Test set for videos: 50 | Proposed method has lowest mean square root error, mean absolute error compared to other visual-based methods |
| Sharma et al. (2018a) | EEG signals, Wavelet-based features, Time–frequency wavelet filter bank, Ten-fold cross-validation technique | Department of Psychiatry, Government Medical College, India, MDD: 15 patients, N: 15 subjects | Ac: 99.6 |
| Cai et al. (2018) | EEG signals, Traditional classifiers, Linear + nonlinear features, Ten-fold cross validation | Construction of psychophysiological database, MDD: 92 patients, N: 121 subjects | K-nearest neighbour, Ac: 79.2 |
| Eichstaedt et al. (2018) | Facebook status data, Latent Dirichlet allocation, tenfold cross-validation | Facebook data, D: 114 patients | Area under the curve: 72.0 |
| Venkataraman et al. (2018) | Facial videos, Facial feature extraction | 90 images | Overall negativity in videos may be used to estimate depression level |
| Stankevich et al. (2018) | Bag-of-words, word embeddings, n-grams feature sets, Traditional machine learning models | CLEF/eRsik 2017 dataset, Text data from 887 Reddit users | The best F1 and recall scores were obtained by the support vector machine model |
| Cacheda et al. (2019) | Textual spreading, time gap, time span as input features from social media networks, Dual model(2 random forest classifiers) | Reddit database, MDD: 135 patients, N: 752 subjects | The dual model is able to perform better than current models by more than 10% in early detection of depression |
| Author, year          | Features and methods                                                                 | Database/data collection and Participant information                                                                 | Findings/result (%)                                                                 |
|----------------------|--------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------|
| DeMelo et al. (2019) | Spatio-temporal features extracted from full face and eyes of subjects               | AVEC 2013 + 2014 datasets                                                                                  | Proposed method has lowest mean square root error, mean absolute error compared to other methods |
|                      | 2d convolutional neural network + convolutional 3d network                            |                                                                  | Using spatio-temporal features directly is more promising for depression diagnosis       |
| Ay et al. (2019)     | Deep convolutional neural network + long-short term memory model                      | Psychiatry Department Medical College, India (Depression dataset)                                             | Ac: 99.12 (right hemisphere)                                                         |
|                      | EEG signals                                                                          |                                                                  |                                                                                       |
| Victor et al. (2019) | Multimodal deep model                                                                 | Data collection during human–computer interaction 671 participants                                           | The proposed model can aid mental health professionals in identifying symptoms of depression |
|                      | Questionnaire                                                                        |                                                                  |                                                                                       |
|                      | Video + audio + speech data                                                           |                                                                  |                                                                                       |
| Chlasta et al. (2019)| Convolutional neural network                                                          | DAIC database D: 30 N: 77                                                                                  | Ac: 77                                                                               |
|                      | Spectrogram images from speech samples                                                |                                                                  |                                                                                       |
|                      | Local binary patterns                                                                 |                                                                  |                                                                                       |
| Hussain et al. (2019)| Development of socially mediated patient portal application                           | Facebook data 4350 users’ information                                                                       | Proposed method enabled the identification of Facebook features for depression detection |
|                      | Centre for epidemiological studies depression scale                                   |                                                                  |                                                                                       |
|                      | Observed variables from users                                                         |                                                                  |                                                                                       |
| Mallol-Ragolta et al. (2020)| Global vectors word embedding model 5 Hierarchical networks local–global attention network | DAIC-WOZ dataset Audio, visual, linguistic information | Hierarchical contextual attention network is the most ideal configuration for depression detection |
| Trotzek et al. (2020)| Posts and comments from social media(reddit.com) User-level linguistic data classification Early risk detection error score Convolutional neural network model | Reddit database MDD: 135 Patients N: 752 subjects | The combination of deep model and classification of linguistic data serve as state-of-the-art methods for early diagnosis of depression |
| Vazquez-Romero et al. (2020)| Audio data Ensemble learning Convolutional neural network model fivefold cross-validation | AVEC 2016 dataset Training + test set: 189 audio files for depression | Proposed method shows improvement in F1 score compared to the baseline system |
| Owen et al. (2020)   | Twitter data Support Vector Machine model Language models                              | Construction of tweet dataset Training: 900 tweets, Test set: 150 tweets for depression                      | Ac: 74.7                                                                            |
| Stankevich et al. (2020)| Text messages from social network Psycholinguistics, stylistic markers Machine learning techniques Questionnaires | Data from Russian social network (VKontakte) 1020 profiles for depression | F1 score: 66.1%                                                                    |
| Author, year     | Features and methods                                                                                           | Database/data collection and Participant information                                                                 | Findings/result (%)                                                                 |
|------------------|---------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------|
| Quatieri et al. (2020) | Vocal features (vocal tract resonances, speech phenome labels)  
Facial expression features (puckered lips, lowered brows)  
High-level features (based on timing and coordination) extracted from vocal and facial expression features  
High-level features used to train the classifier | AVEC 2014 dataset  
100 depressive patients for training, 50 for testing | The proposed method could be used to assess depressive disorder and other neurological disorders |
| Pampouchdou et al. (2020) | Depression and anxiety analysis  
Facial expressions (motion history images + appearance-based feature extraction)  
Deep CNN model  
Leave-one-subject out cross-validation | ImageNet database  
D: 20 patients  
N: 45 subjects | Comparable performance was achieved on the benchmark AVED 2014 dataset  
Proposed technique is more accurate in identifying visual signs linked to self-reported anxiety symptoms |
| Uyulan et al. (2020) | 3 deep CNN models  
EEG signals from 4 frequency bands  
Extraction of spatial and temporal features | Collection of EEG data at Neuropsychiatry Istanbul Hospital  
MDD: 46 patients  
N: 46 subjects | Delta frequency band with ResNet-50 model:  
Ac: 90.22%  
Area under the curve: 0.9 |
| Shinade et al. (2020) | Acoustic features of speech  
Statistical features computed from extracted audio features  
CNN model | AVEC 2014 Depression dataset:  
Dataset A:  
Depression: 30 samples  
N: 77 samples  
Dataset B:  
D: 720 samples  
N: 1848 samples | Proposed technique has found strong evidence that vocal prosody reveals the change in depression severity |
| Qiao et al. (2020) | EEG signals  
Structural and connectivity features in frequency bands  
T-test  
CNN model | Beijing Anding Hospital, Capital Medical University  
MDD: 16 patients  
N: 16 subjects | Ac: 94.13 |
| Yamashita et al. (2020) | Resting-state functional connectivity patterns  
Functional magnetic resonance imaging data  
Beck depression Inventory-II score | Rs-fMRI dataset  
1584 participants with depression | Ac: 70% with independent validation dataset |
| Thoduparambil et al. (2020) | CNN-LSTM model  
Feature extraction from EEG signals for depression detection | Patient repository (University of Mexico)  
EEG recordings | Ac: 99.0 |
| Saeedi et al. (2020) | EEG signals  
Extraction of entropy, frequency-based features for depression detection  
Genetic algorithm  
Conventional classifiers | Hospital Universiti Sains, Malaysia  
MDD: 34 patients | Enhanced KNN classifier  
Ac: 98.4 |
| Quayyum et al. (2020) | EEG signals  
Convolutional neural network + gated recurrent units  
tenfold cross-validation | EEG depression dataset | Ac: 99.7 |
| Author, year | Features and methods | Database/data collection and Participant information | Findings/result (%) |
|--------------|----------------------|-----------------------------------------------------|---------------------|
| Zhang et al. (2020) | Recorded voice samples, Acoustic, prosodic, and linguistic feature vectorizations, Questionnaires | Data collected through Mental Health America website, 535 audio files for depression | Area under the curve: 82.1 |
| Alsagri et al. (2020) | Traditional machine learning classifiers, Social media analysis | Twitter dataset | The support vector machine model obtained the best accuracy metric combinations |
| Saidi et al. (2020) | Hybrid CNN-SVM model, Feature extraction using CNN model, classification of features by SVM classifier | DAIC-WOZ dataset: Audio, visual, linguistic information | Proposed method yields a higher classification accuracy of 68%. In comparison to that of the baseline CNN model |
| Khan et al. (2021) | EEG signals, Convolutional neural network | Hospital Universiti Sains Malaysia, CISIR data repository | Ac: 100.00 |
| Tao et al. (2021) | Ensemble classifier, Quality of life scales | NHANES dataset | Ac: 95.4 |
| Saeedi et al. (2021) | EEG signals, Convolutional neural network models(1-dimensional, 2-dimensional), Long short-term memory model | EEG dataset | Ac: 99.24 |
| Espinola et al. (2021) | Support vector machine, Acoustic features, Feature extraction from voice signals | Data collected from Hospital Das Clinicas, Federal University of Pernambuco, Brazil | Ac: 89.14 |
| Li et al. (2021) | Recording of kinematic skeleton data, Gradient boosting classifier, Kinect V2 device | Shandong Mental Health Centre | Ac: 76.92 |
| Safa et al. (2021) | Textual tweets, N-gram language models, Linguistic inquiry and word count text analysis, Automatic image tagging, Bag-of-visual-words, Traditional classifiers | Data extracted from public posts in Twitter (for depression) | Ac: 91.0 |
| Wang et al. (2021) | Variance of spatiotemporal, time, and frequency domain features, Gait characteristics, Negelkerke’s R² measure, Support vector machine classifier | Private dataset | Best performance results obtained with only time and frequency domain features |
| Guo et al. (2021) | Deep belief network, long short-term memory model, 2-dimensional facial images + 3-dimensional facial points, audio + video recordings, tenfold cross-validation | Dataset constructed from 7 psychiatric hospitals with specific scale, 15,600 facial images | Integrated 2D and 3D features with Deep belief network is more practical and widespread as compared to other methods for depression detection |
| Author, year | Features and methods | Database/data collection and Participant information | Findings/result (%) |
|--------------|----------------------|-----------------------------------------------------|---------------------|
| Sharma et al. (2021b) | EEG signals  
Fast Fourier Transform  
Time–frequency + local features  
CNN-LSTM hybrid neural network | EEG dataset obtained from Psychology Department, University of Arizona, USA  
D: 126 patients  
N: 121 subjects | Ac: 99.1 |
| Seal et al. (2021) | EEG signals  
Convolutional neural network  
Patient Health Questionnaire to quantify depression level | EEG recordings  
D: 15 patients  
N: 18 subjects | Ac: 99.4 |
| Bai et al. (2021) | EEG signals  
Feature extracted from sub-bands  
Linear and nonlinear features | Data from Beijing Anding Hospital, China  
D: 142 patients  
N: 71 subjects | Complexity nonlinear feature on gamma band, with KNN classifier  
Ac: 79.63 |
| Albuquerque et al. (2021) | Voice recordings  
18 acoustic features  
Hospital anxiety and depression scale  
Self-report questionnaire | Original data recorded from the Center region of Portugal  
Voice recordings from 112 adult participants | Participants with increased depressive symptoms presented higher vowels, longer total pause, and short total speech duration  
Ac: 88.9 |
| Tong et al. (2022) | Discrete adaboost with pruned decision trees  
Features extracted from users’ profiles (linguistic, social interaction, profile,  
Data describing users’ online behaviours | Twitter datasets (Tsinghua Twitter depression dataset, CLPsych 2015 Twitter datasets)  
D: 477 users  
N: 873 subjects | Twitter data:  
(Two sentiment datasets)  
Sentiment_140 dataset: 1.6 million tweets  
Sentiment_tweet3 dataset: 14,000 tweets  
LSTM model performs better than other models for depression detection |
| Gupta et al. (2022) | Five machine learning classifiers  
Psychological assessment by analysing texts, extracting facts, features and crucial information from users’ opinions | DAIC-WOZ dataset:  
Clinical interviews conducted for the diagnosis of anxiety, depression and post-traumatic stress disorders | The proposed method increased the accuracy of depression detection |
| Park et al. (2022) | Bidirectional Long-Short Term Memory model combined with Bidirectional encoders from transformers convolutional neural network  
Connection of feature vectors from speech and text data | DAIC-WOZ dataset:  
Clinical interviews conducted for patients | High F1 score of 0.92 was obtained for depression detection |
| Yadav et al. (2022) | Linguistic information obtained from patient interviews  
Bidirectional Gated Recurrent Unit network  
Fully coupled network | DAIC-WOZ dataset  
Clinical interviews conducted for patients | Proposed method performs better than other audio-based models with around 7% improvement (F-measure) for depression detection |
| Sardari et al. (Sardari et al. 2022) | Convolutional autoencoder model  
Raw audio data  
Cluster-based sampling method | DAIC-WOZ dataset  
Audio data | Proposed method outperforms existing methods with an accuracy of 76.27%, in depression detection |
| Rejaibi et al. (2022) | Recurrent neural network  
Audio features  
Expansion of training labels and transferred features | DAIC-WOZ dataset  
Audio data |  
| |  |  |  |
Albuquerque et al. 2021). Additionally, some authors have widely analysed the brain signals (Sharma et al. 2018a, 2021b; Ay et al. 2019; Faust et al. 2014; Acharya et al. 2015; Bairy et al. 2016; Liao et al. 2017; Cai 2018; Uyulan et al. 2020; Qiao et al. 2020; Thoduparambil et al. 2020; Saeedi et al. 2020, 2021; Xie et al. 2020; Qayyum et al. 2020; Khan et al. 2021; Seal et al. 2021; Bai et al. 2021). Some authors have also scoured and analysed texts from social media such as Twitter, Facebook and Reddit (Thoduparambil 2020; Saeedi 2020; Xie et al. 2020; Islam et al. 2018; Eichstaedt et al. 2018; Cacheda et al. 2019; Trotzek et al. 2020; Owen et al. 2020; Ramirez-Cifuentes et al. 2020; Safa et al. 2021; Tong et al. 2022; Gupta et al. 2022; Stankevich et al. 2018, 2020; Hussain et al. 2019; Alsagri and Ykhlef 2020). A few authors have explored the combination of audio and textual features (Alhanai et al. 2018; Park and Moon 2022), audio and visual recordings (Yang et al. 2017; Mallol-Ragolta et al. 2020; Saidi et al. 2020) while some others have used unique methods such as a combination of time series signal features (Zhou et al. 2015), measurement of electrodermal activity (Kim et al. 2018), magnetic resonance imaging (Kipli et al. 2013; Yamashita et al. 2020; Boeke et al. 2020), kinematic skeleton data (Li et al. 2021), photo-plethysmogram (PPG) signal features extraction (Khandoker 2017), gait characteristics (Wang et al. 2021) and optical flow visual-based method (Zhu et al. 2018). Haritha et al. 2017 explored respiratory signals for anxiety detection. However, apart from Ramirez et al. 2020 all these studies had only investigated the detection of depression and/or anxiety disorder alone, without linking to suicidal ideation. Ramirez et al. 2020 had uniquely assessed the suicide risk among social media users using text-based, statistical, behavioural, and image features. The study concludes that textual and behavioural features are the most promising for suicide risk assessment.

**Discussion**

Figure 4 details the different sources of data utilized by authors for the detection of depression and/or anxiety disorder. The figure shows that publicly available databases were used most widely, followed by data obtained from hospitals or research centres. The recording or construction of data were probably less commonly considered as these are often time-consuming and tedious, as compared to obtaining data from publicly available databases effortlessly. From Fig. 5, it is observable that mostly audio and/or facial video features, followed by EEG signals and texts from social media, were analyzed for the detection of depression and/or anxiety disorder. Also, from Fig. 6, it is evident that there are more studies on the detection of depression as compared to the detection of anxiety disorder or depression and anxiety disorder jointly. Furthermore, it can be reckoned from Fig. 6 that the trend for depression

| Table 3 | Summary of study for the detection of anxiety disorder using AI tools |
|---------|-------------------------------------------------------------------|
| Boeke et al. (2020) | Functional magnetic resonance images | Brain Genomics Superstruct Project (publicly available data) |
| | Structural magnetic resonance images | Images from 531 participants |
| | Regression models | Results were not conclusive for the identification of a generalizable anxiety biomarker |

| Table 4 | Summary of study for the detection of suicidal ideation using AI tools |
|---------|-------------------------------------------------------------------|
| Ramirez et al. (2020) | Combined users’ data from Twitter and Reddit(sentences related to suicide) | Twitter + Reddit datasets (for suicidal ideation) |
| | Two labeling stages | Suicidal ideation: 84 users |
| | Combination of features based on bag of words and n-grams, lexicons, relational, statistical, and behavioural information, image analysis | Focused control: 84 users |
| | Traditional classifiers and convolutional neural network | Generic control: 84 users |
| | (1,214,474 tweets, 305,637 images in total) | Using a combination of features as proposed outperforms the accuracy of using each feature separately |
detection has been increasing from 2013 to 2022. It is also noticeable that more studies have been conducted for depression and/or anxiety disorder detection from 2019 to 2022. Within the same year range, a study on suicidal risk assessment was conducted in 2020. These could possibly be due to the hike in depression and anxiety disorders during the COVID-19 pandemic in children and adolescents (Śniadach et al. 2021). Figure 7 shows the number of studies that employed conventional machine learning and advanced deep learning models. From the figure, it is comprehensible that conventional machine learning techniques have been most commonly developed for the detection of depression and/or anxiety disorders. Furthermore, deep learning models have been explored since 2017, peaking in 2020, contending that these models have been gaining popularity in recent years.

Table 5 Summary of studies for the detection of depression and anxiety disorder using AI tools

| Authors (Year) | Methods | Dataset | Results |
|---------------|---------|---------|---------|
| Afsan et al. (2018) | Voice quality, cepstral features | Depression database | Using voice quality features coupled with mel frequency cepstral coefficients and i-vectors improved depression diagnosis |
| Gavrilescu et al. (2019) | Videos of facial expressions | Facial recognition technology (FERET) database | Depression |
| | Facial Action Coding System | | |
| | Depression anxiety stress scale | | |
| | Multiclass support vector machines | | |
| Guntuku et al. (2019) | Visual features (extracted from profile pictures and posted images) | Facebook + 2 Twitter datasets | Image features can be used to predict depression and anxiety |
| | Depression and anxiety scores | | |
| | Pairwise ranking of image pairs | | |
| | VGG-Net image classifier | | |
| Owen et al. (2020) | SVM model | Twitter’s Stream API | Language models perform well and better than traditional ones |
| | Tweets | | |
| | Pre-trained language models | | |
| Xie et al. (2020) | EEG signals | Depression and anxiety: 10 patients | Ac: 67.7 |
| | Functional connectivity of brain networks + convolutional neural networks | | |
| Ahmed et al. (2020) | Convolutional neural network | Anxiety dataset, depression dataset | Convolutional neural network |
| | 4 conventional classifiers | | |
| Matteo et al. (2021) | Data collected from Android application | 112 Canadian adults (nonclinical population) | Behavioural data collected from smartphone are predictive of anxiety disorder and depression |

MDD Major depressive disorder, N Normal, D Depression, AD Anxiety disorder
Records identified from: IEEE, Google Scholar, PubMed, Science Direct, Springer Link Databases (n = 5)
Records removed before screening: Duplicate records removed (n = 2622)
Records screened (n = 45785)
Records excluded** (n = 27841)
Reports sought for retrieval (n = 17944)
Reports not retrieved (n = 1900)
Reports assessed for eligibility (n = 16044)
Reports excluded based on inclusion/exclusion criteria: 15968
Studies included in review (n = 76)

Fig. 3 Selection of relevant articles based on PRISMA guidelines

Identification of studies via databases

Identification

Records identified from: IEEE, Google Scholar, PubMed, Science Direct, Springer Link Databases (n = 5)

Screening

Records screened (n = 45785)
Records excluded** (n = 27841)
Reports sought for retrieval (n = 17944)
Reports not retrieved (n = 1900)
Reports assessed for eligibility (n = 16044)
Reports excluded based on inclusion/exclusion criteria: 15968

Included

Studies included in review (n = 76)

Fig. 4 Different sources of data

Unknown
Data obtained from social media
Data obtained from research centre/hospitals
Data recording/data construction/privata dataset
Publicly available

Number

[Diagram showing different sources of data with categories and number of each]
Rejaibi et al. (2022) discussed that their recommended method of employing the recurrent neural network on audio features has some limitations wherein the generalization ability of this method to other datasets may be weaker as the shift from ideal circumstances of speech acquisition to speech in the rough conditions will increase the error rate of the method. They also compared the findings from other multimodal experiments and discussed that adding more features to the deep model enabled it to gain more knowledge about the identification of depression.
and was hence able to detect depression with higher accuracy. However, the computational complexity increases. They also stated that while adding visual features to the model increased the model performance by 20%, it appeared to be intrusive and invasive to patients. Park et al. (2022) conferred that their proposed method has limitations such as the inability to subdivide depression into mild or severe due to the way the model was developed in their study. They also discussed that the multimodal analysis of depression using text and voice data enhanced the classification accuracy as compared to using single data. Nasir et al. (2016) discussed that using geometric together with facial marker features improved the F1 score of their i-vector model compared to using the features separately. Adding polynomial feature sets to this resulted in a decline in model performance due to overfitting. They asserted that the i-vector model performed the best for audio features and polynomial parameterization of facial and geometrical features acted as the best video feature set. Yang et al. (2017) discussed that their developed hybrid DCNN-DNN model performed better than existing models, wherein text and semantic features had also been fused for depression detection besides audio and visual features.

Ramirez et al. (2020) debated that their observational study presents some limitations such as having no access to personal and medical information. Hence, the study lacks representativeness wherein analyses on gender, age, and location of users were not performed due to the lack of such information on Twitter. They also reported that while they had used text-based, statistical, behavioural, and image features for suicide risk assessment, the results could be improved by increasing textual and relational features.

Some authors also conducted a review study on depression detection. For instance, Wu et al. (2022) conducted a similar review study on depression detection using speech signals. While the authors reported that there has been a shift from exploring auditory features to deep model for speech depression recognition, they recommended overcoming depression detection challenges by collecting clinical information on depression to explore the core mechanism of speech in depression. They also concluded that combining multiple modalities for accurate and effective depression analysis is a possible trend in future research. While the review study by Wu et al. (2022) is also on depression detection, the authors focus more on employing deep learning methods with speech signals for depression detection, in contrast to this review study, which focuses on machine learning and deep learning models using various types of datasets for depression detection. We also quite differently propose the feature fusion method for future work. Nasser et al. (2020) conducted a review study on depression detection based on traditional machine learning methods using visual facial cues. The authors concluded that the Support Vector Machine technique is recommended for visual feature extraction methods for depression detection, due to the high accuracy obtained with a large number of subjects and with the usage of action units of full face. This review deviates from ours, as it only focuses on traditional machine learning techniques and visual facial cues as features for depression detection. In contrast to our study, William et al. (2021) conducted a review study on depression detection based on texts from social media. Based on the findings from the review, it has been established that the use of classifiers, support vector machines and probabilistic classifiers is the most common approach for depression detection using text analysis and that the BiLSTM combined with attention method generated the best results.

Salas-Zarate et al. (2022) also conducted a review study on detecting depression signs using social media. While the focus of this study is different from ours, the findings also vary. It has been established from the study that Twitter was the most studied social media, and word embedding was the most commonly employed linguistic feature extraction method and the support vector machine was the most prominent classifier that was used, for depression detection. In contrast to our study, Liu et al. (2022) reviewed studies that focused on a machine learning to determine depressive symptoms based on text mining for sentiment identification using social media data. The authors concluded that machine learning techniques could be effective in depression detection using text data from social media. In a different review study conducted by Guntuku et al. (2017), the authors analyzed the diverse approaches that were used to collate social media data comprising information regarding the users’ mental health. This varies from our study, which focuses on detecting depression and anxiety. The authors concluded that while depression and other mental illnesses are identifiable in many online environments, the generalizability of these studies to wider samples and benchmark for clinical criteria has not been determined.

Zhang et al. (2021) had conducted a review study on depression detection using virtual reality. The authors construed that while using virtual reality for depression detection has been increasingly acknowledged and virtual reality games have the potential to be designed for depression detection, they need to be improved. In another review study, Joshi et al. (2022) analysed how facial expressions, images, texts on social media, and emotional chatbots can effectively detect an individual’s emotions and depression. Various AI methods that have been employed for the analysis were discussed. From the findings, the authors established that depression, mood, and emotion could be detected by analyzing texts, videos,
speech, gestures, or images through the employment of various machine learning and artificial intelligence-based models. In the review study by Aleem et al. (2022), the authors described various machine learning algorithms, along with their objectives and drawbacks, used for depression detection. They concluded that the support vector machine was the most prevalently used model, yielding high accuracies of above 75% for depression detection.

Hence, from the discussions above, it is clear that our review study differs from existing reviews in terms of focus and findings. Furthermore, based on the limitations and effects of modalities collated from some studies, it can be elucidated that using a fusion of features such as audio, visual, textual, and so on generally increases the classification accuracy of a deep model for depression detection, as the model gains more knowledge about depression identification. For instance, combining text and voice data improved the model’s performance as compared to using just a single data in the study by Park et al. (2022). However, one needs to be cautious about the type of features being analysed for different types of deep models. For instance, while adding visual features on top of speech signals increased the model’s performance in the study by Rejaibi et al. (2022), the computational complexity of the model increased. Furthermore, obtaining visual features can also appear as being intrusive and invasive to patients. Also, while the combination of the geometric and facial marker features improved the performance of the i-vector model, the addition of other features, like the polynomial, caused a decline in the model’s performance due to overfitting. Thus, while feature fusion is recommended, the types and number of features used depend on the type of deep model being developed, as quick depression detection is imperative in real-time settings.

From Tables 2, 3, 4 and 5, it is also notable that most authors had employed AI techniques for the studies. Some studies report high classification accuracies (95% and above) (Sharma et al. 2018a, 2021b; Ay et al. 2019; Afshan et al. 2018; Faust et al. 2014; Acharya et al. 2015; Uyulan et al. Jun. 2020; Thoduparambil et al. 2020; Saiedi et al. 2020, 2021; Qayyum et al. 2020; Khan et al. 2021; Seal et al. 2021; Khandoker 2017; Lech 2018; Tao et al. 2021) asserting the efficacy of using AI techniques for the detection of depression and/or anxiety disorder. There are advantages of using AI techniques for depression and/or anxiety detection, but there are pitfalls. Hence, the advantages and disadvantages of this review study are discussed below.

**Advantages**

1. Detection of depression and/or anxiety using AI can be more rapid hence individuals with suicidal ideation can be identified faster.
2. Depression and/or anxiety can be more accurately detected using AI tools, enabling suicidal ideation to be identified accurately.
3. Using AI tools is cost-effective in diagnosing anxiety and/or depression, hence identifying suicidal ideation.

**Limitations**

1. Using AI techniques for suicidal ideation may be presented with ethical (McKernan et al. 2018) and privacy issues (Gomes de Andrade et al. 2018).
2. This study has not identified large databases of various ethnicities to better represent the global population.
3. While this review discusses AI techniques for detecting depression and/or anxiety disorder, the features that best determine suicidal ideation in patients with depression and/or anxiety disorder have not been discovered.

**Future avenues for research**

Our review study underscores the significance of depression and/or anxiety disorder detection for identifying suicidal ideation, especially due to the unprecedented challenges brought about by the current COVID-19 pandemic. Findings from our review study demonstrate that audio and/or facial video features have been analyzed predominantly to detect depression and/or anxiety disorder. Furthermore, that machine learning techniques effectively detect depression and/or anxiety disorder. However, the features that best determine suicidal ideation in patients with depression and/or anxiety disorder have not been identified. Hence in our future work, we plan to gather large data from various ethnicities and propose to extract features such as facial images, EEG signals, speech signals, visual and clinical history features from huge population. The combination of features that best reduce the computational complexity of model, will be selected. The deep learning model which would train this feature set, would be kept in a secured cloud server. The classification result of the model (suicidal ideation is present/not present) would then be sent instantly to the mobile phones of involved clinicians, such as a psychiatrist, to assist in the stratification of clinical care. This idea is elucidated in Fig. 8.
Conclusion

Suicidal rates have been increasing globally, with adolescents having the highest prevalence rates of mental illness at 39%, wherein depression and anxiety mental health disorders have been identified as the main contributors to suicidal ideation. Traditional diagnostic methods such as self-report questionnaires and clinical interviews exhibit several limitations. AI tools have been employed to diagnose various diseases, including neurological illnesses. Hence this review paper summarizes studies that employed AI tools for the automated detection of depression and/or anxiety disorders. From the summary, it is apparent that AI tools are promising and can overcome the limitations of traditional depression and/or anxiety diagnostic methods. This study has also established that audio and/or facial video features have been most commonly analysed, followed by EEG signals, to detect depression and/or anxiety disorder. However, one main limitation of this review study is that the features that best determine suicidal ideation in patients with depression and/or anxiety disorder have not been discovered. Leveraging the recommended features for suicidal risk assessment by Ramirez et al. (2020), we hope to address this limitation in our future studies.

Author contributions All authors have contributed to an acceptable and satisfying level.

Data availability Not admissible.

Declarations

Conflict of interest The authors have declared that no competing interests exist.

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