DIFFERENT APPROACHES IN DETECTING ANXIETY DISORDERS AMONG POTENTIAL PATIENTS THROUGH DEEP LEARNING AND AI

Kavita Bhatt[*1]**& 2 Dr. S. Mohan Kumar**[2]
[*1]PHD Scholar School of Engineering and Technology, CMR University Bangalore-560037, Karnataka, India
[2]Director, Professor School of Engineering and Technology CMR University Bangalore-560037, Karnataka, India

Abstract:
A form of the mental condition known as anxiety disorder is characterized by intense feelings of fear and worry. Tools that help doctors forecast mental diseases and provide better patient treatment have greatly benefited in the last few years from the development of ML approaches. This study's comparative literature review focused on the machine learning prediction of certain anxiety disorders and suicidal propensity. A literature search is conducted on studies released between 2014 and May 2023. A comparative literature evaluation included studies on the application of ML approaches to the prediction of anxiety disorders. Analysis of 20 research showed that ML models may be utilized to forecast anxiety disorders, while analysis of two studies might be used to forecast suicidal inclinations. The accuracy of the outcome changes depending on the type of anxiety problem and the techniques employed to forecast it.

Keywords: Medical imaging, Deep learning, AI, Anxiety disorders, Autoencoders, Medical image datasets, Annotation, Segmentation, Image storage, medical image analysis, neuroimaging, Psychiatric diagnosis Social Anxiety Disorder, Random Forest Classifier, SVM, Generalized Anxiety Disorder, posttraumatic stress disorder, agoraphobia, and a history of suicide.
DOI: 10.24297/j.cims.2023.05.21

1. Introduction

Mental illness affects a person's intellect, emotions, and conduct, in addition to their physical health. It encompasses, among other things, illnesses including depression, ADHD, schizophrenia, and autism spectrum disorder (ASD). Statistics indicate that 450 million people worldwide suffer from these illnesses. [2] A large portion of the population is said to be affected by depression, which has alarmingly become a common condition globally. In 2015, 322 million people worldwide were projected to have depression, which corresponds to a 4.4 percent prevalence rate globally, according to a WHO study on mental diseases. Depression increases the likelihood of substance addiction, economic difficulties, and suicide. By 2030, depression is expected to overtake all other diseases globally, according to current WHO forecasts.

[3] Depression and anxiety are common but very serious mental illness that is marked by a loss of interest, constant feelings of sadness that make it hard for a person to focus on work, school, and other routine activities. Each year, one in fifteen adults is affected by depression, and it plays a significant role in over fifty percent of suicide attempts. The sixth main condition, anxiety, is led by lack of sleep, energy, hunger, inspiration, and anxious thoughts [4] [5]. A person who experiences anxiety is prepared to handle the pressures and tensions of everyday life on a cognitive, behavioral, and physiologic level. In addition to adults, children and adolescents under the age of 18 are at risk for acquiring mental health disorders. Additionally, one of the most significant and persistent public health challenges has been mental health disorders. [6] For instance, depression is one of the primary causes of disability and increases the likelihood of both suicidal thoughts and suicide attempts. Anxiety disorders (AD) are the most alarming mental illness worldwide, impacting 264 million people. These startling figures have spurred researchers to create cutting-edge technology to boost well-being and lower associated morbidity, death, and healthcare costs. The clinical interview is also the gold standard for determining the severity of anxiety and other mental illnesses in kids and adults. It is not always quick or simple to schedule an appointment with a mental health professional, and by the time a psychologist is available, a person's life may already be at risk.

[7] In the medical field, computer-assisted detection utilizing Deep Learning (DL) and Machine Learning (ML) is expanding rapidly. Medical images are regarded as the actual source of relevant data necessary for disease diagnosis. One of the most significant factors in reducing the mortality rate associated with cancer and tumors is the early detection of disease using a variety of techniques. Modalities assist radiologists and clinicians in studying the internal structure of an identified illness to retrieve the necessary characteristics. Because of vast volumes of data, ML has limits with the current modalities, but DL works efficiently with any quantity of data. As a result, DL is regarded as an upgraded approach of ML in which ML employs learning techniques and DL learns how computers should respond in the presence of humans. To learn more about the datasets utilized, DL employs a multilayered neural network.

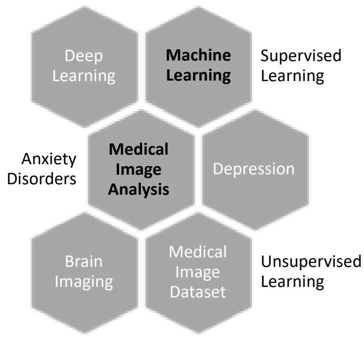

Figure 1: Anxiety Disorder and applications of deep learning, machine learning and medical image analysis/processing

[1] Psychiatrists and psychologists may now use artificial intelligence (AI) tools to help them make judgments based on past patient data, such as medical records, behavioral data, social media activity, and other data. Deep learning (DL), one of the most recent iterations of artificial intelligence (AI) technologies, has demonstrated superior performance in a variety of real-world applications, including computer vision and healthcare. According to Mallick et al. in [8] deep learning can categorize medical data, identify objects, recognize voice, translate languages, and speed up knowledge discovery processes. Deep learning can categorize medical data, identify objects, recognize voices, translate languages, and speed up knowledge discovery processes. Convolution neural network (CNN) and autoencoder are two examples of effective and efficient deep learning models that are discussed after conducting a thorough review based on cutting-edge machine learning approaches that take into account trends, gaps, and challenges in scenarios involving mental health disorders.

20 main studies that were obtained from renowned publications and conferences between 2014 and 2023 underwent a thorough investigation. It provides an overview of various approaches based on ML and DL for detection and prediction, as well as the classification of anxiety disorder, imaging modalities, evaluation tools and techniques, and a description of datasets. The majority of the diagnostic or prediction models were based on images. To create a deep learning model that is capable of accurately diagnosing disorders like Alzheimer's, arrhythmia, lung cancer, and breast cancer, among others, these techniques significantly depend on vast datasets. Early diagnosis of depression is a significant barrier to effective and expeditious treatment. The study examines the body of research on using ML in the early identification of depression. We have evaluated the body of research that has been done on depression using mobility traces, audio, video, multi-modal fusions, imaging biomarkers, and text. This publication aims to stimulate and accelerate research in the early identification of depression and accurate response prediction to therapy.

2. Overview Of Deep Learning And Machine Learning Techniques

The fundamental machine learning (ML) ideas utilized in medical diagnostics are outlined in this section. In this section, we'll also examine the corpus of prior research that employs different deep learning and ML techniques. Traditionally, supervised and unsupervised learning methods have been categorized into two groups. However, there are subtle distinctions between the two. In essence, ML is an area of AI that developed from the study of statistics. Modeling a program to learn from a collection of information (i.e., data) to make a prediction based on a new data point or examine correlations in the dataset. However, the focus of these is often prediction rather than interpretation. Instead of trying to create unbiased estimators of them and understanding the significance of the coefficients, the majority of machine learning consists of locating models that accurately predict test data.

Kavita et.al in [9] Deep learning is a subcategory of supervised ML models. It does "feature learning," which is also called "automatic supervised feature extractions." It models abstractions using database aids, graphs with multiple processing levels, and transformations that are both linear and nonlinear [10], [11].Authors in [11], [12], [13] discussed applications for machine learning that are widely used in all aspects of biomedical imaging. The neural network's anatomy [14], which is at the heart of machine learning, is developed from a brain-like structure where artificial neurons, or interned-connected nodes, are used by algorithms to interpret information. Machine learning created an artificial neural network called an ANN [14] to imitate this system and recognize and forecast patterns in brain signals. [15] .

Supervised learning
is a part of machine learning using labeled data. Future unanticipated inputs can be handled by the approach. In addition to regression algorithms like linear, polynomial, logistic, and others, further supervised learning approaches include classification techniques like decision trees, ANN, SVM, CNN, and RNN [9]. A function that attempts to mathematically express an underlying generalization of an input to an output based on sample input-output pairs is learned using the supervised learning approach. Alternatively said, it extrapolates a function from a training set of labels. This "inferred function," which is used to forecast the outcome of a previously unobserved data point, is created by a supervised learning model by analyzing the training data. However, as this is only true for a hypothetical optimal approach, supervised learning methods can only reasonably translate the output in a probabilistic manner. Using test data without tags to conclude is the practice of doing so classified or labeled is called **unsupervised learning** [9].Instead of generating a generalization from unobserved data, it examines the unlabeled training dataset to determine whether there is a structure or connection there, which is how it differs from the supervised learning strategy. The effective development of a predictive model by lowering the number of features from a large unlabeled dataset, known as dimensionality reduction, is made possible by this. Unsupervised learning is used to identify characteristics from high-dimensional medical data to create precise prediction models. Altaf et al. in [11] describe **unsupervised learning** techniques that lack task-specific sample label inputs, supervised learning makes use of training data containing labels. Author in [15], ML technique which uses an algorithm that relies on unlabeled training data. The only known outputs from training data are the inputs. Based on the results of the relations and patterns, it creates a training data model. It can be further broken down into three primary categories: Dimensionality Reduction, Anomaly detection, and Clustering (K-Means technique). Kishor et al. in [15] the algorithm used in **semi-supervised** training use partially labeled training data. Both the labeled and unlabeled sets of data in this case produce better training models.

Future unanticipated inputs can be handled by the approach. In addition to regression algorithms like linear, polynomial, logistic, and others, further supervised learning approaches include classification techniques like decision trees, ANN, SVM, CNN, and RNN. [36] Altaf et al. in [36] describe unsupervised learning techniques that lack task-specific sample label inputs, supervised learning makes use of training data containing labels. Kishor et al. in [15] the algorithm used in **semi-supervised** training use partially labeled training data. Both the labeled and unlabeled sets of data in this case produce better training models. Some underlying assumptions about data distribution, such as cluster assumptions, smooth assumptions, multiple assumptions, low-density assumptions, and self-training. The merit-based **reinforcement training** system is based on the learning supervision paradigm. To find the rewards is done based on a trial-and-error methodology. In the examination of medical images, it is not as important. Author in [12] says the distinction is in how training data is handled. [12], [16] To continue with supervised learning, **weak supervision** generates fresh labeled data by removing the noisy data from the unlabeled data. Although the newly labeled data is not entirely accurate, it can be utilized to build or improve a predictive model.

Different Machine Learning Algorithms

Support Vector Machine (SVM):

[17] SVMs are models that conduct classification and regression analysis on data in supervised machine learning. The idea behind a support vector machine is that any pair of coordinates, such as A and B, may be identified by simply drawing a line between them and designating one side A and the other side B. If the points are just in two dimensions, then it is merely a line. If they are in two, a plane separates them, and if they are in three or more, a hyperplane does the same thing. The "best" line to split the points, determined by an SVM, is the one that creates the largest separation between the points and itself. That line is called the greatest margin hyperplane because it separates the sides while leaving the widest margin. When determining where to draw the line, it turns out that the majority of the points are irrelevant since they're so far away. As only the nearby points are relevant, we call them the support vectors because they "support" the location of the line.

Convolutional Neural Network (CNN):

[17] Neural Nets are brain models that have been simplified. Neurons, which can be active or inactive, and synapses, which link the neurons together, are present in the brain. Simple boolean values are used to represent neurons, while little integers between -1 and 1 are typically used to represent synapses. The state of a neuron is determined by the "weight" of all its connected synapses. An input layer, one or more hidden layers, and an output layer are the layers that make up a neuron. The input layer contains a representation of the information we're trying to learn. The weights of the neurons in the layer below are affected by these activated neurons. These weights have an impact on the activity of the neurons in that layer, which has an impact on the weights in the next layer, and so on. At some point, the output layer of the network generates a prediction. If the forecast is wrong, we adjust the weights of the network until it starts to predict tasks accurately. The most popular kind of neural network for analyzing visual images is CNN. A multi-layer perceptron variant used by CNNs was created to need the least amount of preprocessing possible.

Bayesian networks are graphical representations of the probabilistic relationships between a set of attributes [18], [19]. A collection of conditional probability tables is combined with a directed acyclic graph of nodes and connections to create the network's structure. Each node in the network has a matching probability table that presents the conditional probability distribution of that node given its parental nodes. A node's probability distribution is unconditional if it has no parents, but if it has one or more parents, it is a conditional distribution, meaning that the likelihood of each attribute depends on the parent values. The structure of a Bayesian Network can be inferred from a given training set using a suitable training method [19]. The Naive Bayes algorithm is probably the one in this class that is used the most. Simple learning incorporates the presumption that each attribute is independent of the other attributes considering the state of the class attribute.

ANNs (Artificial neural networks) are parallel computational models with highly connected, flexible processing units that have an innate propensity to both learn from the past and unearth new information. An ANN is made up of several units (neurons), which are connected in a specified way. By adding up the values of the inputs it receives, an artificial neuron mimics how a biological neuron function. It transmits its signal to its output, which is subsequently received by other neurons if this is greater than a certain threshold. A neuron need not give each of its inputs the same amount of weight, nevertheless. The network is trained on a set of paired data in the first stage of the classification process to establish the input-output mapping and then fix the weights of connections between neurons. In the subsequent phase, the classifications of new data are determined by the network [20].They often outperform other categorization approaches in terms of efficiency and accuracy because of their great capacity for self-learning and self-adaptation [17], as a result, have undergone substantial research and are widely applied in numerous fields. However, the fundamental drawback of ANNs is the computational expense of the training process, which may be very time-consuming.

According to [21]**decision trees** are one of the most popular and commonly utilized models for supervised categorization learning. They use a set of training examples and a recursive construction to build a model with a tree structure that separates examples into different categories. Decision trees have the benefit of developing models that are simple to understand since they can be depicted as influence diagrams and may graphically illustrate the choices to be made, the events that may happen, and the consequences linked to combinations of decisions and events.

3. Types of Anxiety disorder

As per several research studies, Panic Disorder, GAD (Generalized Anxiety Disorder), Obsessive-Compulsive Disorder Post-Traumatic Stress Disorder, Social Anxiety Disorder, PD (panic disorder), ST (Suicidal Tendency), SAD (Social mental disturbance), and AG (Agoraphobia) are few anxiety disorders.

Figure 2: Types of Anxiety Disorders

GAD is described by a persistent, excessive, and irrational preoccupation with commonplace matters. This worry could be caused by issues with money, health, family, or the future. It is overpowering, hard to manage, and usually followed by a broad range of generalized physical and psychological symptoms. It continues for almost six months. Along with restlessness, fatigue, difficulty concentrating, irritability, increased muscle tension, and trouble sleeping, anxiety may also cause you to feel these other symptoms.

Panic Disorder:

[22] It affects up to 5% of subjects at some point in their life. When agoraphobia causes difficulties, is linked to severe functional morbidity, and lowers the quality of life. As noticed by growing healthcare expenditures, increased absenteeism, and lower employee productivity, the condition is also costly to individuals and society. Although certain medical diseases, such as asthma, and some lifestyle factors, such as smoking, increase the risk for the illness, the precise processes behind it are yet understood.

Social Anxiety Disorder:

A chronic mental condition wherein encounters with others cause irrational anxiety. During typical social interactions, people with social anxiety disorder feel irrational concern, dread, self-consciousness, and humiliation. Possible symptoms include excessive fear of judgment, anxiety over humiliation or disgrace, or tension about offending someone. [23] SAD is the most common kind of anxiety. It often appears at a young age—by age 11 in around 50% of cases and by age 20 in approximately 80% of cases—and is linked to subsequent mental illness and drug addiction. Insula and amygdala activity is greater in those with social anxiety disorder, according to functional neuroimaging studies, and genetic research is increasingly focusing on this and other core traits (i.e., personality trait neuroticism) to identify risk loci.

Post-Traumatic Stress Disorder:

It is marked by strong responses to memories of a traumatic event that don't go away, a change in mood, a sense of impending danger, trouble sleeping, and being on high alert all the time.

Anxiolytics, antidepressants, and cognitive behavioral therapies can all help to lessen discomfort [24].

Agoraphobia is characterized by a dread of and avoidance of places or situations that may cause distress and feelings of immobility, helplessness, or embarrassment. For example, you could be afraid of using public transportation, being in limited or open spaces, standing in line, or being among lots of people. [25] Although there has been extensive research on the effectiveness of psychological treatment for PD with/without agoraphobia, it is still unclear what role specific strategies like exposure, cognitive therapy, relaxation training, and breathing retraining play. This research includes a meta-analysis of 65 comparisons between a treatment and a control group drawn from 42 papers published between 1980 and 2006 using random- and mixed-effects models.

4. Methods

According to PRISMA criteria, the search strategy was focused on choosing relevant peer-reviewed papers using all appropriate combinations of the terms and phrases below [26]: 'Machine Learning,' 'depression, 'GAD,' 'PD,' 'obsessive-compulsive disorder, 'PTSD ', ‘SAD’, ‘social phobia,' as well as the general terms "detection", "prediction. Each report's citation list was further checked for other research in addition to these computerized searches. These were the inclusion criteria: (1) Specific cases of any anxiety disorder (2) Geographically aligned studies (3) Age and gender-specific studies (4) Different or multiple approaches to identify any type of anxiety disorder (5) Machine learning algorithms were used to detect any sort of anxiety Using any dataset is not restricted. We chose papers from 2014 to May 2023 because we were interested in the most recent technical advances, like using machine learning and AI to spot anxiety illnesses.

5. Machine Learning Algorithms For Detection And Prediction Of Anxiety Disorders

Elif et al. in [27] has looked at using artificial intelligence approaches to evaluate people who have anxiety disorders. The authors have further analyzed recent research studies on anxiety and its different type. AI techniques yield critical information to diagnosis and clinicians with the help of diagnosis, personalized treatment, and prognosis. Five types of disorders are identified and as elaborated in previous sections were studied using the databases of DSM -5: “Diagnostic and Statistical Manual of Mental Disorders”.

[28] Here are some instances of machine learning techniques that might be used in the study of anxiety disorders:
• Identification or identification of an anxiety disorder
• Prognosis of future anxiety disorder risk.
• Predicting how medical therapy for an anxiety problem will work.

Machine learning algorithms may classify the existence or absence of a certain anxiety disorder, risk levels, or therapy response levels.

In Figure 3 classification process is explained. A variety of sources, such as demographic information, health records, medical histories, various measuring devices, etc., can be used to gather data. The data may be used to extract a large number of features, and significant features can be chosen using a suitable feature selection technique. The classifier's training and testing data sets make up these characteristics. The last phase involves choosing and fine-tuning a good classifier based on performance measures from the training data set.

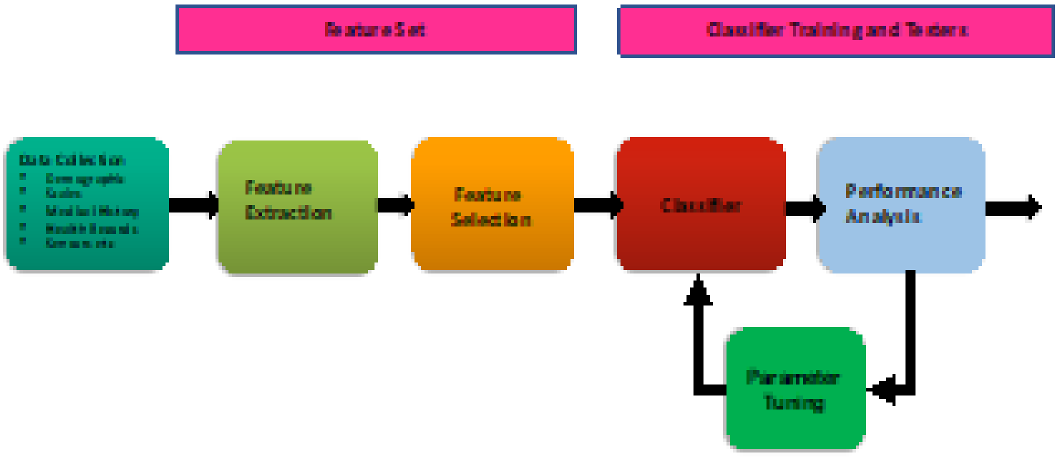

Figure 3: Classification of anxiety disorders Image reference

Elif et al. [27] has looked at using artificial intelligence approaches to evaluate people who have anxiety disorders. The authors have further analyzed recent research studies on anxiety and its different type. AI techniques yield critical information to diagnosis and clinicians with the help of diagnosis, personalized treatment, and prognosis. Five types of disorders are identified and as elaborated in previous sections were studied using the databases of DSM -5. Authors in [27] have identified 30 different algorithms to validate the detection. One of the most important algorithms of AI. The Random Forest Algorithm has been studied extensively and few comparisons are made among different algorithms.

[3] has discussed approaches to detecting anxiety disorder as well as depression using supervised learning. To diagnose the different levels of mental syndrome author has proposed a model which leverages the standard psychological assessment and ML algorithms. In developing nations, depression and anxiety are two of the main factors that contribute to significant impairment. The author has studied 5 different algorithms to detect anxiety disorders viz

- CNN
- SVM
- Linear discriminant analysis

• k-NN Classifier
• Linear Regression on the two datasets of depression and anxiety

ELECTRODERMAL (EDA): UTILIZING A DEEP NEURAL NETWORK AND AN AUTOENCODER NETWORK

[29] This alarming problem necessitates early diagnosis and treatment, particularly for adolescent students with these disorders, who frequently go undiagnosed and impeding their development during a pivotal period of their lives. An inexpensive automated system, like EDA (electrodermal analysis), may aid in the early diagnosis of depressive disorder. To identify the degree of depression in 38 university students, this research covers the creation of EDA-based machine learning employing AEN (Autoencoder Networks) and DNN (Deep Neural Networks). The five types of depression were classified using the developed AEN and DNN algorithm with testing and training accuracy of 94.5% and 96.5%, total network accuracy of 92.0% and 94.0%, and good specificity and sensitivity rates.

EFFECTIVE AUDIO-BASED AUTOMATIC DEPRESSION DETECTION (ADD)

[30] Depression is a significant psychiatric condition that affects many individuals and requires prompt treatment and diagnosis. In severe cases, the illness may lead to suicide ideation. Recently, the research community has become increasingly aware of the importance of developing an effective audio based ADD: "Automatic Depression Detection" system. The majority of depression-identification methods disclosed to date rely on manually extracted audio data features. They take into account a wide range of audio-related factors to improve categorization performance. However, adding several manually created characteristics, both relevant and extraneous, could enlarge the feature space and cause problems with high dimensionality, since not all of the characteristics would contain essential depression-related information. High feature counts can make it more difficult to identify patterns and raise the risk of overfitting. To get beyond these restrictions, we describe an audio-based framework for depression diagnosis that applies an adaption of the DL technique to automatically extract the most relevant and condensed feature set. The end-to-end CNN-based Autoencoder (CNN AE) approach is used in this suggested framework to extract the most significant and discriminative features from the raw sequential audio data, improving the identification of sad persons. We also use a cluster-based sampling strategy to solve the sample imbalance issue and greatly lower the likelihood of bias toward the dominating class (non-depressed). To assess the functionality and efficacy of the suggested pipeline, we do tests on the DAIC-WOZ (Distress Analysis Interview Corpus-Wizard of Oz) dataset and compare the outcomes to manually crafted feature extraction techniques and other noteworthy works in this area. The results show that the suggested technique beats established audio based ADD models by at least 7% in detecting depression.

APPLICATION OF AUTOENCODER IN DEPRESSION DIAGNOSIS:

[31] The DSM-IV-TR and ICD-10 are well-known questionnaires frequently used to diagnose depression. MDD (Major depressive disorder) sufferers and healthy controls (HC) can be distinguished using individual structural neuroimaging scans. In addition, it has been demonstrated that structural neuroimaging data can be used to diagnose depression in a multiethnic sample community. Combining neuroimaging data with machine learning techniques may be used to investigate an efficient method for diagnosing depression, as demonstrated by these studies. Using an autoencoder, the pre-training parameters of a method for dimensionality reduction employing a three-dimensional convolution network were learned. Our method performs the best in terms of classification compared to the other three feature extraction methods. The model may employ to identify conditions that resemble MDD.

MULTI AI ALGORITHMS TO DETECT ANXIETY DISORDERS:

The author in [3] determined the utility and efficacy of five distinct AI models: CNN, SVM, Linear discriminant analysis, k-NN Classifier, and linear regression on two anxiety and depression datasets. Our model's CNN algorithm achieves the maximum accuracy of 96% for anxiety and 96.8% for depression when comparing the results based on several measurement parameters (precision, accuracy, and recall). Our data also reveals that among Bangladeshi women between the ages of 18 and 35, 7.4% have severe anxiety and 15.6% experience chronic depression.

STACKED SPARSE AUTOENCODER AND MACHINE LEARNING BASED ANXIETY CLASSIFICATION USING EEG

SIGNALS

[32] Anxiety is caused by tension and a sense of unease, heaviness, and hopelessness, according to the definition. Statistics show that only 2% to 4% of the general population exhibits severe symptoms of anxiety disorders. With increased performance, the author of this paper has identified anxiety levels using DL and ML models. The DASPS Database (Database for Anxious States based on a Psychological Stimulation), which is open to the public, is used in this work. The dataset consists of EEG recordings taken when 23 people were exposed to psychosocial stimuli that caused anxiety. To enhance outcomes and eliminate feature redundancy, this study employs RFECV with the classifiers. We get the highest classification accuracy of 83.93 percent and 70.25 percent for two-class anxiety classification using Stacked Sparse Autoencoder and DT, correspondingly.

APPLICATION OF AUTOENCODER USING PRE-TRAINING PARAMETERS

[33] A minimum of two weeks of widespread depression are required for the diagnosis of MDD. Using resting-state fMRI data to diagnose MDD is difficult because of the high dimensionality, small sample size, noise, and individual heterogeneity. To diagnose MDD, no approach can automatically identify differentiating information from the fMRI images' origin time series. In this study, we put forth a fresh approach to feature extraction along with a methodology that

enables feature extraction and classification to be done automatically without any prior information.

• 3-D convolution network-based dimensionality reduction method’s pre-training parameters were learned using an autoencoder. The author's approach has produced the greatest classification accuracy when compared to the other three feature extraction techniques. This approach can be used to diagnose other illnesses that are similar to MDD as well.

The data set used: two classical questionnaires (DSM-IV-TR and ICD-10)

PREDICTION OF GENERALIZED ANXIETY LEVELS USING SVM

[34] Many countries implemented precautionary measures, such as complete lockdowns, in response to the Covid-19 pandemic's fast spread. The degree of anxiety around the world has increased as a result of these lifestyle changes. Therefore, efforts to prevent oncoming public mental crises are urgently needed by decision-makers. Machine learning can effectively predict many diseases at an early stage. This research uses data gathered in Saudi Arabia during the Covid-19 outbreak to categorize early two- and three-class anxiety disorders. To gather the data, 3017 participants from all across the Kingdom took part in an online survey that asked questions from the GAD-7, a diagnostic instrument for generalized anxiety disorders, as well as questions on variables that impact anxiety levels. It was decided to create the prediction models using the J48 Decision Tree due to its interpretability and understanding as well as the Support Vector Machine classifier's dependable results in medical data. The findings of an experiment were promising for the early categorization of two- and three-class anxiety disorders. The SVM classifier performed better than the J48 Decision Tree, with 100% classification accuracy, 1.0 precision, 1.0 recall, and 1.0 f-measure with 10 features.

Audio based anxiety disorder detection:

[28] Pitch, speaking tempo, articulation, and certain spectral and timing qualities, among others, might provide information about a sad individual. You may use these audio signal features to forecast speech anxiety as well. As a result, it is possible to determine a person's emotional state from their audio conversations and talking on social media, and such hints may be useful in the early diagnosis of depression and anxiety. The author in [28] has done research on the diagnosis of anxiety disorders via video was also emphasized. TikTok videos, video chatting, and other social media activities can all aid in the identification of anxiety or sadness. Face identification models may be used to recognize and track faces in the video, and facial indications like head movements, eye movements, etc. may be utilized as possible anxiety and stress indicators. Recently, considerable work has been performed in this region.

6. Results And Discussion

[31] used a 3-D convolution network, Automated Anatomical Labeling (AAL) template using fMRI (functional magnetic Image Resonance) as a dataset. They determined the presence of serious depression. DSM-IV-TR and ICD-10 are two well-known questionnaires used for

diagnosis. Participants in this study were 24 major depressive disorder patients (8 males and 16 females; average age: 51.2 10.6 years; range: 24 to 65 years) and 24 HC (8 males and 16 females; average age: 47.8 11.0 years; range: 25 to 65 years. They used Sparse Autoencoder, Linear Support Vector Machine algorithm, and Spectral dynamic causal model (spDCM) to estimate the effective connectivity.

[2]used mobility traces, imaging biomarkers, and multi-modal fusion of audio, video, and text to detect depression using CNN and SVM. It has been determined that the sparse imaging dataset on depression is what is to blame for the seeming lack of progress in the field.

[34] using a dataset gathered in Saudi Arabia during the Covid-19 outbreak allowed for the early classification of two- and three-class anxiety issues. To conclude the data, they employed the J48 decision tree and SVM. With the use of correlation-based feature selection, the most significant features were assessed. By achieving a classification accuracy of 100%, precision of 1.0, recall of 1.0, and f-measure of 1.0 utilizing 10 features, the SVM classifier beat the J48 DT.

[35]used fMRI (functional magnetic Image Resonance) Voting classifier using RF, SVM, and Logistic Regression models was used to analyze people with clinical anxiety at age 14 (N = 156) and HC (N = 424). They found that while MRI regional volumes improved the prediction performance of GAD, they did not improve the prediction performance of prospective pooled anxiety disorders with respect to psychometric features alone. The caudate and pallidum volumes were among the most important contributing features.

[36] used Alternating Decision Trees they discovered a brief question-set that evaluates the likelihood of an anxiety condition, which might be the first step in creating and validating a quick screening tool appropriate for use in pediatric clinics and daycare/preschool settings.

[37]Based on a Lifeline sample of 11,081 Dutch people's data, for AP, GAD, SAD, and PD, the model's AUC values were 0.9515, 0.9228, 0.8737, and 0.9596, correspondingly. This study's goal was to rank biomarker traits in connection to the various forms of interest-group anxiety disorders (i.e., AP, GAD, SAD, and PD) using machine learning methods and variable significant calculations. The variable-important hierarchy of biomarker characteristics is established using the variable importance retrieved from multiple models. They used the Generalized Linear Model, Random Forest, SVM, Gradient Boosting Model, and Neural Net. Author has extracted the variable importance hierarchy of the biomarkers with respect to each type of anxiety disorder and found significant and low correlations between GAD, AP, PD, and SAD. This information will help design the experimental setup for clinical trials involving the influence of the biomarkers on the type of anxiety disorder. The first result is that the four anxiety disorders of concern are connected, although weakly (ranging from 0.17 between agoraphobia and GAD to 0.3 between agoraphobia and panic disorder). This demonstrates the rarity of co-occurring anxiety disorders. According to the combined machine learning findings, the biomarkers within

each of the four clusters of biomarkers were discovered to be related to the four anxiety disorders of interest. Third, when integrating the relevant anxiety illnesses into a single "anxiety disorder," the author found similar biomarker traits from all four biomarker clusters.

[38]After 127 engineering students were given this questionnaire, the degree of anxiety was measured, and its sources and consequences were determined. The dataset was subsequently put through a number of statistical validity and reliability tests. After being trained on existing data sets, ML methods are then utilized to classify the anxiety level based on its consequences. The accuracy for the SVM, NB, DT, RF, and other techniques was 75.5 percent, 71.05 percent, and 78.9 percent, correspondingly. These techniques were used in addition to one another by the author. The Cronbach's alpha for the whole dataset was determined to be 0.723, while the dataset's Pearson correlation coefficient was determined to be 0.823.

[39] has employed MD without GAD ($n = 14$), GAD ($n = 19$), and HC patients ($n = 24$). The sample was free of psychopharmacological medications and matched for age, sex, handedness, education, and gender. machines with binary support vectors. The data from the questionnaire were suitable for classifying cases but not disorders (accuracies: 96.40%, p .001; 56.58%, $p >.22$). The imaging data (case-classification GM/WM: 58.71 percent, $p =.09$; 43.18 percent, $p >.66$; disorder-classification GM/WM: 68.05 percent, $p =.034$/58.27 percent, $p >.15$) showed the opposite trend from the cortisol data (38.02 percent, $p =.84$; 74.60 percent, $p =.009$). With the combined data, cases were categorized with 90.10% accuracy (p.001), whereas diseases were categorized with 67.46% accuracy ($p =.0268$).

[5]A t-test on independent samples was carried out to compare the statistical differences between the two categories. With a p-value of 0.05, 11 out of the 23 characteristics displayed a statistically significant variation in the mean. When 8 Principal Components (PCs) were taken into account for the PCA on the dataset, 95% of the information was retained. For additional analysis, the author trained all models on 8 PCs. The number of datasets for testing and training increased as datasets were divided into smaller periods (5,10, and 30 minutes). For both segmented dataset types, ECG and respiratory signal characteristics were employed to train ML models. The author employed SVM, k-NN, DT, and Logistic regression. The resulting properties of the ECG signal can be utilized to detect ADy in people with anxiety disorders. Although it will need a lot of datasets and processing time and might not yield the greatest classification accuracy, a deep neural network-based model can also be utilized. 11 estimated traits were determined to be statistically important for the classification out of the 23 total criteria. We separated the signals into 5-, 10-, and 30-minute intervals to construct generalized models. Ensemble techniques like boosting were used to correct data imbalance. The RF, SVM, and Gradient Boosting classifiers demonstrated the highest levels of accuracy for segmented datasets of 10 and 30 minutes (AUC = 0.76, 0.81, and 0.84; cross-validation accuracy of 81.64%, 82.2%, and 79.06%).

7. Challenges And Findings

The author in [6] has highlighted the below challenges in leveraging medical imaging algorithms in the early detection of anxiety disorder.

1) Lack of datasets or very tiny datasets is the main problem with efforts in diagnosing and predicting MDD using medical imaging. On a large dataset, other strategies have worked, but they haven't made much progress.

2) We also observed the mapping of a link between movement patterns and melancholy mood using smartphone-derived mobility data. The work only employed GPS data as its only modality, but there is plenty of room to also incorporate data from other sensors and apps.

3) All of the research in the section on neuroimaging employed essentially the same features, but with the expansion of the data bank, we may now observe new methods. The availability of larger datasets will determine the future directions for these types of investigations.

4) Detecting depression using multimodal auditory, textual, and visual cues has not seemed to be very ground-breaking either. However, considering that it is still in its early stages, there remains hope for the near future.

5) When compared to the exciting advancements in other medical diagnostic disciplines, work on the early detection and effective treatment of depression using medical imaging data seems to be significantly trailing. Considering the effectiveness of CNNs for classification tasks in various medical diagnosis sectors. We require further ML algorithms before we can make any innovative advancements.

Figure 4: Challenges of Machine learning and deep learning in detecting anxiety disorder

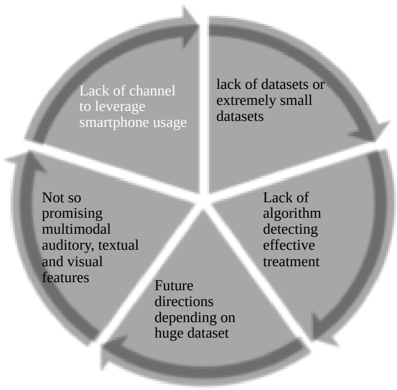

Figure 4: Challenges of Machine learning and deep learning in detecting anxiety disorder

8. Future Direction

According to the author in [6] below are a few parameters that play a pivotal role in shaping the research in detecting anxiety disorder using machine learning and deep learning.

Sample Size:

Due to the lack of medical imaging data, fMRI samples must be of comparable size to those of other maladies. The study is unable to test alternative methods and characteristics due to the lower dataset restriction. The analysis of the fMRI datasets reported in the earlier research makes this extremely clear. A bigger sample size for future research would be possible if there is an open-access repository with international contributors. This would enable scientists and medical experts from across the world to work together to produce a far larger dataset. In turn, this may have an impact on the test and training set, increasing the accuracy and reliability of any model that was eventually created and moved on to clinical testing.

Clinical Application:

There have been a lot of studies done on sadness, but it's not clear how useful they are. If the aforementioned problems are resolved, perhaps in the future it will genuinely help with clinical diagnosis. The range of applications and systems that might not only support clinical processes but also help with depression, which is still mainly underdiagnosed and undertreated would go a long way toward reducing an illness that looks to be on an exponential increase in this fast-evolving century, but also be directly supplied to the non-clinical population.

Mobile Computing:

Mobile devices' widespread usage may allow researchers to find previously unrecognized insights. Future research may include information from more sensors and create a program that not only gathers data but also communicates with people in an intelligent way [22].

Imaging Data:

The cost of doing fMRIs has been the main factor holding back progress in the diagnosis of neurological disorders utilizing ML. fMRI is a costly and sophisticated imaging method that can only be performed by a few number of qualified medical personnel. As a result, additional modalities should also be investigated in the research. The potential of fusion models for text, video, and audio is something we can take note of. Given the developments in affective computing and human-computer interaction, it would also be quite surprising if these technologies would not soon converge with medical diagnostics.

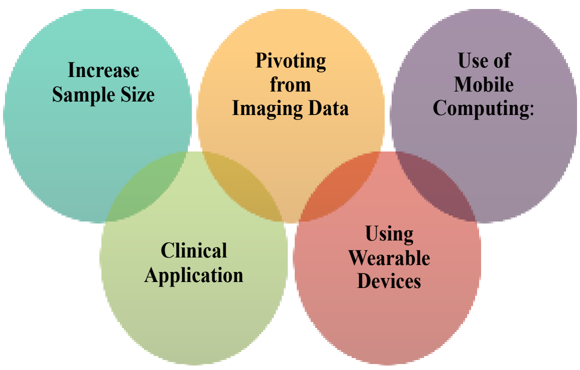

Figure 5: Future direction

Shortly, wearable technologies that can analyze ECG waveforms in real time may be able to give a more thorough examination of AD during the day. Thus, it is anticipated that clinical medicine and outpatient treatment would place a greater emphasis on wearable technology that may noninvasively detect AD. Most ECG analysis techniques have been very straightforward, and the field of utilizing ECG signals to detect (or monitor) various kinds of AD is still relatively young. The statistics show that many published results that examined the relationship between ECG characteristics and AD are inconclusive and that much of the research used relatively small sample sizes. The majority of researchers simply employed ECG signals, although a handful also used additional bio signals.

9. Conclusions

We may infer that extensive research has been done on machine learning algorithms for anxiety prediction. However, in the future, we could be able to attain greater accuracy ratings, which might result in improved patient care assistance.

10.Acknowledgment

We thank the Directorate of Research and Innovation (DORI) CMR University for training and support. The research is funded by the CMRU student research & innovation fund.

References

1. C. Su, Z. Xu, J. Pathak and . F. Wang, "Deep learning in mental health outcome research: a scoping review," Translational Psychiatry, vol. 10, no. 1, 2020.
2. P. Kharel, K. Sharma, S. Dhimal and S. Sharma, "Early Detection of Depression and Treatment Response Prediction using Machine Learning: A Review," Second International Conference on Advanced Computational and Communication Paradigms (ICACCP), pp. 1-7, 10.1109/ICACCP.2019.8882891 2019.
3. A. Ahmed, R. Sultana, M. T. R. Ullas, M. Begom, M. M. I. Rahi and M. A. Alam, "Md. Ashraful," in 2020 IEEE Asia-Pacific Conference on Computer Science and Data Engineering (CSDE), 10.1109/CSDE50874.2020.9411642, 2020, pp. 1-6.
4. B. N. Teelhawod, , F. Akhtar, M. B. B. Heyat, P. Tripathi, R. Mehrotra, A. B. Asfaw, O. A. Shorman and M. Masadeh, "Machine Learning in E-health: A Comprehensive Survey of Anxiety," in 2021 International Conference on Data Analytics for Business and Industry (ICDABI), 10.1109/ICDABI53623.2021.9655966}, IEEE, 2021, pp. 167-172.
5. A. Saj George, A. Vijayanatha Kurup, P. Balachandran, M. Nair, S. Gopinath, A. Kumar and H. Parasuram, "Predicting Autonomic Dysfunction in Anxiety Disorder from ECG and Respiratory Signals Using Machine Learning Models," International Journal of Online and Biomedical Engineering (iJOE), vol. 17, no. 7, p. 143–155., 2021.
6. M. Elgendi and C. Menon, "Assessing Anxiety Disorders Using Wearable Devices: Challenges and Future Directions," Brain Sciences, vol. 9, no. 3, 1 March 2019.
7. M. Rana and M. Bhushan, "Machine learning and deep learning approach for medical image analysis: diagnosis to detection," ultimedia Tools and Applications, 2022.
8. S. Mallick and M. Panda, "Application of Deep Learning in Mental Disorder: Challenges and Opportunities," pp. 295-308, Jan 2022.

9. K. Bhatt and S. M. Kumar, "DEEP LEARNING DATA AUGMENTATION MODEL AND METHODS USED IN MEDICAL IMAGE SEGMENTATION," IJRAR - International Journal of Research and Analytical Reviews (IJRAR, vol. 10, no. 2, April 2023.
10. I. Sarker, "Deep Learning: A Comprehensive Overview on Techniques, Taxonomy, Applications and Research Directions," SN COMPUT. SCI, vol. 2, no. 6, p. 420, 18 August 2021.
11. F. Altaf, S. M. S. Islam, N. J. Akhtar and N. K. Anjua, "Going Deep in Medical Image Analysis: Concepts, Methods, Challenges, and Future Directions," vol. 7, pp. 99540-99572, 2019.
12. R. Yousef, G. Gupta, N. Yousef and M. Khari, "A holistic overview of deep learning approach in medical imaging," Multimedia Systems, vol. 28, no. 3, 2022.
13. S. Shurrab and R. Duwairi, "Self-Supervised Learning Methods and Applications in Medical Imaging Analysis: A Survey," PeerJ Computer Science, vol. 8, p. e1045, 20 07 2022.
14. J.Jiang, P.Trundle and J.Ren, "Medical image analysis with artificial neural networks," Computerized Medical Imaging and Graphics, vol. 34, no. 8, pp. 617-631.
15. K. Balasubramanian and N. L.A., Machine Learning and Deep Learning Techniques for Medical Science, Boca Raton: CRC Press, 2022, p. 412.
16. D. Nie, Y. Gao, L. Wang and D. Shen, "ASDNet: attention based semi-supervised deep networks for medical image segmentation," in International conference on medical image computing and computer-assisted intervention, Springer, 2018, pp. 370--378.
17. T. Kotsilieris, E. Pintelas, I. Livieris and P. Pintelas, "Reviewing machine learning techniques for predicting anxiety disorders," Research Gate, october 2018.
18. F. V. Jensen, "An Introduction to Bayesian Networks,," 1996.
19. T. Mitchell, Machine learning, 1997.
20. C. Bishop, Neural Networks for Pattern Recognition, Great Clarendon street: Oxford university press, 1995.
21. L. Rokach and O. Maimon, "Data mining with decision trees: theory and applications,," in Machine Perception and Artificial Intelligence, vol. 69, World scientific.
22. P. P. R.-B. a. M. G. C. a. M. B. Stein, "Panic disorder," The Lancet, vol. 368, pp. 1023-1032, 2006.
23. M. B. S. a. D. J. Stein, "Social anxiety disorder," The Lancet, vol. 71, pp. 1115-1125, 2018.
24. M. I. L. M. a. C. M. M. Arieh Shalev, "Post-Traumatic Stress Disorder," NEJM, 22 June 2017.
25. A. I. R.-A. F. M.-M. A. G.-C. ulio Sánchez-Meca, "Psychological treatment of panic disorder with or without agoraphobia: A meta-analysis, Clinical Psychology Review," vol. 30, no. 1, pp. 37-50, 2010.
26. A. Liberati, D. Altman, J. Tetzlaff, C. Mulrow, P. Gøtzsche, J. Ioannidis, M. Clarke, P. Devereaux, J. Kleijnen and D. Moher, "The PRISMA Statement for Reporting Systematic Reviews and Meta-Analyses of Studies That Evaluate Health Care Interventions: Explanation and Elaboration," PLoS Med., vol. 6, pp. 1-28, 2009.
27. E. Altıntaș, Z. Uylaș Aksu and G. D. Zeynep, "Machine Learning Techniques for Anxiety Disorder," Avrupa Bilim ve Teknoloji Dergisi, no. 31, pp. 365 - 374, 2021.

28. M. a. B. A. a. M. G. a. S. T. a. A. N. a. A. N. a. A. M. Arif, "Classification of anxiety disorders using machine learning methods: a literature review," Insights Biomed Res, vol. 4, no. 1, pp. 95-110, 2020.
29. V. Sharma, N. Rup Prakash and P. Kalra, "Depression status identification using autoencoder neural network," Biomedical Signal Processing and Control, vol. 75, p. 103568, 2022.
30. S. Sara, N. Bahareh, N. R. Mohammed and E. Peter, "Audio based depression detection using Convolutional Autoencoder," Expert Systems with Applications, vol. 189, p. 116076, 1 March 2022.
31. G. Xiang-Fei and . X. Jun-Hai, "Application of Autoencoder in Depression Diagnosis," 3rd International Conference on Computer Science and Mechanical Automation (CSMA 2017).
32. S. M. Agrawal, M. A. Anwar and . D. Sethia, "Stacked Sparse Autoencoder and Machine Learning Based Anxiety Classification Using EEG Signals," ACM Digital Library, 10.1145/3486001.3486227 2021.
33. X.-F. a. X. J.-H. Geng, "Application of autoencoder in depression diagnosis," DEStech Trans Comput Sci Eng (csma), pp. 146--151, 2017.
34. F. Mashel Albagmi, A. Alansar, D. Saad, H. Yaagoub AlNujaidi and S. O. Olatunji, "Prediction of generalized anxiety levels during the Covid-19 pandemic: A machine learning-based modeling approach," Informatics in Medicine Unlocked, vol. 28, p. 100854.
35. A. V. e. a. Chavanne, "Anxiety onset in adolescents: a machine-learning prediction," Molecular Psychiatry, Vols. https://doi.org/10.1038/s41380-022-01840-z, 8 December 2022.
36. S. P. C. R. S. G. E. H. Carpenter KLH, "Quantifying Risk for Anxiety Disorders in Preschool Children: A Machine Learning Approach," PLOS ONE, vol. 11, no. 11, 23 November 2016.
37. V. W. Sharma A, "Understanding importance of clinical biomarkers for diagnosis of anxiety disorders using machine learning models," PLoS ONE, vol. 16, no. 5, 10 May 2021.
38. J. A. O. R. S. Shaurya Bhatnagar, "Detection and classification of anxiety in university students through the application of machine learning," rocedia Computer Science, vol. 223, pp. 1542-1550, 2018.
39. K. L. U. M. M. B.-B. K. Hilbert, "Separating generalized anxiety disorder from major depression using clinical, hormonal, and structural MRI data: A multimodal machine learning study," Brain Behav., vol. 7, 2017..