Detecting Anxiety via Machine Learning Algorithms: A Literature Review

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Abstract—Recent machine learning (ML) advances have opened up new possibilities for addressing various challenges. Given their ability to tackle complex problems, the use of ML algorithms in diagnosing mental health disorders has seen substantial growth in both the number and scope of studies. Anxiety, a major health concern in today's world, affects a significant portion of the population. Individuals with anxiety often exhibit distinct characteristics compared to those without the disorder. These differences can be observed in their outward appearance—such as voice, facial expressions, gestures, and movements—and in less visible factors like heart rate, blood test results, and brain imaging data. In this context, numerous studies have utilized ML algorithms to extract a diverse range of features from individuals with anxiety, aiming to build predictive models capable of accurately identifying those affected by the disorder. This paper performs a comprehensive literature review on the state-of-the-art studies that employ machine learning algorithms to identify anxiety. This paper aims to cover a wide range of studies and categorize them based on their methodologies and data types used.

Index Terms—Anxiety Disorder, Machine Learning, Artificial Intelligence, Mental Disorder, Social Signal Processing, Affective Computing.

1 INTRODUCTION

ANXIETY is defined as a natural response to stress or threats. It is characterized by feelings of worry, unease, or apprehension and is usually associated with physical reflections including an increase in heart rate, muscle tension, restlessness, etc [1], [2]. While anxiety can be helpful by preparing individuals for dangerous situations, when it becomes excessive or prolonged it is considered a disorder. Anxiety manifests itself in different forms including Generalized Anxiety, Panic Disorder, Social Anxiety Disorder, Specific Phobias, Obsessive-Compulsive Disorder (OCD), Post-Traumatic Stress Disorder (PTSD), Separation Anxiety, and Agoraphobia. There are biological similarities between stress, fear, and anxiety; however, the main difference is that fear occurs through external factors, stress is a situation in which an individual cannot respond adequately to environmental factors [3], whereas anxiety is an emotional state that results from the inability to cope with stress and fear-inducing situations [4] and depends on uncertain threats [5].

Anxiety disorder is a prevalent mental health concern, affecting around 4% of the world population [6], [7] (according to the WHO 2019 report). It is shown in studies that anxiety is correlated with negative behaviours and other mental health conditions including substance abuse, mood disorder, insomnia, depression, or suicidal tendencies [8], [9], [10]. Although the underlying causes of anxiety disorders remain unknown, several studies suggest they probably have a neurodevelopmental basis, and their initial symptoms begin to emerge during childhood [11], [12]. This means that early detection of anxiety is crucial in characterizing the mental health of individuals. However, the accuracy of clinical approaches in detecting GAD is fairly low [1], [2]. Several methods have been proposed in the literature to improve the accuracy of diagnosis which include using biomarkers [13], neuroanatomical predictors, cortisol levels [14], [15], and where neuroimaging or blood tests are not available, self-report screening measures [16].

Anxiety is an interesting subject to study as it occurs in two forms, state and trait anxiety. State anxiety is defined as a "temporary state influenced by the current situation where the respondent notes how he/she feels right now at this moment [17]", while trait anxiety is "a general propensity to be anxious where the respondent notes how he/she feels generally" [17]. Trait anxiety refers to an enduring characteristic of an individual's personality, reflecting a predisposition to perceive a wide range of situations to experience anxiety. State anxiety refers to a temporary emotional condition characterized by feelings of nervousness, worry, or apprehension in response to a specific situation or event. It is argued that the measurement of state anxiety can capture some degree of trait anxiety as individuals with higher levels of trait anxiety are more likely to experience heightened state anxiety. On the other hand, individuals with high trait anxiety are more likely to experience heightened state anxiety in certain situations due to their cognitive biases and susceptibility to anxiety disorders, as explained in Eysenck's cognitive theory. This suggests the existence of a complex interplay between the two constructs.

There are several ways in which anxiety can be measured, including self-report, physiological, and behavioural methods [18]. However, there is low concordance between these measures [19] which is multifaceted [18]. There are two main types of biases that affect anxiety measurements. One is the measurement biases that arise when different assessment methods are employed and the other is the attentional, interpretive and memory biases inherent in trait anxiety (as described in Eysenck's cognitive theory). Eysenck's model suggests that individuals with high trait anxiety typically display cognitive biases, such as an automatic attentional focus on threatening or anxiety-inducing stimuli, a tendency to interpret ambiguous situations as more threatening, and an enhanced memory for anxiety-related information. These biases are central to the experience of excessive anxiety and are not simply artefacts

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of measurement. Such low concordance is not peculiar to anxiety measurement but is a characteristic of all forms of psychology measurements. The issue of low concordance is complex and stems from multiple factors. These include the overlap of anxiety symptoms across various DSM disorders (as highlighted by the NIMH's history with the Research Domain Criteria initiative), the poor reliability of DSM diagnostic classifications, the arbitrary criteria and cutoff points used in the DSM, and the fact that behavioural measures can vary in validity depending on context (such as cultural values). Additionally, there is the flawed assumption that physiological markers can differentiate anxiety from other psychopathological phenomena.

Recently, Machine Learning (ML) techniques have developed to a great extent and have found applications in a variety of subjects [20], [21], specifically in healthcare [22], [23]. Employing ML approaches in clinical settings can provide increased accuracy and reduced diagnosis times. In the field of psychiatry, ML algorithms have been used in a wide range including the identification of depression [24], [25], people personality [26], sleep disorders [27], children attachment [28] etc.

Because anxiety manifests itself in a wide range of symptoms that can affect people, to identify anxiety, various clues from different sources can be used. The most apparent indicators of anxiety appear in one's facial expressions [29]. For example, it was observed that anxious people may exhibit decreased eye contact, higher blinking rate, gaze disturbances, change in face skin colour, change in lip movement, and higher head movement [30]. This led to the development of a series of research that process video signals and try to find clues and extract features from these signals. The other apparent change in people when anxious is observed in their voice quality. It was observed that anxiety is related to speech features like source, formant, emotional tones, and spectral properties [31]. Anxiety can manifest itself in the text people generate, suggesting Natural Language Processing (NLP) can be used to identify the disorder. Sentiment analysis is an NLP technique that uses ML algorithms to asses emotions in text data. Recent developments have revealed that NLP can successfully be used to detect depression and anxiety [32], [33]. Anxiety also leaves its footprints on more hidden characteristics of patients. It is shown in the literature that people with anxiety exhibit some abnormalities in their brain morphology and functional connectivity networks, for example, hyperactivity of the posterior cingulate cortex and precuneus regions is shown to be correlated with the level of anxiety [34]. These differences can be captured by tools like fMRI and used to identify the issue in patients. The existence of such a wide range of features that are representative of anxiety means that there is great potential for ML algorithms to be employed to build predictive models.

A set of relevant review papers in the field already exists targeting studies that use ML algorithms in mental health and anxiety detection. An overview of these papers has been presented in supplementary materials. While these papers cover a good range of studies, they are either focusing on specific domains, (e.g. anxiety in children, detecting anxiety using wearable devices, etc.), covering studies relative to other mental health issues (depression, stress, etc.) or they have covered a relatively small number of studies in the area. The work in this paper is distinct from the existing literature in the sense that it covers a large number of studies, only focuses on anxiety, and covers all types of data that are used for anxiety detection. In this paper, we tried to be as comprehensive as we could to cover all relevant papers and put them in the whole picture about detecting anxiety via ML algorithms. This paper contains a range of technical terms related to the algorithms and data types. A list of phrases and their description is provided in section III of the supplementary materials.

The rest of this paper is organized as follows. Section 2 reviews the papers that use ML algorithms for analysis. Section 3 provides an overview of the studies that use clinical test data to identify anxiety. In section 4, the group of works that use text data and Natural Language Processing techniques are presented. Section 5 performs a survey on the studies that use signals such as audio, video, or images to identify anxiety. The studies that use patients' background information, like demographic or lifestyle data are covered in section 6. In section 7, the works that collect data that capture the psychological characteristics of the patients are reviewed. In section 8 we cover the papers that use a mixture of features to train their ML model. Section 9 reviews the papers that use ML algorithms to treat people with anxiety, and finally, section 10 concludes the paper.

2 Using Machine Learning Algorithms for Analysis

While the main objective of this paper is to review the papers that use machine learning to identify anxiety in subjects, in some research, these algorithms have been used to analyze some aspects of anxiety. In this section, we cover this set of papers.

To identify the risk factors associated with anxiety, some demographic and general laboratory examination data were collected in [35], and then machine learning algorithms were used to analyze these data. The authors report the risk factors as well as the protective factors for the condition. Similar work was performed in [36], in which the variables that make students anxious were identified. It is known in psychology that depressive and anxiety disorders are highly co-occurring with overlapping symptoms that make the diagnosis a hard task. In [37], [38], the ML algorithms are used to identify the symptoms that are more representative of each of the disorders. To identify the attributes in EEG signals that demonstrate anxiety, in [39] ML techniques have been used. It is shown in this study that there are some differences in the frontoparietal regions in the brain of people suffering from anxiety to those of healthy people. It is believed that sleep patterns can affect anxiety. To study this, in [40] the sleep quality of subjects is studied along with their anxiety level, then ML algorithms have been used to find the relationship between these attributes.In [41], fMRI images are used and processed via deep learning techniques to identify functional connectivities in the brain and determine if there are coherent sub-types of anxiety that can be defined by these connectivities. These findings suggest the identification of specific risk factors can lead to more accurate treatment plans for individuals. By recognizing lifestyle and demographic factors that contribute to anxiety, preventive strategies can be designed to target at-risk groups, reducing the incidence of anxiety disorders. The identification of differences in brain activity between anxious and non-anxious individuals may lead to new insights into the neurological basis of anxiety, which could inform the development of new treatments or therapeutic interventions.

In order to identify salient features that are representative of Autism, Anxiety, or Psychosis, machine learning algorithms are used in [42]. In this work, the authors collect data from patients diagnosed with these problems and identify these features. Machine learning algorithms are used in [43], to understand the role of clinical bio-marker measures that are associated with anxiety. The authors outline the significant and low correlation features in their work. These suggest that the combination of identifying salient features and understanding biomarker correlations could lead to the development of more sophisticated diagnostic tools that integrate both behavioural data and biological markers.

It is argued in [44], that posts shared in terms of tweets contain valuable emotional information and can reflect social atmosphere and public opinion. To analyze changes in the social atmosphere both spatially and temporally, ML algorithms are used in the work to measure the changes in the anxiety level in society. In another work [45], ML algorithms are used to study the relationships between five personality traits and anxiety due to COVID-19. In this work, the authors use Twitter data to identify the level of anxiety and conclude that introverts experience a higher level of anxiety compared to extroverted individuals. These studies highlight the potential of using social media data as a barometer to monitor and respond to societal and individual mental health trends, especially during times of crisis. Also, these could inform the development of targeted mental health interventions based on personality traits and real-time social sentiment.

3 Test Data

It was shown in the literature that clinical characteristics such as comorbidity [46] , increased triglyceride, decreased HDL cholesterol [47], lower birth weight, older age at first walking [48], pain intensity, duration and severity [49], young age of onset [50], and parental history [51] can affect anxiety. This led many researchers to use these features in ML algorithms to identify anxiety. This section reviews these studies.

Blood Test: It was shown in many studies that inflammatory molecules, like chemokines and cytokines play roles in various brain processes including neurogenesis and cognition. Thus, these indicators may affect brain development and be associated with psychiatric disorders including anxiety [52], [53]. For example, immune system abnormalities have been observed in patients with anxiety disorders. In some research, these tests have been used to identify people with anxiety. In [54], immune system abnormalities are used as features in a machine learning algorithm, and a system is developed that predicts anxiety. In another work, serum levels of immune markers of blood are used to predict anxiety [55]. These studies collectively emphasize the significant role that inflammatory molecules such as chemokines and cytokines play in brain processes, including neurogenesis and cognition. This suggests that the immune system and its regulatory molecules are not only crucial for physical health but also deeply intertwined with mental health. Understanding these connections can lead to a more holistic approach to treating psychiatric disorders like anxiety. Also, the findings demonstrate the need for an interdisciplinary approach between immunologists, neuroscientists, and data scientists. While these studies establish a correlation between immune markers and anxiety, further research is needed to explore the causality of these relationships. Understanding whether immune dysregulation causes anxiety, or is merely a byproduct, is crucial for developing effective interventions. This requires longitudinal studies to assess how changes in immune markers over time are related to the onset or progression of anxiety disorders. These studies also can be expanded to include other psychiatric conditions, such as depression or schizophrenia, to provide insights into whether similar immune mechanisms are involved across different disorders or if they are specific to anxiety.

Clinical Features: Clinical data that are collected from patients in hospitals can, in some cases, be representative of anxiety conditions in people. In some works, these data are used to identify anxiety in patients. In [56], cancer-related clinical data are collected from cancer patients and are used as features to predict anxiety. In another work [57], electronic health records of patients, which include 59 biomedical features are collected from some students, and then a machine learning algorithm is used to predict the level of anxiety in these subjects. Neural networks have been used in [58], to predict the level of anxiety in pregnant women after they give birth. The paper uses a set of clinical parental features from these women. In [59], a machine learning algorithm is developed to identify anxiety in people suffering from epilepsy. Some clinical data from these patients, including type of epilepsy, seizure frequency, duration, etc. are collected and used as a feature in the diagnosis process. These demonstrate that clinical data from various medical conditions—such as cancer, epilepsy, and pregnancy—can be leveraged to predict anxiety. This means that anxiety can be linked to a wide range of clinical factors, highlighting the need to consider a broader context of a patient's health when assessing mental health conditions. These studies also highlight the importance of focusing on high-risk populations, such as cancer patients, pregnant women, and individuals with epilepsy.

These findings suggest that both blood tests and clinical features provide valuable insights into anxiety disorders. Blood tests offer biological markers like cytokines that reflect immune system involvement, while clinical data capture broader health-related factors. Integrating these approaches into a unified anxiety detection system could enhance the accuracy and personalization of predictions. By combining biological, clinical, and real-time physiological data, future systems could offer a more holistic and reliable method for diagnosing and managing anxiety.

4 Text Processing and NLP

People use social media platforms to communicate with others and to expose the difficulties they are facing including their mental health issues. The reason for such a tendency is multifactorial, from lack of access to treatments to shame, and loneliness. This allows researchers to dig into the data available on these platforms and extract valuable information that is related to people's mental health [32].

Texts From Blogs: In an attempt to measure the anxiety level of people from the texts they put in their blogs, in [60], [61], text processing approaches are used to extract features from blogs. The authors discover that there is a reverse relationship between perceived anxiety and outcomes like social anxiety. In another work [62], text data were collected from a Chinese social media platform, called Weibo, then a simplified Chinese linguistic inquiry was used to extract linguistic features from the text data. The authors argue that the method can predict anxiety with good accuracy. The discovery of a reverse relationship between perceived anxiety and outcomes suggests that how individuals express anxiety in their writing might not always align with their actual social anxiety levels. This highlights the complexity of anxiety as a construct and suggests that linguistic analysis could reveal nuanced aspects of mental health that may not be immediately apparent through self-report measures.

Text From Comments: In certain contexts, the comments people leave on online platforms can provide insights into their level of anxiety, particularly when these comments are analyzed in conjunction with other behavioural indicators and linguistic patterns. However, it's important to consider factors such as the platform's anonymity, the nature of the discussion, and the individual's communication style, which may influence the accuracy of anxiety detection. In [63], the comments posted on YouTube are analyzed to extract features for anxiety (for more details on the feature extraction methods please see Table II in supplementary materials). In this work, KNN, SVM, and some other ML algorithms are used to predict the level of anxiety. To automatically recognize anxiety, DAC stacking, a method that integrates stacking ensembles and Deep Learning is proposed in [64]. In this work, comments left on Reddit are used and their features are extracted to train the learning algorithms. In [65], comments left on Reddit are processed via NLP techniques to identify anxiety. The authors perform a comparative study and show that RF algorithms perform the best on these data. One main concern about the findings of these studies is the results can be prone to biases, particularly if the models do not account for the diverse ways in which people leave casual comments. The implications of being monitored through online comments could have psychological impacts on users, potentially increasing anxiety if not managed sensitively.

Text From Communications: People often convey subtle information about their internal feelings through various aspects of their communication, such as tone, word choice, and body language. Research has shown that these cues can sometimes reflect underlying emotional states, though the accuracy of such inferences can be influenced by factors like context, cultural norms, and the medium of communication (e.g., spoken language vs. written text). In [66], text data from spoken communication are collected, and then after applying text processing techniques, features are extracted to predict anxiety levels. In a similar work, in [67], the audio from communication data is transcribed and the text data are used to assess anxiety. Unlike written text, spoken communication often captures more spontaneous expressions of mental state. A multimodal approach—analyzing both the content of what is said (text) and how it is said (audio) could offer better assessments of anxiety. This could involve analyzing prosodic features like tone, pitch, and speech rate alongside the textual content.

Text From Emails: It is argued in [68] that the way people write their emails can reveal information about their level of anxiety. The authors use features like the usage of words, the topic, the sentiment of the message, and the style of writing to train their predictive model.

Text From Interviews: It is shown in some research that the communications in interviews and therapeutic sessions contain information that can be used as indicative of anxiety. In [69], messages from text-based therapy sessions are collected and processed to extract features. Then ML algorithms are used as predictive models. It is argued in [70] that around a third of veterans suffer from Post-Traumatic Stress Disorder (PTSD). To support these patients, texts are transcribed from interviews with the patients, and ML algorithms are used to predict their level of anxiety. This research demonstrates the critical importance of tailored mental health interventions for high-risk groups. This could help identify particularly vulnerable veterans in need of additional support. In [71], teleconference open-ended interviews were conducted with participants and the interviews were transcribed. The participants' level of anxiety was then measured via the GAD-7 scheme. Then SVM was used to classify these participants based on their level of anxiety.

Text From Social Networks: The content people share on social media is another indicator of their level of anxiety. In order to predict the level of anxiety in university students, NLP algorithms are used in [72] to extract features from the shared contents by the students on Facebook. Then machine learning algorithms are adopted to identify anxiety. Social Anxiety Disorder (SAD or social phobia), which is one of the most important mental disorders, is defined as a long-term, overwhelming fear of being in social situations. To identify this disorder, ML algorithms are used in [73] which process the features extracted from social network data. In [74], ML algorithms are used to identify the level of anxiety based on the positive and negative feedback people leave on social media. It is argued in this paper that negative feedback is representative of anxiety and positive ones is that of hope. In another work [75], texts from online psychological forums are used to identify anxiety in people. Social Appearance Anxiety (SAA) is the type of anxiety that occurs when people are exposed to images of others and get concerned about their own appearance. In [76], ML algorithms are adopted to extract features from social media contents and detect SAA in participants. This study highlights the significant role that social media plays in influencing individuals' concerns about their appearance. Exposure to images of others on social platforms can trigger anxiety related to self-image, demonstrating the powerful impact of social comparison facilitated by these platforms. The findings also suggest that the social media environment itself can influence anxiety levels, with negative feedback and social comparisons contributing to higher anxiety. This highlights the need for social media platforms to consider the mental health impact of their design and algorithms, potentially leading to changes that promote healthier interactions.

Text From Suicide Notes: Many people leave a note before they commit suicide. These notes usually contain valuable information about the mental state of people. In [77], 142 suicide notes are analyzed, and using NLP methods, their features are extracted to predict the level of anxiety among these people.

Text From Tweets In some research, tweets have been used to identify anxiety among people. In order to identify the level of anxiety in people, in [78]tweets were used to extract features for ML algorithms to identify the level of anxiety caused by COVID-19.

While NLP techniques can effectively extract features and predict anxiety, interpreting these results requires careful consideration of context. The way anxiety is expressed in text can be influenced by various factors, such as cultural norms, the platform used, or the purpose of the writing, which can complicate the analysis.

The analysis of text data from various sources, including blogs, comments, social networks, and even suicide notes offers a rich way of understanding and predicting anxiety. Each data source provides unique insights into how anxiety is expressed, whether through personal reflections in blogs, casual comments on social media, or formal communication in emails and interviews. However, these approaches also present challenges, such as interpreting context, cultural differences, and the influence of social platforms. By integrating insights from these diverse text sources, future systems could offer more comprehensive anxiety detection tools, potentially improving individual diagnosis and broader public health monitoring. A holistic approach that combines text data with physiological and clinical signals could further enhance the accuracy and depth of anxiety assessment.

5 SIGNALS

In many studies, some signals are collected from subjects and are then processed to extract features. These signals could be one-dimensional, examples of which include electrical signals from the brain or heart or voice signals, could be two-dimensional which usually are in the form of images, like fMRI images, or could be three-dimensional signals in the form of video or a series of images. In this section, we review this set of papers.

5.1 Bio-Signals

Bio-signals (physiological signals) are the type of multichannel readings that are collected from the central and autonomic nervous system [79]. These signals usually carry significant information about the inner state of people. Examples of these signals are cardiac activity, electrodermal activity, electromyographic activity, temperature, etc. A more comprehensive list of these signals can be found in Table II in supplementary materials. In [80], an anxiety recognition system is developed that uses fuzzy logic and regression trees to analyze cardiac and electrodermal activities to measure the level of anxiety in people. It is argued in [81], that people with social anxiety produce excessive catecholamine which leads to an increase in arterial blood pressure. The authors use this feature, along with pulse transit time to predict the level of anxiety in subjects. The variety of bio-signals mentioned suggests that a multi-modal approach, which combines several physiological measures, could provide a comprehensive assessment of anxiety.

Another signal that can convey valuable information about anxiety is respiratory information. In [82], time and frequency statistics of respiratory signals are used to extract features. The features are then used in an SVM algorithm that measures the level of anxiety. This study opens opportunities for interdisciplinary research, combining expertise from fields such as psychology, respiratory physiology, and machine learning leading to the development of more comprehensive models offering a more holistic approach. Future research could investigate how different types of anxiety manifest in respiratory patterns.

Electrocardiogram (ECG) signal is used in [83] to extract features, and then are fed to an SVM algorithm to detect physiological changes that are related to anxiety. In another work [84], in order to automate the detection of real-time social anxiety, subjects are asked to use an online platform and present to a group audience. Then, their level of anxiety is predicted via SVM based on features extracted from their heartbeat. In order to detect anxiety in people with arachnophobia (fear of spiders), wearable sensors are used in [85] to collect ECG and respiration signals. Then Bagged Trees are used to detect the level of anxiety in these people. In [86], ECG and Galvanic Skin Response (GSR) were used to identify anxiety in arachnophobic subjects. They were exposed to spider images and then the signals were collected and fed to an ML algorithm. In [87], the ECG signals are collected from body-worn sensors and ML algorithms are used to identify anxiety in people.

These studies demonstrate the effectiveness of ECG and GSR signals in detecting anxiety related to specific phobias. This suggests that physiological monitoring could be particularly useful in identifying and managing anxiety in people with specific triggers (like arachnophobia). While these studies focus on specific cases like arachnophobia and social anxiety, the methods and findings are likely applicable across a wide range of anxiety disorders. This could lead to the development of generalized anxiety monitoring systems that can be adapted to various anxiety conditions.

It is argued in [88], that heart rate variability is correlated with emotional arousal resulting from anxiety. In order to develop an automated anxiety detection system, this work uses a deep learning algorithm that extracts features from ECG. The authors use a 1-D CNN to extract features. Panic disorder shares many of its characteristics with anxiety and distinguishing these two problems from from each other is a well-established field in psychology. In [89], ANN with features from heart rate variability signal is used to discriminate panic disorder from other anxiety disorders. Using wearable devices to measure ECG, and Breathing-Rate Variability (BRV), The authors in [90], propose an ML algorithm that extends the existing works on the relationship between HRV/BRV and anxiety.

Anxiety among university students is a multifaceted issue that can significantly hinder academic performance and overall well-being. While there is a growing body of research addressing this concern, one study [91] contributes to this effort by exploring the use of the Intelligent Internet of Medical Things which is a network of wearable belts to collect ECG data to monitor and potentially alleviate anxiety symptoms. The data is then used in an ML algorithm to detect anxiety among these students. The authors then study the effect of some treatments including Yoga on students suffering from anxiety. However, it is important to recognize that this study is just one piece of a much larger puzzle, and further research is needed to fully understand and effectively address anxiety in academic settings. Also, Cultural differences, age groups, and individual variations in self-expression and disclosure can all impact how accurately online comments reflect a person's internal feelings or anxiety levels.

Photoplethysmography (PPG) refers to an optical technique that is used to detect volumetric variations in blood peripheral circulations. It is non-invasive and low-cost and is performed at the skin surface. It is argued in [92], that psychological emotions reveal themselves in terms of pulse waves in blood. To put this into practice, the authors use ML algorithms and features extracted from PPG to identify state anxiety. In [93], a remote PPG method is proposed to identify anxiety. The study uses remote videos captured by people and applies CNN to the images to extract features. Then uses the features in the PPG technique to measure blood circulations. When this information is extracted, an SVM algorithm is used to predict anxiety among these subjects.

It is shown in [94] that finger pulse wave signals can carry information about anxiety levels in people. The authors extract the frequency information from finger pulse signals, and then process them in the form of images via Convolutional Neural Networks (CNN), to automatically detect anxiety. Hand shivering is usually a symptom of anxiety. In [95], the patients' smartphone is used to measure hand shivering, which is then used as a feature to detect anxiety.

Anxiety usually results in physiological changes including tense feelings, high blood pressure, and perspiration. Abnormal perspiration can change the electrical properties of skin, like its conductivity. Skin Conductance (SC) can be measured via sensors that apply a small voltage to the skin. The effects of anxiety can also be observed in terms of muscle response or electrical activity in response to nerve stimuli. This is because abnormal brain activity can result in muscle contracts that produce a burst of electrical activity. The authors in [96] believe these signals can be used to identify anxiety in people. To test this, they use SVM and KNN as classifier algorithms and show good classification accuracy. The effectiveness of SC and muscle response measures depends on the accuracy and calibration of the sensors used. Ensuring that these devices are reliable is essential for their successful implementation. The authors do not report any study on this, but for future work, studying different calibration and uncertainty reduction methods can be considered.

The Circadian Clock, also known as Circadian Rhythm, is the internal clock in the human brain that regulates the 24-hour day cycles alternating from sleepiness to alertness. This system regulates itself with light changes in the environment. The authors in [97] argue that mood disorders, including anxiety, are associated with disruptions in this rhythm. The disruptions in this rhythm are linked to polymorphisms in Circadian Clock genes. To predict anxiety in human subjects, ML algorithms are used in [97], that analyze clock genotype combinations. The study identifies multiple genotypes that are predictors of anxiety. The findings show that circadian misalignment results in an elevated risk of anxiety. These findings suggest that managing circadian rhythm disruptions could be a key component of anxiety treatment. Interventions such as light therapy, sleep regulation, and lifestyle modifications aimed at realigning circadian rhythms could be incorporated into treatment plans to address anxiety. Also, identifying individuals with genetic predispositions to circadian disruptions could enable early interventions to prevent the onset of anxiety, where lifestyle adjustments and behavioural therapies might be recommended as preventive measures for those at higher genetic risk. Future research could explore other genes and genetic variations related to circadian rhythms and their impact on anxiety. This could expand the understanding of the genetic basis of mood disorders and improve predictive models. Longitudinal studies examining how circadian rhythm disruptions and genetic factors influence anxiety over time could provide deeper insights.

Polysomnography is a test that is used to study sleep and diagnose sleep disorders. The test records the oxygen level in blood, heart rate and breathing, leg movements, and brain waves during sleep. In [98], Polysomnography data were used to train a deep-learning algorithm that predicts anxiety in subjects. The relationship between sleep disturbances and mental health is often bidirectional. For instance, anxiety and depression can lead to sleep problems, and poor sleep can exacerbate these mental health issues. By analyzing PSG data, researchers can better understand these interactions and their implications for treatment. Future research could explore additional sleep metrics and their relationships with anxiety and depression. This could include studying variations in sleep architecture, such as REM and non-REM sleep, and their impact on mental health.

5.2 Brain-Related Signals

Recent developments in neuroimaging techniques have provided insights into the development of the disorder. For example, neuroimaging studies suggest that people with anxiety disorder exhibit abnormalities in their brain structure biomarkers such as their grey matter volume, neural activation, and white matter connectivity within their amygdala, cingulate, and prefrontal cortex [99]. Neuroimaging studies suggest that quantitative information about brain activities, such as EEG, and fMRI can provide valuable insights about mental health [100]. Information about the brain, that is captured via signals, usually reveals a great deal about people's inner thoughts. This information can be in the form of images (e.g. fMRI) or a one-dimensional (e.g. EEG). In this section, we review the works that use signals collected from the human brain to detect the level of anxiety in people.

Electroencephalogram (EEG) Data: It was shown in the literature that EEG signals carry information that can be used to detect various emotional conditions, including stress, depression, and some mental health conditions [101], [102], [103]. It is argued in [104], that stress and anxiety leave a footprint on the level of oxyhemoglobin and deoxyhemoglobin in the prefrontal cortex. To discover further, the authors collect data from Cerebral Blood Oxygenation in the Prefrontal Cortex using infrared spectroscopy and train a Bayesian framework to predict the level of anxiety in patients. To study the relationship between reward processing and anxiety, EEG signals are analysed in [105] via machine learning algorithms. The signals are used to classify individuals into levels of anxiety. It is argued in [106], that there is asymmetry in frontal brain-wave activity among individuals with anxiety. To detect anxiety, ML algorithms are employed in [106] to analyse EEG signals and identify the asymmetries.

The performance of EEG-based systems depends on the feature extraction methods employed. In [107], different feature extraction methods are applied to EEG signals and the performance of ML algorithms under different feature sets is compared.

Several studies have shown that changes in emotional states can result in changes in autonomic nervous system signals such as EEG [108], [109], [110], [111]. In an attempt to predict anxiety in people, features are extracted from EEG brain signals, and the SVM algorithm is adopted in [112]. It is argued in [113], that functional connectivity of brain networks has characteristics that can be representative of anxiety and so can be used to detect anxiety. The authors use the Phase Lag Index to extract features from the functional connectivity of brain networks and provide them as input to a CNN algorithm that predicts the level of anxiety and depression in people. One of the challenges in using EEG and functional connectivity for anxiety detection is the variability between individuals. Future research should focus on developing models that account for this variability, possibly through the use of larger and more diverse datasets.

Different learning algorithms including Logistic Regression (LR), Random Forest (RF), and Multi-Layer Perceptron (MLP) are compared in [114] in the identification of the level of anxiety in people via EEG signals. It is argued in [115], that although the evidence suggests that psychiatric disorders are associated with abnormal communication in brain regions, there are some works that study brain electrophysiological disconnectivity. The authors in [115], try to study this further by using ML algorithms and EEG signals to detect these disconnectivities and identify anxiety based on these signals. This research sheds light on how anxiety may manifest as disrupted neural communication. This supports the idea that anxiety is not just a generalized increase in brain activity but may involve specific patterns of dysfunctional connectivity.

To detect anxiety based on EEG signals, ML algorithms are used in [116]. In this work, the EEG signals are first pre-processed via noise filtering techniques to remove artefacts. Then, using statistical methods, channel selection is applied to select the significantly different electrodes. The frequency signal is measured and the features are selected. In [117], graph theory algorithms were used to process EEG data and extract features to identify anxiety. In this work, the directed information flow of four EEG bands was measured via partially directed coherence and topological networks. This allows the authors to assess the causal interactions between neuronal units in the brain. These features were then used for an SVM algorithm to classify the subjects. Future studies should investigate the development of adaptive machine-learning models that can account for individual differences in EEG patterns and anxiety responses. Exploring how genetic and epigenetic factors influence EEG patterns related to anxiety could lead to personalized diagnostic tools that are tailored to an individual's biological makeup.

Recently, Adaptive Mixture Independent Component Analysis (AMICA) has shown its power in processing signals. In [118], AMICA is used to process EEG signals and extract features to classify individuals into different cortical states. The authors suggest this can provide the foundation for real-time anxiety state detection. An explainable ML algorithm is proposed in [119], which is a fusion of some deep learning algorithms. In this work, lightweight CNN algorithms are used to perform time-frequency analysis of EEG signals, and an attention network is applied to integrate the output of these CNNs. To facilitate the training phase of the algorithm, the authors propose a subject-aware contrastive learning algorithm that ensures subject representation in the training step of the algorithm. This boosts self-supervised cross-subject feature learning. Future research could focus on optimizing AMICA and other signal processing techniques for real-time applications, ensuring that these systems are both efficient and accurate in detecting anxiety. More studies are required to validate these advanced models across diverse populations to ensure their generalizability and effectiveness in different demographic groups.

In [120], the frequency domain features, as well as time domain and statistical features were extracted from EEG signals. These features were then selected via correlation method and SVM was used to detect anxiety in students. It is argued in [121], that existing methods meaning focus on extracting EEG features during resting states, with limited use of Event-Related Potential (ERP). The authors use a deep learning technique called the EEGNet model to predict social anxiety based on EEG data.

In [122], different feature extraction methods are used, and the resulting features are compared in identifying anxiety and depression in people. The work uses feature extraction methods like Higuchi Fractal Dimension, correlation dimension, approximate entropy, Lyapunov exponent, and detrended fluctuation analysis. For future work, refinement of feature selection methods, possibly through automated or hybrid approaches, could lead to the discovery of more potent indicators of anxiety within EEG data.

To identify anxiety in adolescents with autism, a deep Long-Short Term Recurrent (LSTM) algorithm is used in [123], [124] that processes EEG signals. The application of LSTM networks, points to the importance of temporal dynamics in EEG signals. LSTM's capacity to capture temporal dependencies makes it useful for contexts where the timing and sequence of brain activity are critical for understanding anxiety. To detect anxiety in patients who suffer from alcoholism and depression, EEG data from patients in a hospital were collected and used in [125]. The authors also use fMRI data to train their ML algorithms. Their finding suggests that the brain structure allowed them to differentiate the patients. They also found that the cortical thickness of the brain structure was an indicator of anxiety. To establish such findings, longitudinal studies should be performed to examine how cortical thickness and other brain structures change over time in response to anxiety treatment. This could provide insights into the effectiveness of different interventions and the potential for reversing structural abnormalities associated with anxiety.

In [39], the EEG signal is analyzed, and its features including multiscale entropy, permutation entropy, fuzzy entropy, and transfer entropy are extracted to create a diagnosis system to detect SAD. One limitation to such a study is that entropy-based analysis can be difficult to interpret in a clinical context and clinicians may find it challenging to relate these complex mathematical features to the underlying neurobiology of SAD or to the symptoms experienced by patients. The study might benefit from providing more accessible explanations of how these features relate to the clinical presentation of SAD. Also, the use of multiple entropy measures could lead to an increased risk of overfitting, especially if the study involves a relatively small dataset.

Event-based, or event-driven signal processing refers to a paradigm in which the signals or data streams are treated as a specific sequence of events or changes in the input rather than continuously processing data at a fixed sampling rate [126]. In [127] it is argued that the individual's reactions to stimuli can be used to detect anxiety. The authors use event-based methods to extract features from EEG signals which are then used in CNN algorithms to processes.

While these studies focus on anxiety, the methodologies could be applied to other mental health disorders, expanding the scope of EEG and functional connectivity research. EEG signals are highly complex and noisy, which presents challenges for both feature extraction and model training. Future research must focus on refining these techniques to improve the robustness and reliability of anxiety detection models. Another line of research could include large, diverse populations to ensure that findings are generalizable across different demographic groups, including variations in age, gender, ethnicity, and socio-economic status.

Functional Magnetic Resonance Imaging (fMRI): In many studies it has been shown that there is a correlation between brain structure and mental disorders. In this respect, fMRI images can provide valuable information that can be used to identify the patterns in the brain structure that may be representative of anxiety. In [128], voxel-based morphometry of grey matter volume (GMV) was measured and its discriminative features were identified. Then, these features were used in an SVM algorithm to classify groups of people into anxious and non-anxious people.

To identify the emotional facial expressions that are predictive of anxiety, pattern regression analysis was performed in [129]. The authors believe that brain signatures change during these dynamic facial expressions. To capture these brain signatures, fMRI data are collected when the participants apply dynamic facial expressions like fearful, angry, and happy faces. Using ML algorithms it is shown in this paper that these features can be used to predict anxiety in people. The study's findings may be limited by the specific conditions under which the fMRI data were collected. Also, fMRI studies often involve small sample sizes due to the high cost and time-intensive nature of data collection. This limitation could apply to the study in question, raising concerns about the generalizability of the results.

Research in psychiatry has tried to identify biomarkers that can diagnose patients, predict treatment response, and identify individuals at risk of illness. While ML algorithms have been promising in providing the community of science with the tools to identify these biomarkers, they still have not found their way into practice. In [130], ML algorithms are applied to fMRI images to identify such bio-markers. The author's findings suggest that there is no evidence that a generalizable anxiety biomarker exists.

One cognitive effect of anxiety is the dysregulation of the emotional interpretation of facial expressions, which is associated with neural activities in the amygdala and prefrontal cortex. This usually leaves its footprint on fMRI results. In [131], differential fMRI responses to emotional faces, e.g., angry versus fearful faces are used as features to train an ML algorithm to identify generalized anxiety, separation anxiety, and social anxiety in children. One limitation to these studies could be that the translation of ML-based biomarkers into clinical practice remains a significant challenge.

To build a predictive model of anxiety, brain morphometric features of the brain and network analysis are used in [132]. In this work, structural fMRI brain images of participants were decomposed into independent covarying grey and white matter networks. The authors report that two covarying grey and white matter independent networks were predictive of trait anxiety. One included parietal and temporal regions such as the postcentral gyrus, the precuneus, and the middle temporal gyrus. The other network included frontal and parietal regions like the superior and middle temporal gyrus, the anterior cingulate, and the precuneus. The study's findings also suggest that anxiety is positively associated with catastrophizing, rumination, and other self-blame and negatively associated with positive refocusing and reappraisal. Also, they suggest that anxiety is negatively correlated with age. The identification of two distinct brain networks suggests that anxiety is associated with complex, distributed brain patterns rather than localized abnormalities. The negative correlation between anxiety and age suggests that younger individuals might be more susceptible to anxiety, or that the structural brain features associated with anxiety might change over time. Future research should integrate structural and functional neuroimaging data to provide a more comprehensive understanding of how brain networks relate to anxiety. Also, the causal mechanisms underlying the relationship between brain networks and anxiety should be studied.

One difficulty in identifying anxiety in children via fMRI data is the limited scan time and their reluctance to remain still during the imaging. To manage this, in [133], fMRI data from adolescents is collected and used to build an ML model based on parcel-wise brain features. The proposed model in this work identified contributing brain regions that exhibit a correlation with anxiety symptoms. The authors suggest that pooling brain features from the three modalities did not enhance classification accuracy. To predict the level of social anxiety, in [134], brain functional radiomic features including the regional homogeneity, the fractional amplitude of low-frequency fluctuation, fractional resting-state physiological fluctuation amplitude, and degree centrality were used. The study suggests that the orbitofrontal cortex and the degree of centrality were the most representative features. Given the identification of specific brain regions like the orbitofrontal cortex, future work could explore targeted interventions that modulate activity in these areas. This could include cognitive-behavioural therapies tailored to influence these regions or neurostimulation techniques designed to alter their function.

It is argued in [135], that topological characteristics of brain networks can be used as features to identify anxiety. To test the idea, fMRI data were collected from some subjects, and their brain structure as well as topological networks were studied. The findings suggest that it is feasible to employ these features to diagnose anxiety. The study in [136], tries to study people diagnosed with chronic insomnia disorder with comorbid anxiety. In this work, fMRI data were used to compare the brain structure of people with anxiety, and an SVM algorithm was used to build a diagnosis model. It is found in this paper that people with anxiety exhibit heightened functional connectivity strength in their right dorsomedial prefrontal cortex. Together, these findings imply that anxiety may be associated with both global network properties and local connectivity patterns. Given the identification of specific brain features associated with anxiety, future work could explore interventions e.g., neurofeedback, that specifically target these features.

Brain Structure: To identify anxiety in aged people, in [104], near-infrared spectroscopy data were collected from the prefrontal cortex to measure oxy- and deoxy-haemoglobin concentration changes during a 3-min resting stage. To identify anxiety among the subjects, a state-trait anxiety inventory was used and a Bayesian ML algorithm was employed to perform the task. Functional neuroimaging of anxiety suggests altered neural activation to threat-provoking stimuli focally in the fear network. However, structural differences are distributed over the frontal and temporal cortices. The authors in [137] use the SVM algorithm to distinguish these differences. Their findings suggest that SVM reaches better accuracy when structural information from the whole brain is used compared to when the region of interest information is used. This, the authors argue, may suggest that structural changes in anxiety are distributed rather than being localized to specific regions. Anxious depression is a major disorder associated with impaired social life. In [138], RF algorithms are employed to analyse brain structure in these patients. The authors report a significant difference between the grey matter volume in the left middle temporal of people suffering from anxiety. In a similar attempt [139], five different ML algorithms are employed to detect anxiety based on grey matter volume. The studies underscore the importance of considering both functional and structural aspects of brain activity when studying anxiety. The focus on structural data might overlook important functional aspects of anxiety, such as how these structural differences manifest in neural activity during anxiety-provoking situations. Further research should investigate how structural changes in the brain interact with functional connectivity and activity patterns to produce anxiety symptoms.

5.3 Speech and Audio Signals

Speech characteristics are unique to each individual and the way people use voice to communicate not only shows their personality but also reveals their mental health. It is difficult to conceal speech expressions as they are expressed subconsciously. There is an increasing body of studies that use acoustic and semantic features of speech and ML algorithms to detect anxiety [140]. In newer approaches, deep learning algorithms are employed which usually show better performance [141].

If left untreated, childhood anxiety and depression are associated with long-term negative outcomes which include increased suicide risk. The problem is that these issues in children often go undiagnosed. To identify anxiety in children, ML algorithms are employed in [142] that process speech features. In this work, the children are given a 3-minute speech task and then their speech signal is processed to extract representative features. A similar work is presented in [143], in which the authors also use text and video signals. To identify anxiety in children aged 3-7 years old, in [144], voice signals are recorded from these children, and the most critical features of speech are identified. To estimate the impactors for anxiety, in [145], sleep quality, and mood, voice signals are collected from subjects, and their acoustic and linguistic features are extracted. Then deep neural networks are used to create a predictive model. The inclusion of factors such as sleep quality and mood, emphasizes the multifaceted nature of anxiety which suggests that anxiety is influenced by various factors. Future studies should consider integrating contextual factors, such as the child's environment and recent life events, into the analysis.

In [146], voice signals are collected from participants by asking them to form spontaneous utterances and respond to instructions to consent or refuse commands of alleged peers. Then, the vocal features of these signals were extracted and analyzed. To build a system that estimates the level of public anxiety based on speech signals, ML algorithms are used in [147]that take acoustic features of speech signals. Smartphones can easily record and transmit audio, thus providing accessible frameworks for screening and monitoring of mental health. In [148] a mobile application called Ellipsis app is used to collect voice signals from subjects. Then, these audio signals are processed to extract acoustic features of the signal to extract features to identify anxiety. For future work, Efforts should be made to develop more interpretable ML models that provide clear insights into how vocal features relate to anxiety.

The CREMA-D dataset [149] is designed to contain audio signals from multiple ethnicities, and so the data includes more factors other than gender as there could be differences in the pronunciation of words which may result in differences in the way people reveal their inner feelings. In order to study the differences between the acoustic features of different ethnic groups and the way they may affect anxiety detection, CNN algorithms are used in [150]. The authors compare the performance of SVM with CNN and show that CNN can achieve better performance. In [151], anxiety, depression, and apathy were evaluated in elderly people. Then, videos were recorded from the subjects, and features from their voice and video were extracted. The features include acoustic features from voice and facial expressions from video signals. The audio features were extracted via the Geneva Minimalistic Acoustic Parameter Set (eGeMAPS) which extracts 88 acoustic features. The authors develop an ML algorithm to diagnose anxiety in these people. It is argued in [152], that most studies using speech and sound signals to identify anxiety ignore two important facts, the comorbidity and the temporal changes. To manage this, the authors employ CNN algorithms to process acoustic features extracted from speech signals. The CREMA-D dataset's focus on ethnic diversity is important, but cultural differences in emotional expression may not be fully captured. Additionally, differences in data collection methods and recording conditions across ethnic groups could introduce biases.

5.4 Video Signals

Darwin argued that facial expressions are universal, regardless of race or culture [153]. Recently, there has been growing attention to the application of facial expression analysis for identifying mental health issues. Some works have studied the effectiveness of using facial expressions extracted from video signals to identify anxiety [29]. For example, it was shown in [30], that people with depression exhibit less eye contact and lower mouth corners. Anxiety mainly reveals itself on the human face by changing the features of the eye (blinking, pupil size, gaze, eyelid twitching, etc.) and the mouth (lip deformation and mouth activity), the cheek, the head movements, strained face, and facial pallor. For example, it was shown that anxious people have higher overall head motions [154], move their head more rapidly [155], and more frequently [156]. Head nods and shakes were used in [157] to collect features to identify anxiety. Although blinking can be voluntary, it is often a reflex to internal or external stimuli and it usually increases when people are anxious [158]. Internal stimuli that can affect blinking rate include lying [159], depression, Parkinsons [160], and schizophrenia [160]. Also, it was shown that anxiety changes the gaze direction and congruence, the size of the gaze-cutting effects [161], gaze instability [162], and saccadic controls [163]. Anxious people are usually more attentive and make more saccades when looking at fearful and angry faces [164]. Pupil size also changes with anxiety, for example, pupil diameter increases with the level of anxiety [165], and people with higher levels of anxiety show elevated response in pupil dilation to negatively valenced images [166]. Pupil size may increase in response to negative or positive sounds compared to emotionally neutral sounds [167]. All this evidence suggests that facial expressions are good indicators of anxiety.

A set of facial features is used in [168] to detect anxiety in subjects. The participants were given some video clips to watch, and while watching a video was recorded from their faces. The features extracted in this work include head motion, face color for heart rate estimation, eye-related features, and mouth-related features. In [169], eye movement analysis is performed via Hidden Markov Models, and ML algorithms are adopted to predict anxiety. In order to identify anxiety, in [170], dynamic descriptors of facial expressions are used which include motion history images. In this work, appearance-based features, including local binary patterns and histograms of oriented gradients as well as visual geometry group features derived from deep neural networks are exploited and used to build an ML algorithm. In [171], CNN and LSTM algorithms are employed to process video images from the subjects to identify anxiety. Video surveillance data are used in [172] to detect anxiety. The authors use facial expression features extracted via CNN algorithms to perform this. One limitation of these studies is that facial expressions and eye movements can vary widely between individuals, influenced by cultural, emotional, and contextual factors. This variability can complicate the development of universally applicable anxiety detection systems. Future work should study how individual differences, including cultural and contextual factors, impact facial expressions and anxiety detection.

To detect anxiety, videos from smartphones and Zoom calls were collected in [173]. In this work, features from selfie images and ecological momentary assessment effects were extracted. To make the participants more engaged in the data collection phase, the authors use gamification, which involves incorporating fun and engaging game elements into the practice. The authors use cheek deformation, eye gaze, and blinking rate as features. While gamification can be beneficial, it is important to assess its impact on natural behaviour. Other methods should be explored to engage participants without altering their emotional responses, and evaluate the effectiveness of different engagement strategies. In [174], gait videos (the way people walk) are collected and processed to identify anxiety. In this work, static and dynamic time and frequency domain features are extracted and used to train an ML algorithm. A new architecture is presented in [175] to estimate the posterior probabilities of disorders that perform a clustering sequence of emotional states. In this work, a CNN algorithm is used to extract features from the visual and thermal face image sequences. A Hidden Markov Model (HMM) was then developed to cluster the sequence of the emotional states.

5.5 Signals From Wearable Devices

In recent years, smartphones and wearable devices, like smartwatches and wrist bands have been increasingly used to collect and process data from people to predict their behavior and psychological state [176]. For example, GPS data can be used to get insights about momentary behavior and one's mental health [177]. Integrating new sensors into these devices has given them the capability to collect a new range of data about their health that was previously possible only in hospital settings [178].

Motion Sensors: In [179], ActiGraph AM-7164 devices were used to collect data from participants. The participants wore the devices via an elasticized fabric band on their right hip. The device was used during the daytime and removed before bedtime. Several features were collected from the participants including wear time, entropy, lags, stability, trends, nonlinearity, etc. In order to identify anxiety, in [180], motion signals from an accelerometer and gyroscope were collected from individuals and the data were used to predict the level of anxiety among these people. In [181], an app was installed on participants' wearable devices, and data were passively collected about their social contacts (including incoming and outgoing calls and texts) and movements (accelerometers). The work uses an ensemble of extreme gradient boosting machines (XGboost) to identify anxiety among participants. In [182], wearable sensors are used to collect data about the participants' movement and sleep patterns. These data are then processed to extract features to identify anxiety. It is argued in [183] that gait and balance can be used to identify anxiety. In this work, APDM mobility sensors were used to collect data from the participants and identify their gait and balance. Then these data were used in a random forest algorithm to identify anxiety.

To identify anxiety in children, in [184], three types of wearable sensors were attached to children: MC10 BioStamps, Empatica E4 wrist device, and a smartphone. The BioStamps have an accelerometer, gyroscope, and a sensor that measures surface biopotential. One limitation to these studies is that the effectiveness of wearable devices depends on participant compliance, such as consistently wearing the device and using it as instructed. Non-compliance can lead to incomplete or biased data.

Physiological Data: In [185], skin temperature, heart rate, and electrodermal activity (EDA) were collected from the subjects, and using different ML algorithms a model was generated to identify anxiety. In [186], Photoplethysmography (PPG) and EDA data were collected from the individuals and were used to build an ML algorithm.

Heart Signals: In [187], data from wearable devices were collected and used to measure heart rate and RR interval as features to identify anxiety. The authors use these features to train an SVM algorithm. ECG sensor was used in [188] to measure heart rate and photoplethysmography was used to measure skin temperature of participants. The authors use KNN and decision tree algorithms to identify anxiety. Wearable devices are used in [189] to collect features like blood volume pule, EDA, and body temperature from the participants. In [190], Fourier–Bessel domain adaptive wavelet transform (FBDAWT) is employed to extract features from ECG signals. The ECG signal is collected from participants via a wearable device. Using the increment entropy and energy features, the XGBoost algorithm is used to detect different stages of anxiety. The EEG signals collected via wearable sensors were used in [191], to train a probabilistic binary pattern algorithm to detect anxiety. To extract features from the signals, a q-factor wavelet transform was used. As a direction for future work, studies should be conducted across a broader range of populations, including different ages, cultures, and clinical conditions, to ensure that the models are widely applicable and not biased towards specific groups.

Sleep Patterns: In [192] data from wearable devices were used to identify the sleeping and wake-up time of workers, who work in five general companies. The authors use a Balanced Random Forest to identify anxiety among these people.

Brain Signals: Recently wearable EEG headbands have become popular. Wearable MUSE EEG headsets monitor and record the electrical activities of the brain by placing electrodes on the scalp and detecting brain activities. In [193], a wearable EEG device is used to record the brain signals of participants in an open-eye state. After preprocessing, features were collected from these signals, and using a wrapper method, the most representative features were used to train a model.

Behavioral Data: In [194], the participants were asked to install the "Behavidence Research App" which collects data such as screen time, app usage, etc. from them. The authors then use the XGBoost algorithm as the classification model. In [195], a mobile app was used to collect behavioural data including app usage frequency, app usage time, entertainment and social app usage frequency, number of SMS, phone usage frequency, incoming phone calls, etc. These features were processed and used in an ML algorithm. In [196], smart glasses are used to collect data from drivers. In this work, features like head orientation, neck posture, hands on the glasses, and gaze direction were collected from the participants and used to develop an ML algorithm to detect anxiety. A possible limitation to these works is that behavioural data can be influenced by various contextual factors such as stress from other sources, lifestyle changes, or personal habits. It is important to account for these factors to avoid misleading interpretations. As a figure work, rigorous validation should be conducted to identify the most relevant features for anxiety detection. Use feature selection techniques and validate findings across different datasets to avoid overfitting.

Various data types such as bio-signals, brain-related signals, speech, video, and wearable device data have shown great potential in detecting anxiety, with each approach leveraging unique features from the respective data modalities. For instance, bio-signals like ECG or EEG capture the physiological and neurological states associated with anxiety, while speech and facial expressions reflect more outward emotional cues. Wearable devices provide continuous monitoring of behavioural patterns and physiological metrics, adding another layer of information. To build a holistic anxiety detection system, integrating these modalities could provide a more comprehensive view. For example, combining physiological signals with speech or facial expression analysis could enhance real-time anxiety detection, while wearable devices offer a continuous stream of contextual data to improve predictive accuracy. Future systems could benefit from multi-modal fusion, where insights from one domain can complement or validate those from another, creating a synergistic effect that leads to more reliable and personalized anxiety assessments. This integration could drive advancements in creating more adaptable, real-time anxiety detection frameworks.

6 Background Features

It is shown in the literature that personal characteristics and experiences can affect anxiety [197]. For example, family disfunction [198]and childhood experiences [199], finance [200] can affect mental health. Another contributing factor to anxiety is social support which includes objective support, subjective experience, and utilization of social support [201]. Lack of social support normally exerts a negative impact on anxiety level [202]. In this regard, data about subjects' backgrounds can provide valuable information about their anxiety. Some studies have delved into understanding the relationship between these factors and anxiety and have tried to use these features in ML algorithms. In this section, we review these studies.

6.1 Demographic Features

Anxiety in Children: In [203] demographic factors including the number of parents in the home, number of siblings, poverty, impairment, etc were used to develop an ML algorithm to identify anxiety in children.

Anxiety in Military Personnel: It is believed that people in military service are prone to many stressors and thus are susceptible to anxiety. To identify hidden patterns of mental stress and anxiety, in [204], socio-demographic data were collected from some Ukrainian males in the military and the k-means algorithm was used to categorize them. The findings in this paper suggest that there is no clear relevance between the experience of military actions and the level of anxiety. The authors suggest that other factors like feelings about their mental conditions are more crucial determinants. Future work can conduct quantitative analyses with interviews or focus groups, to gain deeper insights into the subjective experiences of military personnel. This can help understand the context and personal factors influencing anxiety and how subjective well-being, personal coping strategies and mental health perceptions relate to anxiety.

Anxiety in Patients: People with immune-mediated inflammatory disease (IMID) are at higher risk of anxiety. In [205], ANN and random forest algorithms are used to predict the level of anxiety among these patients. In [206] demographic data from depressed patients were collected and build an ML algorithm. The authors then perform a 2-, 4-, 6-, and 9-year follow-up to study the long-term performance of the algorithms.

Anxiety in Students: Mental disorders like anxiety are prevalent in students and can significantly impact their academic and social activities. In [207], data from online platforms is collected and used to develop an ML algorithm as a health monitoring system for students. To predict the level of anxiety in students, in [208], demographic data are collected from students in Lebanon and used to train ML algorithms. In [209], demographic data are collected from 127 engineering students in India, and ML algorithms are used to predict their anxiety levels. In [210], regression model algorithms were used to predict the level of anxiety in students. One limitation to these works is that data collected from online platforms may suffer from biases (e.g., selection bias, self-report bias) and issues related to data privacy.

Foreign Language Anxiety: Foreign language anxiety is characterized by feelings of nervousness, stress, and apprehension when attempting to learn or use a foreign language. Common symptoms of this anxiety include sweating [211], avoidance [212], negative self-talk [213], difficulty with spontaneous speech [214], fear of making mistakes [215], and lack of confidence [216]. In [217], features such as age, gender, education level, English level, exercise score, etc. were used to train an XGBoost algorithm to detect anxiety. One limitation of this work is that the effectiveness of the XGBoost heavily depends on the quality and representativeness of the features. The performance of XGBoost should be compared with other ML algorithms or ensemble methods to ensure that it is the most suitable for detecting foreign language anxiety.

General Community: In [218], data from a total of 339,781 participants were collected via an online platform to develop an ML algorithm to predict the level of anxiety. The data includes socio-demographic predictors including gender, age, race, marital status, education level, and occupation. In [219], the DASS-42 questionnaire is used to identify anxiety in participants, and then decision tree, SVM, and random forest algorithms were used to predict their level of anxiety based on their demographic information. In [220], the YMM [221] data set is used to train three ML algorithms to predict the level of anxiety in individuals. These works use simple ML algorithms. For future work, it is suggested that more sophisticated ML algorithms be investigated, such as deep learning models (e.g., neural networks), ensemble methods, or hybrid approaches.

These studies suggest that various personal characteristics and experiences significantly influence anxiety levels across different populations, including children, military personnel, students, and the general community. Factors such as family dysfunction, childhood experiences, financial stress, and social support play critical roles in shaping mental health outcomes. The reviewed studies employ demographic features and machine learning algorithms to predict anxiety levels, highlighting the potential of integrating these diverse data sources to create a more comprehensive understanding of anxiety. However, it is essential to acknowledge the limitations in the existing approaches, particularly concerning data biases and the need for more sophisticated algorithms. Future research should focus on enhancing the integration of these findings, considering not only demographic features but also qualitative insights from interviews or focus groups. By fostering a holistic approach, researchers can better elucidate the complex interplay of factors contributing to anxiety, ultimately leading to more effective detection and intervention strategies.

6.2 Lifestyle Features

Anxiety in Students: In order to identify anxiety among students in Saudi Arabia, data were collected from these subjects and used to train the AdaBoost algorithm [222]. The authors use features such as sufficient support from family and friends, salary, number of children, living with parents, marriage status, etc. In order to identify anxiety in students in Dhaka Bangladesh, the SVM algorithm is used in [223]. The studies underscore the importance of considering cultural and regional factors when predicting anxiety. These studies are highly specific to their respective regions. Future work should involve cross-cultural comparative studies that evaluate the performance of anxiety detection models across different regions.

Anxiety in Children: In [224], ML algorithms are used to identify anxiety in school children. The authors identify a list of risk factors that include social support, violence, and physical health. Using a random forest algorithm, children's social anxiety is studied in [225]. The findings in this paper suggest that parents' socioeconomic attributes are strongly correlated with anxiety in children. In [226], ML algorithms are employed to perform real-time analysis of social anxiety in high school students. It is argued in [227] that self-awareness about unhealthy habits can help alleviate anxiety in students. To help the students suffering from anxiety, the study uses ML algorithms to build a comprehensive eHealth proposal system. These studies highlight the significant role that social and environmental factors play in children's anxiety. One limitation of these findings is that the studies primarily analyze data at a single point in time, which limits the ability to understand how anxiety develops or changes over time in response to different factors. A possible future work is conducting longitudinal studies would allow researchers to track the development of anxiety over time

Anxiety in Hospital Patients: In [228], life behaviour data were collected from cancer survivors to train an ML algorithm. The study uses features such as marital status, education level, BMI, etc.

Anxiety in Pregnant Women: In [229], data on pregnant women were collected from five Arab countries during the COVID-19 pandemic. The authors use seven ML algorithms to predict anxiety in these subjects. In [230], the Apache Spark Big Data processing engine is used to build a model of anxiety in pregnant women.

Anxiety in Gamers: While playing games may help some people alleviate stress, in some cases, it may affect mental health adversely. This usually happens when gamers play for long periods of time. In [231] features such as the number of hours playing games, feeling urged to play more, frequency of game playing, etc. are used to train the KNN algorithm. In [232], data from Kaggle are used to predict the level of anxiety in these patients. The studies primarily focus on gaming behavior as the sole predictor of anxiety. However, anxiety is a multifaceted condition influenced by a range of factors, including social, psychological, and environmental variables. Future research should aim to incorporate a wider range of data sources.

Anxiety in Elderly: In [233], features such as self-esteem, alcohol use, loneliness, communication with neighbors, satisfaction with helping others, etc. were used to identify anxiety in elderly people. The authors report that the elderly who felt loneliness, low self-esteem, and low communication with family were at high risk of anxiety.

Anxiety Caused by COVID-19: In order to study and predict anxiety caused by the COVID-19 pandemic, XGBoost algorithm was used in [234]. The findings in this paper suggest that resilience and social support are key factors in predicting anxiety. The authors in [235] argue that the COVID-19 pandemic has resulted in a surge in anxiety and studies suggest that the use of cannabinoid medicines can help improve anxiety conditions. The authors use ML algorithms to study the relationship between the clinical delivery of these medicines and anxiety and to discover patterns between patient features and recommendations, diagnosis, and treatment response. Some works have tried to use ML algorithms to study and predict anxiety caused by the COVID-19 pandemic on students. For example, in [236], the university students at Quebec University, in [237] the university students in Brazil, in [238] the university students in India, in [239] the university academicians in Indonesia were studied, and in [240] the patients recovered from the disease. One limitation to these findings is that the reliance on data collected during a crisis might raise concerns about the quality and representativeness of the data. For example, data collected during the pandemic could be skewed by factors such as access to healthcare, changes in social behaviour, or differences in the availability of support systems, potentially impacting the reliability of the models.

7 Psychological Features

Anxiety can be identified via self-reports and questionnaires; however, self-reports are intrusive and vulnerable to biases. That is these tools can sometimes feel invasive or uncomfortable for participants. When filling out self-reports or questionnaires, individuals may be required to disclose personal and sensitive information about their thoughts, feelings, and behaviours. Additionally, the repetitive or detailed nature of some questions may make participants feel as though their privacy is being encroached upon, potentially leading to discomfort. However, self-report measures are generally viewed as less intrusive than methods like clinical interviews or physiological assessments, as they enable individuals to respond privately and at their own pace. Self-report measures can be more culturally appropriate in certain populations, such as in Asian cultures or among men, where stigma or discomfort surrounding clinical interviews and other intrusive methods might be significant. While self-report measures have their limitations, they offer notable advantages. These include greater accessibility, cost-effectiveness, and the ability to capture subjective experiences that might not be evident through other assessment methods.

Sometimes the participants may conceal their inner feelings. Some psychological attitudes in people, such as insomnia [241], stress degree of fatigue [242], way of coping situations [243], pessimism, loss of pleasure, personality traits [244]early-life anxious temperament [245], self-dislike, panic [246], etc. (for a more comprehensive list of these features please see Table II in supplementary materials) can indicate anxiety. Measuring these features and using them to identify mental health can provide benefits as they are easy to monitor and spontaneously manifest the inner feelings of an individual. In some papers, these features are used to predict anxiety in people.

Personality Traits: In [247], the big five personality trait scores are used as features to predict anxiety. The authors use the Adaptive Neuro-Fuzzy Inference System (ANFIS) as the predictive model.

Depressive Features: In one of the first attempts in this area, a random forest algorithm is used in [248], which gets as input the psychological features such as depressive symptoms, sadness, crying, etc of people and predicts if they suffer from anxiety. In [249]depressive features such as difficulty relaxing, getting scared, etc. are used to train five ML algorithms. In [250], a battery of six cognitive tasks were performed by the participants. The data was used to train a random forest algorithm to assign the participants into clinical groups. The reliance on depressive symptoms to predict anxiety might blur the distinction between these two conditions. While they are often comorbid, treating them as interchangeable could lead to misdiagnosis or inadequate treatment, especially for individuals who primarily suffer from anxiety without significant depressive symptoms. This should be considered for future work.

COVID-19 Stressors: In [222], some COVID-19 stressors including how the pandemic has affected the subjects, whether has it caused worry, have any of your acquaintances got infected, etc. were used to train the AdaBoost algorithm. In [251], ML algorithms are used to predict the level of anxiety incurred due to COVID-19 in Greece. A survey on the research that studies anxiety due to COVID-19 was performed in [252]. The authors use the data in these studies to train an eXtreme Gradient Boosting (XGBoost) algorithm that identifies the main contributing factors to anxiety.

Anxiety in Children: In [253] the Youth Online Diagnostic Assessment (YODA) tool is developed to predict youth disorders using online questionnaires. The platform allowed the authors to collect a wide range of data on self-reported anxiety disorder symptoms. The authors of this study believe that a single set of selected features is not informative enough and thus they use an ensemble of features to improve the accuracy of predictions. A sample of 3984 students at public and refugee schools were studied in [254] to build an ML predictive model for their level of anxiety. In this study, features like PTSD stress level, depression, and psychosomatic symptoms were collected. The authors use 5 ML algorithms to build their predictive model. A significant limitation of the YODA tool and similar studies is their reliance on self-reported data, which is subject to biases such as social desirability, recall inaccuracies, and subjective interpretation of symptoms. Future work should ensure the practical utility of these models, via external validation studies and clinical trials.

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8 Mixture of Features

In this paper, we categorize the studies based on the type of features they have used [255]. In some studies, a mixture of features is used. We review these papers here.

In [256], a dataset composed of biomedical, demographic, and self-reported survey information is used to compare the difference between the performance of CNN, RF, LR and NB algorithms. A predictive model is presented in [257] to identify anxiety from the Consortium for Neuropsychiatric Phenomics dataset (N = 272). The study uses features from clinical scale assessments, resting-state fMRI, and structural MRI. The authors argue that only using MRI or clinical data did not produce good results and improvement was observed when the combination of the features was used. A total of 569 patients diagnosed with anxiety disorders (panic disorder, generalized anxiety disorder, agoraphobia, or social phobia) were collected in [258] and features from five domains, including clinical, psychological, sociodemographic, biological, and lifestyle were collected. These studies appear to rely on static models based on cross-sectional data, which may not fully capture the dynamic nature of anxiety disorders. Future research should explore dynamic modeling approaches which could involve the use of time-series data.

Clinical, hormonal, and MRI data are used in [259], to identify the biomarkers for anxiety. The authors use 8 different classification algorithms to identify anxiety in their subjects. In [260] skin conductance, heart rate, heart rate variability, and EEG signals of 39 participants suffering from anxiety were collected. The authors collect these data from these people when they are suffering from anxiety and when they are in a non-stressful period like talking, resting, and playing time. The authors use the SVM algorithm as the predictive model. The study, with only 39 participants, suffers from limited sample sizes, which can reduce the generalizability of the findings. Future research should focus on increasing the sample sizes and diversity of the participant groups to improve the generalizability of the models. In [261], socio-demographic, clinical, and biological variables are used to train the ML model. In this study, the participants were asked to have an overnight fast, then venous blood was drawn and tested in local labs. The blood test results include metabolic function, triglycerides, free thyroxine, liver function, γ-glutamyl transfers, alanine aminotransferase, kidney function, haematological markers, etc.

To identify anxiety incurred during the COVID-19 pandemic, a set of features including psychopathology, sociodemographic, and virus exposure-related variables were used in [262] to identify anxiety. In [263], the dataset called CPSS from Statistics Canada which was created to monitor the mental health effects of COVID-19 was used. The dataset contains information on demographic, behavioural, health-related, food security, and mental health. The authors exploit SVM to build their model. To study anxiety among language learners, videos were collected in [264] from students in English classes for foreign language learners from which video, acoustic, and textual data were extracted. A multimodal deep-learning algorithm was then used to identify anxiety. These studies underscore the importance of integrating diverse data types—psychopathological, sociodemographic, behavioural, and health-related—to build more accurate models of anxiety. While the focus has been on COVID-19, future work should explore the application of these models to other public health crises, such as natural disasters or economic downturns.

Mathematical anxiety, which is also known as math anxiety or math phobia is a mental health condition that is characterized by feeling tension, apprehension, or fear that occurs when the subject is in a situation that involves mathematics. The subjects experience symptoms such as sweaty palms, racing heart, or in some cases pain attack [265]. The condition can be triggered by factors including negative past experience [266], pressure to perform well [267], social comparison [268], lack of control [269], or negative beliefs. To identify math anxiety, in [270] wearable devices are used to collect electro-dermal activity, heart rate, accelerometer, gyroscope, pupil diameter, head acceleration, etc. One limitation of these findings is while the use of wearable devices provides valuable objective data, there is a risk of overemphasizing physiological measures at the expense of understanding the cognitive and emotional components of math anxiety. So, future research should integrate physiological data with cognitive and emotional measures.

In [271], a mixture of features including psychopathology, temperament/personality, family environment, life stress, interpersonal relationships, neurocognitive, hormonal, and neural functioning, and parental psychopathology and personality were collected from the subjects and then canonical correlation analysis (CCA) was used to select the most important features. The authors suggest that via screening, it is possible to diagnose anxiety in children of age 9 to 12. These findings highlight the importance of early intervention, however, for future work ways to simplify the model or focus on the most impactful features should be explored to make the diagnostic process more practical and feasible in clinical settings.

A combination of MRI-related and psychometric features was used in [272], in which MRI images are used to measure grey matter volumes of interest and psychometric scores that are believed to be correlated with anxiety are extracted. The findings in this paper suggest that MRI features improve the performance of the predictive models compared to using psychometric features alone, with caudate and pallidum volumes being the most contributing features. In the case of psychometric features, neuroticism, hopelessness, and emotional symptoms were the most predictive features. To examine each feature's contribution to predictions and maximize interpretability, the authors use the Shapley additive explanation (SHAP) module [273]. While these findings shed valuable light on the underlying factors of anxiety, there is a risk of overemphasizing biological determinants, which could lead to the neglect of social, environmental, and lifestyle factors. Future work should consider integrating environmental and lifestyle factors with MRI and psychometric data to understand the combined effect of these factors.

To develop a model of anxiety with high temporal resolution, the dynamic changes of state anxiety levels are captured in [274] by inducing the participants' state anxiety through exposure to aversive pictures or the risk of electric shock. Then, multi-modal data were collected from the participants which included dimensional emotion ratings, galvanic skin response, and electrocardiogram. Psychological and physiological features were then collected from the data and used to train an ML model.

9 Using ML for Anxiety Treatment

Traditional care systems are unable to satisfy the needs of the growing mental health population, and many people with psychiatric disorders receive no treatments [275]. To alleviate this problem, ML algorithms can come to help to design low-cost treatment systems. In this section, we review these studies.

Predicting the Outcome of Treatments: Mental health patients respond differently to treatments, some may be responsive and some unresponsive, so there is a need for research to understand and predict when treatment is successful [276]. Cognitive Behavior Therapy (CBT) is a treatment method for mental disorders; however, the response to these treatments is different among patients and a large proportion of patients deteriorate after treatments end. In [277], ML algorithms are employed to predict the outcome of patients' long-term treatments. The study tries to identify neural predictors of clinical response in participants suffering from anxiety. They use fMRI data to analyze the dorsal anterior cingulate cortex as well as the amygdala. To achieve successful treatments it is crucial to identify moderators of response to treatment as it can inform clinical decision making and can result in treatment efficacy. In [278], ML algorithms are used to examine moderators of response to CBT. The authors test the clinical benefit of applying treatment based on the moderators that are identified via ML algorithms. The authors also study the relations between the discovered moderators and the interactions between them in the prediction process. In [279] ML algorithms are used to predict the outcome of treatments in patients suffering from anxiety. The study uses socio-demographic and clinical features to train their ML algorithms. In order to predict the patients' response to digital psychiatric interventions, ML algorithms are used in [280]. In this study, ensemble learning algorithms are used to predict changes in anxiety disorder symptoms from pre- to post-treatment. In [281], a deep learning algorithm is used to predict the patient's response to CBT. The positive impact of homework completion in therapies is well-established, but the role of therapists in reviewing the assignments is still under-investigated. In [282], ML algorithms are used analyse 2,444 therapy sessions and discent action recommendations and their subsequent reviews. These studies rely on specific datasets or populations, which may limit the generalizability of the findings. For future work, cross-validation studies should be conducted across different populations and settings to test the generalizability of the models.

Anxiety in Students: In order to reduce self-identified symptoms of anxiety, in [283], psychological AI methods were used. The study recruits 75 participants from 15 universities across the US and via questionnaires identifies their mental health. Then using AI methods tries to alleviate the symptoms of anxiety in these participants. With a sample size of 75 participants, this study may have limited generalizability. For future work, larger and more diverse datasets should be studied. Students are usually reluctant to get help for their mental health. To tackle this, the data from CCTV surveillance was collected in [284] and used to monitor university students. They process the videos to identify facial landmarks and find the students who show signs of anxiety. The use of CCTV surveillance for mental health monitoring raises significant privacy and ethical concerns. Continuous monitoring of students' facial expressions without their explicit consent may lead to privacy violations and create a sense of being constantly watched, which could itself be stressful.

In [285], the Hamilton Anxiety Rating Scale [286] is used to identify anxiety in people at workplaces, then machine learning algorithms are developed that suggest ways of anxiety management to them. Studies show that music can be used to alleviate anxiety [287]. In order to treat anxiety, in [288] ML algorithms are used to suggest classic Indian music to patients. The algorithms are trained on a dataset of mental disorder parameters and music data sets. The use of classic Indian music as a treatment may limit the generalizability of the findings. The future work can focus on performing studies for culturally tailored approaches.

10 Conclusion

Anxiety is not always evident, especially when in an individual anxiety level remains high for a long period, it is difficult for them to recognize the onset or the associations between the level of anxiety and certain situations. However, the behavioural residue of anxiety in people can provide clues in detecting the disorder. In this paper, we reviewed the studies that use ML algorithms to diagnose anxiety. We tried to be as comprehensive as we could to cover a wide range of studies to show how different types of features are extracted and used. The studies covered in this paper suggest that there is a wide variety of people's characteristics that can provide discriminative features. These features are represented in people's appearance (voice, facial expression, movement, etc), blood test results, brain signals (fMRI, EEG, etc.), the text they produced, lifestyle, psychological traits (big five personality traits, stressors, Neurodegenerative disorders, etc). As the data in Figure 1 in supplementary materials, there is a growing number of studies that employ ML algorithms to identify anxiety which shows the great potential of these algorithms. Note that the current paper was written around the middle of the year 2023, and this is why the number of papers in 2023 is less than the previous year.

In this paper, we tried to categorize the studies based on the type of data they used which are 1- test data, 2- text data, 3- signals, 4- background data, and 5- psychological data. Surely, there might be other ways of categorization; however, we found it more meaningful if the studies with the same type of data were grouped together as this would provide a more understandable picture of the literature.

While the papers covered in this paper provide valid and interesting findings, there appear to exist some limitations regarding the studies. First, all these papers have collected data from specific locations, with specific cultural, economic, and sociodemographic backgrounds. It can arguably be suggested that if a model is trained on data with such limitations, then the predictive performance of the system is not generalizable to people with different backgrounds. A good line of research for future work could be to study how these features change from one location to another and how this can be incorporated into the modeling methodologies. For example, to study and understand if the effect of lifestyle features on anxiety is different in India from that of the USA. Some features, like facial expressions, EEG, or voice signals may be less dependent on people's background. In contrast, others like psychological features, demographic features, or lifestyle features may be more correlated with the location. It is also worth noting that within a specific location, the correlations between the features and anxiety may change with environmental factors. For example, the appearance of COVID-19, an earthquake, or a hurricane may significantly affect how features contribute to the modeling process. A study to discover such correlations remains for future works.

Another limitation that we observed in these studies is that they study specific age groups without trying to identify the effect of age on the correlation between the features and anxiety. For example, a feature like drinking alcohol may be more representative of anxiety in young individuals compared to older ones. Or EEG signals may be more predictive of anxiety in old people compared to children. While this line of research for future works can provide good insight into anxiety, it can result in ML models with better predictive performance.

The studies that use data from online platforms like Twitter or Facebook, all have the limitation that the users of these platforms are, on average, younger, more social, and more educated. When such models are built, notes should be taken that the model is not generalizable to the rest of the population. Also, it is known in the literature that online behavior is usually different from the true personality of people as the content people share on social platforms is usually manipulated and different from what people feel and behave in private. This is because people tend to share a more positive view of themselves in social circumstances. In this respect, all the data collected from content on social media suffer from a bias. None of the papers we covered in this paper considered managing this bias in their algorithm. Designing a methodology that builds a model of such biases remains for future work.

All the works that we covered in this paper make the implicit assumption that there exists a static and deterministic relationship between the features and anxiety. In none of the papers that we covered a longitudinal study is performed to understand the way features and their correlation with anxiety level changes with age. For example, blood test results, EEG signals, or voice features of a particular individual may vary with age so their correlation with anxiety may change. Or if someone's anxiety level changes after treatment, then would the features also change, or would they remain the same as prior to treatment measures? These are open questions that have not been answered in the studies we covered in this paper.

Another implicit assumption in the research covered in this paper is that there is a one-way relationship between the factors and anxiety. However, there might exist feedback loop relationships between the features and the onset. That is, for example, while poverty or social support may affect anxiety, being anxious may affect the way other people support the individual or anxiety may worsen poverty. Discovering such relationships can be considered for future work.

It is well-known in the literature that comorbidities exist among many psychological disorders. Someone with anxiety is more likely to suffer from other disorders. Although some of the papers covered in this review tried to study relationships between anxiety and some other disorders, in none of these works we found an analysis on how the correlation between the features and the level of anxiety changes if these comorbidities exist. For example, the correlation between the features and anxiety level may be different when the person is only suffering from anxiety, with when there is a comorbidity between anxiety and depression, schizophrenia, or any other combination of disorders.

The studies we covered in this paper provide a good range of methodologies for anxiety diagnosis; however, we could not find any work that studies the effect of the implementation of such a system in a real-world clinical environment. Although some works have reported the implementation of their algorithms, there is no work that has performed a thorough analysis of the outcome and its implications. One challenge in the implementation of ML algorithms in mental health systems is the reluctance usually observed among clinicians [68]. The authors of the current paper believe that more work and studies are needed to find the best way of incorporating these methodologies into real practice.

Clearly, there are significant differences between the time complexity of different algorithms. Text, video, or voice processing algorithms are all different in nature, and so require different computational power. Some simple methods that use heart signals or temperatures require much lighter ML algorithms, while some video and text processing methods may require high computation machines. An analysis of the computational complexity of different approaches can be considered as a future work.

It was noticed while reviewing these papers that most of the studies in the area have focused on diagnosing the onset rather than suggesting ways of treatments. Although there are some papers that have targeted this, their proportion is very small compared to the rest of the literature, and what they all lack is an analysis to understand the relationship between different treatment measures and the outcome. One important line of research for future work is to develop ML algorithms that discover the complex relationship between the features and anxiety on the one hand and response to the treatments on the other hand. A study on this multidimensional relationship between features, anxiety level, and treatment can provide a baseline for a better understanding of the disorder. Also, such studies can provide an understanding of why some patients respond to some treatments better or worse than others, paving the way for the development of more individualized treatment measures. For example, there might be different effective treatments for people with different personality traits. Discovering such hidden relationships not only helps design better ML algorithms but also be informative for clinicians, who usually rely on the information they have gained through psychiatric research.

Explainable ML is an emerging topic that aims at developing ML algorithms that not only can make decisions but also can explain why they have come to such conclusions. While we did not find many papers that have specifically worked on designing an explainable ML algorithm, it is specifically important in the current subject that the algorithms explain why they have decided that the person is anxious. It will be useful if these techniques can identify and explain the relative importance of factors and discover their interactions with regard to anxiety. For example, there might be a subset of factors with a particular combination that make people more/less prone to anxiety or make them more/less responsive to a certain treatment. It is important if the designed algorithms are to satisfy the task mentioned above.

In recent years, many new AI techniques have emerged. One example is Chatgpt which has shown great potential in many areas. We did not find any paper that uses Chatgpt or other AI techniques in their research to identify or treat patients. This remains a not-yet-explored line of research.

What the authors of the current paper realized is although there are many studies about the subject and many datasets have been collected for this task, all these datasets are small and there does not exist a large scale dataset for the anxiety model. One way of managing this could be to define standard protocols for data collection and create a general dataset that consists of all these small datasets. Maybe, by combining the datasets collected from different regions in the world with different participants' backgrounds, a large-scale dataset can be created that would provide a baseline for a cross-cultural and deeper analysis of the onset. Models trained on such datasets would be less biased with regard to cultural, and background differences. Also, many learning algorithms, like deep learning methods require large data sets to provide accurate results.

In summary, given the importance of the issue and the cost it induces on society, developing ML algorithms that can automatically identify anxiety is a matter of importance. Such a system can be used both personally or in clinical applications to immediate the diagnosis process and to help treatments for people suffering from the disorder. However, it should be noted that the system should be trained on large and comprehensive data sets that cover a wide range of backgrounds.

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