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Survey of Applications of Ml in Stress Detection

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Abstract— Stress is a common and pervasive issue that affects millions of people worldwide. It can lead to a variety of negative health outcomes, including anxiety, depression, and physical health problems. Early detection of stress is crucial for effective management and prevention of these negative outcomes. Stress detection technologies using machine learning algorithms can provide individuals with valuable information about their stress levels and help them manage their stress in more effective ways. This can lead to improved mental and physical health outcomes, as well as increased productivity and overall well-being. Therefore, stress detection is an important area of research that has the potential to positively impact the lives of many people.

This paper presents a survey of techniques applicable to the field of stress detection using machine learning (ML) algorithms. We categorize these techniques based on the approach they take and discuss various challenges, open questions, and future work in this area. We present a taxonomy of existing research and finally discuss gaps and future directions of research to advance the study of stress management using most recent ML techniques. These technologies
provide individuals with valuable information about their stress levels and can help them manage their stress in more effective ways.

Keywords— Stress detection, Social media, Sentiment analysis, Wearable devices.

I. INTRODUCTION

This In this paper, we have presented an overview key of components required for stress detection, as well as a taxonomy of ML methods that use different features for assessing user's stress level. We have also surveyed existing research and discussed gaps and future directions of research to advance the study of stress management using most recent ML techniques. It is clear that stress is a common and pervasive issue that affects millions of people worldwide. However, with the help of technology and machine learning algorithms, we can detect stress early on and provide individuals with valuable information about their stress levels to help them manage their stress in more effective ways. As technology continues to evolve, it is likely that new techniques for stress detection will continue to emerge, further improving our ability to manage this issue. However, it is important to consider ethical concerns surrounding the use of ML in stress detection and ensure that these technologies are used responsibly. Overall, we hope that this paper has shed some light on the various ways in which machine learning can be used to detect and manage stress in individuals.

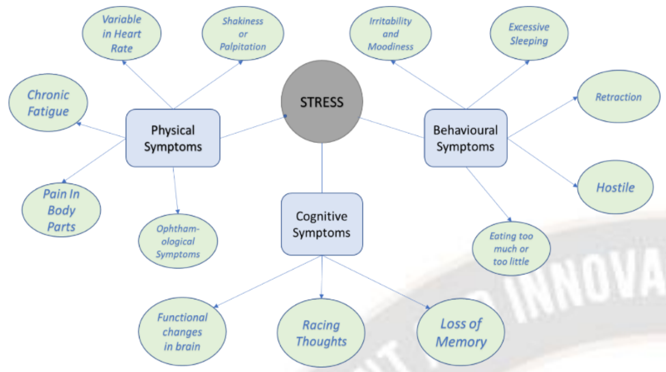
On the other hand, currently, social media plays the role of chief public opinion detector. There are over 4.2 billion active worldwide social media users. With the whirlwind expansion of internet, people have developed a liking to express their thoughts and feelings over the Internet, which has consequently resulted in an increase of user-generated content and self-opinionated data. The openness of the internet and the anonymity it provides allows users to express their feelings and sentiments on the internet without the fear of retaliation or judgement.

In addition, recent advances in Machine Learning and Artificial Intelligence have shown tremendous potential for assisting medical professionals in various fields, including detection of diseases like cancers based on MRI and CT scans [1]–[3], parasitic diseases like Malaria through analysis of blood under microscopes [4], [5], studying protein structures [6]–[8] and many others. However, one key area that has posed significant challenge is that of mental health. While ML methods are very adept at repetitive tasks like image detection, until recently it has been extremely hard to detect human emotions, sentiments, desires and thoughts, which are key components to detect and treat mental stress.

In this paper we present a survey of techniques applicable to this field of stress detection, categorize them based on the approach they take and discuss various challenges, open questions, and future work in this area. The paper is organized as follows. First, we present an overview of symptoms and signs of excessive stress in section 2. Then we present various technologies that leverage these symptoms, using different features to detect and mitigate stress in section 3. We then present a comprehensive taxonomy of ML methods that use

Figure 1 Symptoms of stress and depression

different features for assessing user stress and present a survey of existing research in section 4. Finally, we discuss the gaps and future research to advance the study of stress management and conclude in section 5.



II. Symptoms of Excessive Stress and Depression

According to the National Institute of Mental Health (NIMH), symptoms of stress and depression include loss of interest, persistent sadness, anxiousness, or "empty" mood; feelings of hopelessness or pessimism; feelings of irritability, frustration, or restlessness.

In addition, according to a study conducted by Attia et. al among 1467 randomly selected undergraduate university students during the COVID-19 pandemic, the top 10 prevalent symptoms of stress included headaches, chronic fatigue, hair loss, lower back pain, shoulders and arm pain, ophthalmological symptoms, acne, shakiness of extremities, and palpitations, high and variable heart rate. The most reported symptoms regarding the cognitive, emotional, and behavioral aspects were anxiety and racing thoughts, moodiness and irritability, and excessive sleeping, respectively [9].

In a 2013 publication [10], Sandi reported various cognitive effects of stress include impairment of long-term memory, flexible reasoning. Further, in a later study Sandi and Haller [11] identified social and behavioral effects of excessive stress. These include retraction from social interactions, tendency to be irritable and hostile. They have also identified functional and molecular changes in the brain due to chronic and early-life stress.

Figure 1. Summarizes the various symptoms along three dimensions – physical symptoms, cognitive symptoms, and behavioural symptoms. A person may exhibit more than one symptom at a time but not all. The symptoms also depend on the level of stress, the duration for which the person has been experiencing stress and any mitigating actions taken by them. Hence any system to detect stress must take this into consideration and provide helpful suggestions even when only a subset of symptoms is observed. Accordingly, many machine learning symptoms look at very specific features and try to diagnose very specific symptoms. This allows specialised systems to be built that provide higher accuracy and reliability, instead of a general system that would try to diagnose any and all symptoms. In the next section, we take a look at features that are used by many machine learning systems and motivate the use of each in different scenarios.

III.STRESS DETECTION AND MANAGEMENT OVERVIEW

Stress detection has become a significant area of research, and various technologies have been developed to help people detect and manage their stress levels. These technologies focus on one or few specific symptoms mentioned in section II. We briefly describe these technologies in this section and present a taxonomy and a comprehensive review in the next section.

Wearable Devices: Wearable devices such as smartwatches and fitness trackers have become increasingly popular in recent years. They are designed to monitor various physiological parameters, including heart rate, body temperature, and blood pressure, which can provide insight into an individual's stress levels [12]–[23]. For example, higher-than-normal and variable heart rate can indicate that the individual is experiencing stress. Other devices like EEG, ECG provide a deeper insight into person's mental and physical state and various methods leveraging these have been proposed.

Brain-Computer Interfaces: Brain-computer interfaces (BCIs) are systems that enable communication between the brain and external devices. They are used in a variety of applications, including stress detection [24]–[32]. BCIs can detect changes in brain activity associated with stress, and this information can be used to provide feedback to the individual to help them manage their stress levels. For example, some BCIs use neurofeedback to train individuals to recognize and control their stress responses.

Mobile Applications: Mobile applications have become an integral part of modern life, and they can also be used for stress detection. There are numerous applications available that use techniques such as cognitive-behavioral therapy, mindfulness meditation, and breathing exercises to help individuals manage their stress levels. Some of these applications also incorporate features like heart rate monitoring and mood tracking to provide more detailed insights into an individual's stress levels.

Voice: Voice analysis is another technique that can be used for stress detection [33]–[40]. Stress can affect the tone and pitch of an individual's voice, and this can be detected using voice analysis technology. For example, some applications use machine learning algorithms to analyze an individual's speech patterns and detect changes that may be indicative of stress. This information can then be used to provide feedback to the individual to help them manage their stress levels.

Facial Expression: Facial expression analysis is another technique that can be used for stress detection [41]–[44]. Stress can cause changes in facial expressions, such as increased muscle tension and changes in skin color. These changes can be detected using facial recognition technology. For example, some applications use computer vision algorithms to analyze an

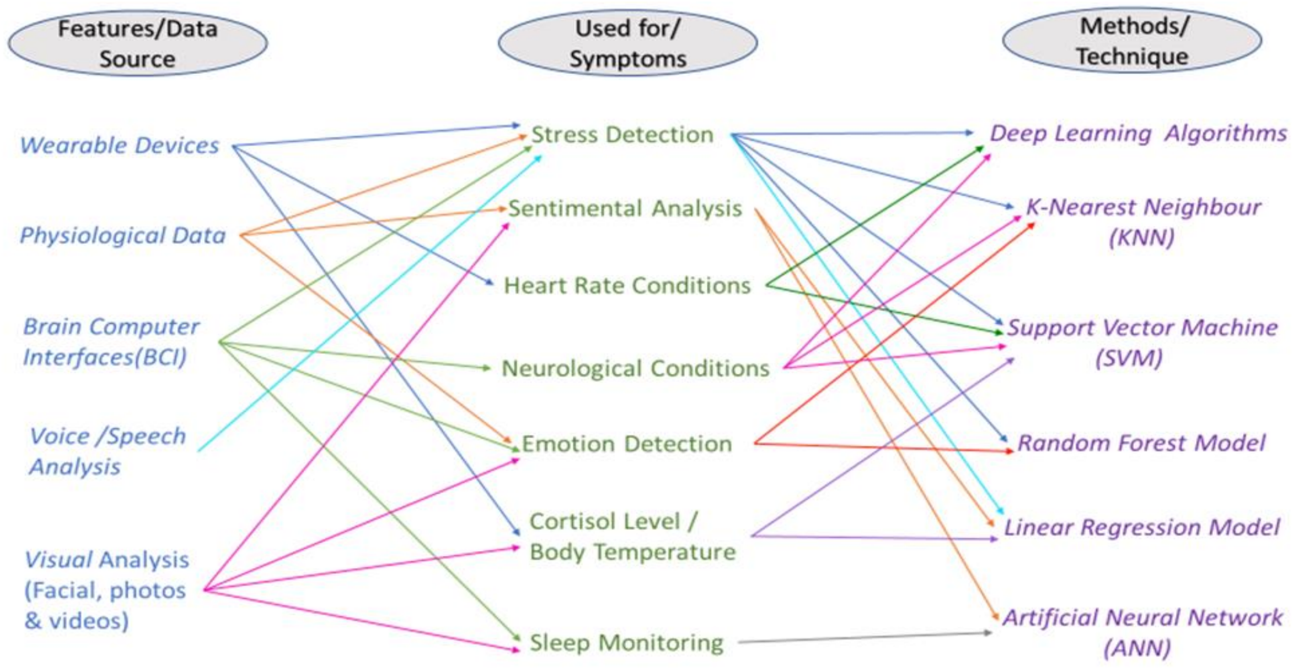


Figure 2 Taxonomy of ML methods for sentiment analysis, emotion and stress detection

individual's facial expressions and detect changes that may be indicative of stress. This information can then be used to provide feedback to the individual to help them manage their stress levels.

Social networks and interpersonal communication: Stress can manifest itself in the language that individuals use, such as using negative words, increased use of first-person pronouns, or changes in the syntax of their speech. Natural language processing (NLP) techniques can be used to analyze the language individuals use, and detect changes that may be indicative of stress [45]–[55]. For example, some applications use machine learning algorithms to analyze an individual's social media posts or emails and detect changes in their language that may be indicative of stress. These changes could include an increase in the use of negative words or a decrease in the use of positive words. The application could then provide feedback to the individual to help them manage their stress levels, such as suggesting stress-reducing activities or offering support resources. Another approach to using NLP for stress detection is sentiment analysis. Sentiment analysis involves analyzing text to determine the sentiment, or emotional tone, of the language used. For example, an individual's email or social media post could be analyzed to determine whether it is positive, negative, or neutral in tone. If an individual's language consistently shows a negative sentiment over time, it could indicate that they are experiencing stress.

These technologies provide individuals with valuable information about their stress levels and can help them manage their stress in more effective ways. As technology continues to evolve, it is likely that new techniques for stress detection will continue to emerge, further improving our ability to manage this common and pervasive issue. Few existing surveys in the field have explored applying machine learning in the detection and management of stress in humans in different contexts. For example, Mittal et. al. [56] reviewed various ML techniques and presented a systematic literature review of applications to stress management in workplace and education context, especially in the aftermath of the COVID-19 pandemic. It discussed the contributing factors for inducing stress, anxiety and depression and presented various supervised and unsupervised ML algorithms in detecting stress effectively. Akhtar et. al. [57] discusses a few studies for detecting and mitigating stress in humans. The results showed that Support Vector Machine (SVM) can classify the signals, but requires further study. In this paper, we explore a much broader field of stress detection using methods that rely on different symptoms presented during high stress situations each with it's own area of research, applicability and accuracy. We also identify gaps present in the current research and discuss future work that will pave the way for researchers to pursue impactful research.

IV. TAXONOMY OF ML METHODS USED FOR EMOTIONS AND STRESS DETECTION

In this section, we will explore various ML methods used in the literature in different scenarios to detect stress and manage mental health. We will explore these methods in the context of stress signals described in section II and individual technologies described in section III.

Figure 2. shows the high-level taxonomy of various ML methods proposed in the literature. We organize them based on the approach used, relevant features and specific ML technique.

In this section we summarize the current state-of-the-research, identify gaps and propose future work in the area.

Wearable devices:

Gedam and Paul [21] presented a review of approaches to detect stress using wearable devices and physiological devices like ECG, EEG and PPG. They propose a multi-modal stress detection system using a sensor-based deep learning technique that combines various of these data sources. They analyze various stress inducers and symptoms of stress overload (for example, cognitive symptoms, physical symptoms, emotional symptoms and behavioral symptoms). These symptoms present various opportunities for stress detection (e.g. sleep problems, inability to focus etc.). In addition, they survey various signals and their correlation to mental stress, e.g. heart rate, and heart rate variability; skin temperature, blood pressure, respiration rate etc.

Sandulescu et. al. [14] uses wearable sensors that measure physiological responses to detect if a person is stressed or not. Specifically, the BioNomadix module from Biopac, model BN-PPGED, is used to measure physiological signals such as electrodermal activity (EDA), which is a measure of skin conductance that can indicate changes in emotional arousal. Other physiological signals that can be measured include heart rate variability (HRV), which reflects the balance between sympathetic and parasympathetic nervous system activity, and respiration rate. These sensors work by detecting changes in electrical conductivity or other physical properties of the body associated with these physiological responses. They use a 4-dimensional vector to represent a human state at a given time. This includes plethysmograph signal (PPG), PPG autocorrelation (ppgau), heart rate (hrv), and EDA. Each sample is labeled according to the person's state as "stressed" or "not stressed". The proposed method used Support Vector Machines (SVM) to cluster and classify the samples in one of the two classes. The approach was tested on five independent datasets of measurements for each participant, and the size of datasets ranged from 11,620 to 13,740 feature vectors. The classification results showed that the approach was able to accurately classify stress with an average accuracy of 80.5%. The paper, however acknowledges factors that can affect the performance of the algorithm, such as individual differences in physiological responses and variations in stress induction methods and leaves it as potential future work.

Dalmeida and Masala studied detecting stress using physiological measurements based on features extracted from common wearable devices. They used Heart Rate Variability (HRV) as the key feature. They also treated this problem as a classification problem, and trained various algorithms, such as K-Nearest neighbors (KNN), SVM, Multi-layer perceptron, Random Forest, Gradient Boosting for the classification. Results showed accuracy ranging from 60% to 85% and F1 scores between 0.61 and 0.79. While these are simple solutions, and fair results, Chalmers et. al [23] studied relation between sleep quality, heart rate variability and stress. They observed that it is important to consider impacts of sleep states when using wearable devices to measure HRV. Such observations are key to building accurate machine learning models to detect stress and more sophisticated multi-modal models need to be built to improve accuracy of stress detection.

In addition to chronic mental stress, wearable devices can be effectively used to detect acute stress and be used for emergency responses. Real-time stress detection has great implications, for example for women safety. Alisha RM et. al., [58] proposed an IOT-based system for women safety. They propose a device worn by the participant that monitors physiological signals, like galvanic skin resistance and body temperature in conjunction with body position acquired using accelerometer data. When a person is under distress, these indicators will present specific patterns. They study several methods, e.g. Naïve Bayes, Boosted NB, Decision trees, Boosted DTR trees etc. to classify the activity into few categories – sitting, standing, sleeping, struggling. They show high accuracy and practicality with easy to use and cheap IOT device.

Brain Computer Interfaces (BCI)

A Brain-Computer Interface (BCI) is a communication and/or control system that allows real-time interaction between the human brain and external devices. It provides a new output channel for brain signals to communicate or control external devices without using the normal output pathways of peripheral nerves and muscles. A BCI recognizes the intent of the user through the electrophysiological or other signals of the brain. BCIs have a wide range of potential clinical applications. They can be used to restore communication and control to individuals with severe motor disabilities, such as those with spinal cord injuries, amyotrophic lateral sclerosis (ALS), or cerebral palsy. BCIs can also be used for stroke rehabilitation, allowing patients to regain motor function by controlling robotic devices with their thoughts. Additionally, BCIs have been developed for medical purposes such as restoring movement to paralyzed limbs or allowing communication for individuals with locked-in syndrome. Other potential applications include the treatment of psychiatric disorders and the diagnosis of neurological conditions such as epilepsy and attention deficit hyperactivity disorder (ADHD) [59].

Khosrowabadi et. al. [27] explored using brain-computer interface for detecting stress, specifically, chronic mental stress by analysing EEG signals. The proposed BCI system extracts features related to chronic mental stress from the EEG data collected from 8 channels on the scalp. The features are extracted using various techniques such as Higuchi's fractal dimension of EEG, Gaussian mixtures of EEG spectrogram, and Magnitude Square Coherence Estimation (MSCE) between the EEG channels. These features are then used to classify the subjects' mental stress level into stressed and stress-free groups. They train two machine learning models, the K-NN and SVM. The results show that the proposed BCI using features extracted by MSCE yielded a promising inter-subject validation accuracy of over 90% in classifying the EEG correlates of chronic mental stress. Specifically, for the K-NN classifier, the accuracy was 92.31%, specificity was 92.31%, and sensitivity was 92.31%. For the SVM classifier, the accuracy was 96.15%, specificity was 100%, and sensitivity was 92.31%. Other works like Parent et. al. [30] and Bagheri[31] have studied similar signals for stress and workload detection using methods like Linear Discriminant Analysis (LDA) and achieved accuracy of 60-

80% in different scenarios, specifically with cross-subject transfer learning approach.

Voice analysis

Stress can affect the tone and pitch of an individual's voice, and this can be detected using voice analysis technology. Pisanski [34] presents the relationship between cortisol and voice-based judgements of stress in humans. The researchers tested whether voice-based judgments of stress co-vary with cortisol levels and vocal parameters by recording speakers in a real-life stressful situation (oral examination) and baseline (2 weeks prior). They then measured the speakers' salivary cortisol levels and vocal parameters, and had listeners rate the stress levels of the recorded voices. Linear regression models were used to examine whether listeners' ratings of stress increased with the speakers' cortisol levels. These models confirmed that listeners' ratings of stress increased with the speakers' cortisol levels. The implications of these findings for understanding human stress detection are that voice-based judgments of stress may be a useful tool for detecting biological markers of stress in speakers. Several methods [35]–[39] have also been studied to detect stress, deception and lies using voice analysis and can be adopted to detect mental stress and depression, but needs further research is needed to determine the accuracy and reliability of this method.

Facial analysis

Several studies have shown human facial expressions, blood flow, temperature variations, pupil dilation to correlate with stress [41]–[44], [60]. For example Hong et. al. [43] study a non-invasive method for assessing stress levels in real-time using thermal imaging. In this study, the thermal imprint was validated against the clinical standard in a controlled lab experiment, in which neurophysiologic responses were invoked from subjects via Trier Social Stress Test (TSST). 20 healthy males and females underwent TSST in a controlled lab. Facial thermal images with established stress markers, such as heart rate and cortisol level, were collected during the experiment. Correlation analysis explored the correlation between thermal imprints and established stress markers to characterize the different phases of the stress cycle. Significant correlations between the thermal imprints and established stress markers were found during the TSST experiment. The Pearson value distinctly illustrated the promising correlation among heart rate, cortisol level, and magnified thermal imprint, all of which had a p value of less than 0.01. Nevertheless, comparatively low correlation factors were achieved between thermal imprint and cortisol level, which may be attributed to the time lag of cortisol level and its sample rate (i.e., cortisol level was collected every 5 min). They used techniques like signal magnification and correlation, however, we envision that various machine learning models can be trained to identify this relation and predict existence of stress and further research is needed to validate.

Giannakakis et. al. [42] proposed a solution to detect stress and anxiety using facial cues from videos. This non-invasive technique is very simple and practical. The facial cues used in the study involved eye-related features (blinks, eye aperture), mouth activity features (VTI, ENR, median, variance, skewness, kurtosis and Shannon entropy), head movement amplitude, head velocity and heart rate estimation derived from variations in facial skin color. These features provide a contactless approach of stress detection not interfering with human body in relation to other related studies employing semi-invasive measurements like ECG, EEG, galvanic skin response (GSR) and skin temperature. They studied various machine learning techniques including K-nearest neighbors (K-nn), Generalized Likelihood Ratio, Support Vector Machines (SVM), Naïve Bayes classifier, and AdaBoost classifier. Each classification method was tested in terms of classification accuracy, i.e. its capacity to discriminate between feature sets obtained during the neutral expression of each phase and feature sets obtained during the remaining, stress-anxiety inducing tasks. They studied the proposed method under various phases, e.g. baseline, cognitive load, Stroop-color test and stressful images, social exposure, public speaking, and mental arithmetic. The classification results demonstrate good discrimination ability for all the experimental phases performed. In each experiment phase, classification accuracy ranged between 80% and 90% considering the most effective classifier. The best classification accuracy was presented in the social exposure phase using Adaboost classifier achieving accuracy of 91.68%. The phase with Stroop-color test and stressful images appeared to be more consistent across classifiers tested. These are very promising results and lays a foundation for applications in various real-life environments including work, and clinical settings, but the authors acknowledge that further research is required in each of those settings as stress can be affected by a multitude of situational factors.

Nisha Raichur et. al. [61], have conducted research on detecting stress using image processing and machine learning techniques. It is crucial to monitor an individual's mental state while working on a computer for extended periods of time to ensure their safety. This research uses real-time non-intrusive videos to analyze an individual's facial expressions and assess their emotional state. Each video frame captures a different emotion, and the stress levels are determined in the hours following the video recording. The authors use a linear regression model. The experiments reveal that the devised method works effectively for individuals of all ages.

Social networks and interpersonal communication

Social media analysis can be crucial for stress detection in humans because it provides an efficient and non-invasive method of monitoring individuals' mental and emotional well-being. Social media platforms allow individuals to express their thoughts and emotions freely, which can give researchers insight into the user's psychological state. By analyzing users' social media activity, researchers can identify patterns of behavior, communication, and sentiment that may indicate high levels of stress. Social media analysis can also help identify early warning signs of stress that may be missed through traditional assessment methods. For example, an individual may not be aware that they are experiencing stress or may be hesitant to seek help. By monitoring their social media activity, researchers can detect changes in behavior and communication patterns that may signal the onset of stress.

Furthermore, social media analysis allows for the analysis of large amounts of data, which can be useful in identifying trends and patterns across a broad population. Researchers can use this data to develop models and algorithms that can predict the likelihood of stress and identify the factors that contribute to it. Finally, social media analysis can also help healthcare professionals and other caregivers to provide more targeted and effective interventions for individuals experiencing stress. By analyzing social media data, caregivers can gain a better understanding of the individual's specific needs, preferences, and concerns, which can help tailor treatment plans and support services to better meet their needs.

Sentiment analysis [62]–[68] is one of the core technique for analyzing user's sentiments and mood. Sahu et. al. [50] discusses the negative effects of workplace stress on employees and productivity, caused by factors such as increasing competition, family problems, discrimination, and politics. To address this issue, the paper proposes a system to detect employees' emotions and calculate their stress levels using facial expressions, sentiment analysis on monthly reviews, and daily feedback. The system generates a report for HR to analyze and counsel employees to improve their mental health and work quality. Pak and Paroubek [69] Twitter as a corpus for sentiment analysis and opinion mining! In this paper, Alexander Pak and Patrick Paroubek explore the potential of microblogging as a rich source of data for sentiment analysis and opinion mining. They focus specifically on Twitter, the most popular microblogging platform, and demonstrate how to automatically collect a corpus for these purposes. The authors built a sentiment classifier using the multinomial Naive Bayes classifier. They also tried SVM and CRF but found that the Naive Bayes classifier yielded the best results. The authors were able to obtain up to 81% accuracy on their test set using the Naive Bayes classifier with a mutual information measure for feature selection. However, they note that the method showed a bad performance with three classes ("negative", "positive", and "neutral"). Several follow-up research have studied different methods of feature selection, and ML methods achieving higher accuracy for sentiment analysis. Naz et. al. [70] use a SVM classifier with four different feature sets (Unigram, Bigram, Trigram, Combination of these three) and three different weighting schemes (Tf, Tf-idf, Binary) for analyzing accuracy results and to study the impact of different weighting schemes on classification accuracy and achieve higher than 81% accuracy.

Pabreja et. al. [71] aims to analyze stress levels among students from several educational institutions in India. The study collected data from 650 respondents using a Likert scale of 5. By utilizing diverse data visualization techniques and a random forest regressor algorithm, the research identified 15 critical contributing factors from a list of 25 features and predicted stress levels with an R-squared value of 0.8042.

V. Conclusion

In this paper, we have presented an overview key of components required for stress detection, as well as a taxonomy of ML methods that use different features for assessing user's stress level. We have also surveyed existing research and discussed gaps and future directions of research to advance the study of stress management using most recent ML techniques. It is clear that stress is a common and pervasive issue that affects millions of people worldwide. However, with the help of technology and machine learning algorithms, we can detect stress early on and provide individuals with valuable information about their stress levels to help them manage their stress in more effective ways. As technology continues to evolve, it is likely that new techniques for stress detection will continue to emerge, further improving our ability to manage this issue. However, it is important to consider ethical concerns surrounding the use of ML in stress detection and ensure that these technologies are used responsibly. Overall, we hope that this paper has shed some light on the various ways in which machine learning can be used to detect and manage stress in individuals.

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