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A Review on Mental Stress Detection Using Wearable Sensors and Machine Learning Techniques

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ABSTRACT Stress is an escalated psycho-physiological state of the human body emerging in response to a challenging event or a demanding condition. Environmental factors that trigger stress are called stressors. In case of prolonged exposure to multiple stressors impacting simultaneously, a person's mental and physical health can be adversely affected which can further lead to chronic health issues. To prevent stress-related issues, it is necessary to detect them in the nascent stages which are possible only by continuous monitoring of stress. Wearable devices promise real-time and continuous data collection, which helps in personal stress monitoring. In this paper, a comprehensive review has been presented, which focuses on stress detection using wearable sensors and applied machine learning techniques. This paper investigates the stress detection approaches adopted in accordance with the sensory devices such as wearable sensors, Electrocardiogram (ECG), Electroencephalography (EEG), and Photoplethysmography (PPG), and also depending on various environments like during driving, studying, and working. The stressors, techniques, results, advantages, limitations, and issues for each study are highlighted and expected to provide a path for future research studies. Also, a multimodal stress detection system using a wearable sensor-based deep learning technique has been proposed at the end.

INDEX TERMS Mental stress detection, machine learning, physiological signals, wearable sensor, feature extraction.

I. INTRODUCTION

Stress is the reaction of a human body marked by great anxiety or duress when faced with a challenging condition. The clinical definition of stress can be a psycho-physiological state of extreme discomfort and distress for an individual that can get extrapolated to acute mental health problems like depression or anxiety attacks.

A stressor is an event or condition present in or around an individual which may tend to trigger stress. The impact of stress on an individual can be positive and negative (also called as good and bad respectively) depending on the way stressful situations are handled. This means that whereas a situation can be extremely stressful for one individual it may happen to be just a mild reaction for another. Moreover, a prior stressful experience provides a defensive mechanism in repeated conditions. For people who like to lead a life full of challenges, stress acts as an adrenalin booster. Hence they consider stress as an affirmative reaction.

Stress which has a positive impact is called Eustress. It is a type of stress an individual feels when some stimulating incident is expected to happen in their surrounding environment. It is marked by an increase in pulse rate but without any underlying feeling of threat or fear. This stress is mostly felt by people when the outcomes of the situation are expected to be positive as like when competing for a promotion or during childbirth. Eustress can reinforce people's mental ability to meet daily challenges and motivate them to achieve their goals and complete tasks more efficiently. Eustress pushes people to come out of their comfort zone which in turn inspires them to learn, grow and become stronger.

Stress which has a negative impact called distress is marked by anxiety or a high level of concern. It can be a short-term or long-term occurrence. The effects of distress can be manifested as a decrease in performance and a lack of mental clarity. Chronic or major diseases can also cause distress which may prove extremely difficult for the human brain and

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the body to handle, possibly even leading to depression and other mental and physical health issues.

External environments like work and internal stimulations like feelings and habitual behavior can also cause distress. Some common sources of distress include fear, worrying about future events, recurring negative thoughts, unrealistic and perfectionist expectations, over-scheduling, improper future planning, excessive job demands, job insecurity, failing to be assertive, etc. Some personal stressors can also cause bad stress like the death of a family member, illness or injury, money problems, unemployment, sleep problems, legal problems, etc. Hence it is important to detect duress as early as possible as it can have a serious impact on people's lives.

Stress is also known as the "fight-or-flight" response as it evolves as a survival mechanism, enabling people to react speedily to life-threatening or challenging situations. An individual's body activates resources for self-protection when met with a threat or challenge. These resources either help face the situation or provide an expedited escape route. This fight-or-flight response is the reaction of the body's sympathetic nervous system that reacts to a stressor by producing larger quantities of chemicals like cortisol, adrenaline, and noradrenaline [1]. This increases the heartbeat, tightens the muscles, increases blood pressure, causes breathlessness, and sharpens the senses. This in turn protects the individual in dangerous and challenging situations by increasing his strength, stamina, focus and enabling faster reaction time, resulting in an expedited decision making about whether to fight or flee from the impending danger.

A list of nomenclature used in this review paper is enumerated in table 1 as follows.

This review paper investigates the following significant aspects of mental stress detection-

- Those stress detection methods are discussed where wearable devices for data collection and machine learning techniques for determining stress levels were used.
- Various commercial devices used for physiological data signal collection are listed.
- Some applications of stress detection methods are discussed.
- Existing surveys and reviews available on this subject are discussed with their advantages, limitations, and issues.
- Stress detection using devices is divided into wearable sensors, ECG, EEG, and PPG.
- Also, some literature is divided into driving, academic, and office-like working environments with research insights for each environment.

A. SIGNS AND SYMPTOMS OF STRESS OVERLOAD

People easily adapt to stress as it starts to feel adjustable and mitigable in due time. They fail to observe the ill effects of the prolonged exposure to even low levels of stress affecting them and causing damage to their health. Hence it is pertinent to be aware of the common warning signs and symptoms of stress overload. Table 2 lists the signs and symptoms of stress overload. Overload of stress can lead to major depression in susceptible people. Generally, chronic stressful life situations can increase the risk of developing depression. Various machine learning techniques play an important role in the identification of depression which is described in [67]–[69].

TABLE 1. List of nomenclature used in this paper.

Nomenclature	Referred To
AB	Adaptive Boosting
ACC	Accelerometer
ANN	Artificial Neural Network
AVNN	Average of all NN (R-R) intervals
BP	Blood Pressure
BVP	Blood Volume Pulse
BN	Bayesian Network
CNN	Convolutional Neural Network
DFA	Detrended Fluctuation Analysis
DNN	Deep Neural Network
ECG	Electrocardiograph
EDA	Electrodermal Activity
EEG	Electroencephalography
EMG	Electromyogram
EOG	Electrooculography
FD	Fractional Dimension
GPA	Grade Point Average
GSR	Galvanic Skin Response
HF	High Frequency
HR	Heart Rate
HRV	Heart Rate Variability
IBI	Inter-Beat-Interval
KNN	K-Nearest Neighbor
LDA	Linear Discriminant Analysis
LF	Low frequency
MCS	Mental health Composite Score
MLPNN	Multilayer Perceptron Neural Network
PCA	Principal Component Analysis
PPG	Photoplethysmography
PSS	Perceived Stress Scale
RBF	Radial Basis Function
RF	Random Forest
RR	Respiration Rate
SCWT	Stroop Color and Word Test
ST	Skin Temperature
STAI	State-Trait Anxiety Inventory
SVM	Support Vector Machine
TSST	Trier Social Stress Test
ULF	Ultra-low Frequency
VLF	Very Low Frequency

B. PHYSIOLOGICAL SIGNALS AND MENTAL STRESS CORRELATION

The physiological signals most commonly used in stress detection approaches are Heart Rate (HR) [17], [22]–[26], Heart Rate Variability (HRV), Skin Temperature (ST) [23]–[26], Skin Conductance (also called Galvanic Skin Response (GSR)) [17], [19]–[22], [24]–[26], [35], [37], Blood Pressure (BP) [23], [37], and Respiration Rate (RR)

TABLE 2. Signs and symptoms of stress overload [1].

Cognitive Symptoms	Constant worrying, Anxious thoughts, Forgetfulness, Disorganization, Inability to focus, Money problem, Being pessimistic (seeing only the negative side), Poor concentration, Poor Judgement.
Physical Symptoms	Aches and pains, Nausea and Dizziness, Frequent cold and flu, Diarrhea or constipation, Chest pain, Rapid heart rate, Loosening of bowel, Choking feeling, Stiff or tense muscles, Grinding teeth, Frequency and urgency of urination, Tiredness, Weight loss or gain.
Emotional Symptoms	Feeling of tension, Irritability or Anger, Restlessness, Worries, Inability to relax, Depression, General unhappiness, Anxiety and Agitation, Moodiness, Loneliness and Isolation, Other mental and emotional health problems.
Behavioral Symptoms	Sleep problems, Difficulty in completing work assignments, Changes in appetite-either not eating or eating too much, Procrastinating and avoiding responsibilities, Increased use of alcohol, drugs or cigarettes, Exhibiting more nervous behaviors such as nail biting, fidgeting and pacing.

[18], [36], [55]. HRV is the beat-to-beat variability and has time-domain, frequency-domain, and non-linear domain indices for analysis. Time-domain indices of HRV quantify the amount of variability in measurements of the period between successive heartbeats, the Inter-Beat-Interval (IBI). The measurement time of observed HRV may range from >1 minute to <24 hours during the monitoring period [73]. In the time-domain, pNN50 and pNN20 are derived from 'pNNx', where 'x' can be arbitrarily selected. The metrics include various parameters which are listed in Table 3.

TABLE 3. HRV time-domain indices [73].

Parameter	Unit	Description
SDNN	ms	Standard deviation of NN intervals
SDRR	ms	Standard deviation of RR intervals
SDANN	ms	Standard deviation of the average NN intervals for each 5 min segment of a 24 h HRV recording
SDNN index (SDNNI)	ms	Mean of the standard deviations of all the NN intervals for each 5 min segment of a 24 h HRV recording
pNN20	%	Percentage of successive RR intervals that differ by more than 20 ms
pNN50	%	Percentage of successive RR intervals that differ by more than 50 ms
HR Max − HR Min	bpm	Average difference between the highest and lowest heart rates during each respiratory cycle
RMSSD	ms	Root mean square of successive RR interval differences
HRV triangular index		Integral of the density of the RR interval histogram divided by its height
TINN	ms	Baseline width of the RR interval histogram

Frequency-domain indices estimate the distribution of absolute or relative power into four frequency bands which are Low Frequency (LF), High Frequency (HF), Ultra-low Frequency (ULF), and Very Low Frequency (VLF). Recording period length limits HRV frequency-band measurement with a minimum recommended 24 hours (ULF), 5 min to 24 hours (VLF), 2 minutes (LF), and 1 minute (HF) [73]. The LF/HF is the ratio of the power of the LF component and the power of the HF component in the Power Spectral Density (PSD). LF/HF ratio is an important indicator of the balance between sympathetic and parasympathetic nerve activity as it represents the balance of the autonomic nervous system [74].

Non-linear indices are associated with precise time-domain and frequency-domain measurements when they are generated by the same process. The advantage of non-linear indices is that they are not affected by nonstationarity as opposed to linear indices. Some parameters of frequency-domain and non-linear indices are listed in Table 4 and Table 5 respectively.

TABLE 4. HRV frequency-domain measures [73].

Parameter	Unit	Description
ULF power	ms^2	Absolute power of the ultra-low-frequency band (≤0.003 Hz)
VLF power	ms^2	Absolute power of the very-low-frequency band (0.0033–0.04 Hz)
LF peak	Hz	Peak frequency of the low-frequency band (0.04–0.15 Hz)
LF power	ms	Absolute power of the low-frequency band (0 .04–0.15 Hz)
LF power	nu	Relative power of the low-frequency band (0.04–0.15 Hz) in normal units
LF power	%	Relative power of the low-frequency band (0.04–0.15 Hz)
HF peak	Hz	Peak frequency of the high-frequency band (0.15–0.4 Hz)
HF power	ms^2	Absolute power of the high-frequency band (0.15–0.4 Hz)
HF power	nu	Relative power of the high-frequency band (0.15–0.4 Hz) in normal units
HF power	%	Relative power of the high-frequency band (0.15–0.4 Hz)
LF/HF	%	LF-to-HF power

A body-heat flux meter can be used as an additional or supplementary measuring tool instead of ST [2]. Many stress detection models have used one or more than one signal for identifying and calculating stress and its levels. These signals can be measured using wearable devices.

A stress test (an artificial stressor) is a stress-inducing event or task which stimulates a scenario that induces physical or mental exertion. These physical and mental stress tests can cause an increase or decrease in the intensity of these signals.

TABLE 5. HRV non-linear indices [73].

Parameter	Unit	Description
S	Ms	Area of the ellipse which represents total HRV
SD1	Ms	Poincaré plot standard deviation perpendicular the line of identity
SD2	Ms	Poincaré plot standard deviation along the line of identity
SD1/SD2	%	Ratio of SD1-to-SD2
ApEn		Approximate entropy, which measures the regularity and complexity of a time series
SampEn		Sample entropy, which measures the regularity and complexity of a time series
DFA α1		Detrended fluctuation analysis, which describes short-term fluctuations
DFA α2		Detrended fluctuation analysis, which describes long-term fluctuations
D2		Correlation dimension, which estimates the minimum number of variables required to construct a model of system dynamics

It was observed that when stress occurs HR, BP, RR, and GSR tend to increase while HRV and ST decrease. But physical activity like doing exercises only results in higher GSR levels and is not correlated to the mental or emotional stress of the person [3]. The ECG and PPG devices are generally used for calculating HRV. Figure 1 shows common places of putting wearable sensors and devices on the human body.

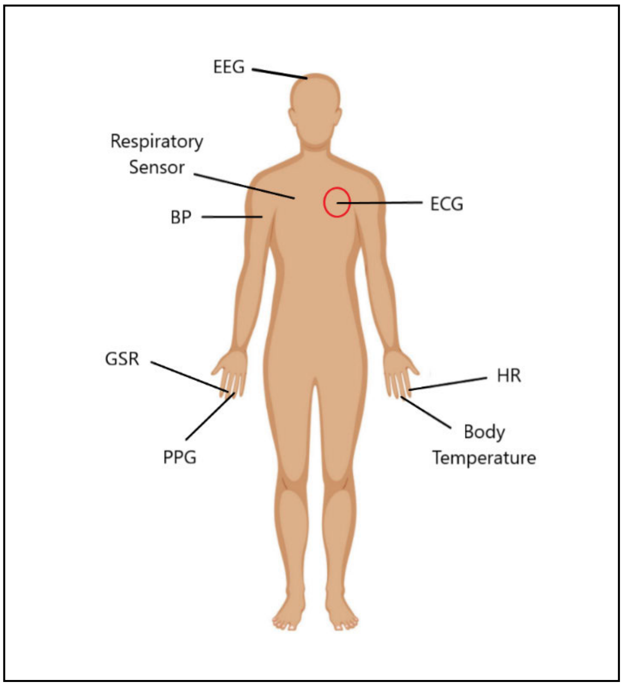

FIGURE 1. Schematic diagram showing common places of wearable sensors on human body.

The Automatic Nervous System (ANS) acts mostly through the sympathetic divisions during stress conditions and parasympathetic divisions during resting conditions. The physiological signals from the effectors of the sympathetic and parasympathetic nervous system such as HR, ST, or Skin Resistance Responses (SRRs) provides the data regarding the cognitive and sensorial state of the subject which can be captured with the help of unobtrusive sensors [4] Recent developments in embedded systems and sensors have led to the development of smart wearable devices that are capable of measuring signals even under natural conditions for the assessment of cognitive and sensorial states.

C. APPLICATIONS OF STRESS DETECTION SYSTEM

Stress is related to every aspect of human life but is applicable more for people with disabilities. A stressful situation for a blind person can be as simple as requiring a decision while walking as to whether to change direction, when to cross a street, and how to avoid a sudden obstacle. Bertrand Massot *et al.* [4] proposed an approach to detect stress induced on blind people because of environmental conditions while walking in an urban space. In such cases, ANS activity is monitored for data collection by using various sensors attached to the body like a sensor for HR, SRR, and ST using an EmoSense device. As a result, skin resistance (SR) is a more reliable signal compared to other physiological signals (HR, ST) for the monitoring and detection of stress levels in blind persons.

Most of the attempts to hack secure facilities involve a high level of positive response in the physiological stress of a person who has attempted to carry out an attack previously. Such attacks can be avoided by measuring the levels of stress of the suspected person using stress detection systems. Alberto de Santos *et al.* [5] proposed a stress detection system based on fuzzy logic using HR and GSR where a stress template is created by collecting the pattern of the previous signals under situations wherein different levels of stress were induced in a person. This system can be embedded in security systems to improve the overall security of access control as it provides 99.5% accuracy in stress detection.

Firefighters and smoke divers are constantly exposed to stressful situations as they engaged in rescue activities involving fire and poisonous smoke. Any stress in such situations may occur mainly due to lack of knowledge about the affected place, fast-changing conditions, time restrictions, exhaustion, disturbing sights, elevated level of heat, or smoke. This exposure to high-risk environments while performing their jobs, leads to various mental and health problems due to constant physical and psychological stress. Hence some researchers have used wearable devices to monitor and detect stress to improve the health and work safety of such personnel. U. Plunkte [6], developed a model to detect and classify physical and mental stress in real-time using HRV data collected with a wearable chest strap sensor in laboratory conditions. The classifier C5 decision tree was found to be better than Support Vector Machine (SVM) with 88% accuracy and precision, recall, and F-score close to 90%. The F-score calculated for this model was 0.88 with C5. This model was applied to 7 firefighters during a training exercise at a rescue Maze. This model successfully predicted the correct stress classes for firefighters.

D. REAL-TIME STRESS MONITORING

Data collection is an important and crucial step in all types of research. The majority of studies in the literature reported on short-term physiological changes in a controlled laboratory environment which included physical tests and questionnaires that relied generally on user-entered data which can be subjective and inaccurate. The hormonal techniques and subjective questionnaires are not suitable for real-time monitoring of stress levels and also require people to get out of their daily routine activities [7]. For the validation of results, it is necessary to measure physiological parameters for an extended time in real-time conditions which can be a real challenge. The recorded signals can be influenced by various context facts like a poster, temperature, and physical activity, and various types of artifacts like motion artifacts [8].

For real-time monitoring of stress, various wearable commercial devices are available in the market. Some researchers have used these devices for data collection and continuous monitoring of stress levels of users while some have developed their own wearable devices [8], [9], [11], [12], [14] made from low-cost sensors for ambulatory monitoring of stress. These devices must measure the signals with minimal error and noise for achieving better accuracy of the algorithm. Table 6 tabulates some of the popularly used devices which were used in previous stress detection approaches for collecting physiological data signals.

This paper is structured as follows. In section II, existing survey and review papers available in the literature are described with their advantages and disadvantages. Section III Methodology describes the search strategy and data collection, inclusion criteria, and exclusion criteria of selected studies. Then section IV describes the brief literature survey about stress detection using wearable sensors and machine learning techniques. A brief discussion is done in section V. In section VI, a conclusive summary of the state-of-the-art technologies is given. Finally, a future direction with the proposed model is illustrated in section VII.

TABLE 6. Commercial Devices used for physiological data signal collection.

Study	Device Name	Data Signals
[3], [35], [60], [65]	SHIMMER platform	ECG, GSR
[3], [65]	Zephyr Bioharness3	ECG
[4]	EmoSense	SRR, ST and HR
[5], [17]	I-330-C2 PHYSIOLAB	Electromyography (EMG), ECG, HR, GSR and RR.
[6], [61]	Polar H7 Chest band	HR, ECG
	NeuLog GSR	GSR
[20], [58]	Affectiva Q-sensor	3-axis accelerometer data (ACC) and skin conductance
[23]	Empatica device	HR, Blood Volume Pulse (BVP), IBI, ST, ACC
[26], [49]	Empatica E4 device	HR, Skin Conductance, ACC, ST, IBI
[33]	Vital Jacket™	ECG
[36]	ABP-10 module	ECG and respiration signal
[40]	Net Amps 200 amplifier	EEG
[42], [45]	Emotiv Epoc device	EEG
[43]	Neurocom monopolar EEG23 channel system	EEG
[44], [47]	Emotiv Headset	EEG
[46], [65]	NeuroSky Mindwave Mobile	EEG
[48]	BioNomadix module BN-PPGED	PPG, HR
[49]	Samsung Gear S1, S2 and S3	PPG, ST and ACC
[61]	LG watch Urabane 2	HR
[66]	Polar H10 Chest belt	ECG

II. EXISTING SURVEYS AND REVIEWS ON STRESS DETECTION

There are some surveys available in this area of automatic stress detection. In [9], the authors studied some physiological parameters and concluded that the best among them was the one that was influenced by pressure and proposed an appropriate framework to use in stress recognition. They also summarized techniques to analyze and recognize stress by using various wearable sensors. According to this review, the detection of stress is more accurate when HR, temperature, humidity, blood pressure, and vocal tone are used together. But since the review was done considering limited papers only, the resulted research outcomes were considered inadequate due to a lack of comprehensive study.

Stress is a growing problem for people in offices due to issues related to their jobs and heavy workloads. Hence it is important to monitor and control the employee's stress levels on a regular scale to detect stress in early stages and prevent any harmful impacts on health. A. Alberdi *et al.* [7] investigated the literature related to stress detection in office environments based on multimodal measurements and summarized the features and parameters from physiological, behavioral, and contextual data. Among all these, physiological data was found to be the best due to its promising results. They also summarized the best classification results according to the accuracy of detection. They concluded that offices have the perfect environment for using wearable smart devices because of availability of necessary infrastructure like the personal computer and Wi-Fi connections for data processing and creating the wireless sensor network respectively. But the presence of multiple users in the same environment needs an improvisation in office infrastructure. The results also advised that ECG using HRV features and EDA are the most accurate signals for stress detection.

S. Elzeiny and M. Qaraqe [10] outlined the importance of identifying mental stress stimuli and the use of early recognition techniques in working places. They suggested some stress prevention strategies for the organization and its workers. The limitations of this study are namely lack of focus on a particular method or approach for detection of stress, use of many physiological and physical signals, and inadequate literature review. Hence a more enriched and improved review that focused on various machine learning approaches to detect stress automatically [11] was done. Stress detection during driving, working, and studying environments was studied and reviewed. Some parameters like measuring stress using nasal ST and videos, wearable sensors, mobile phones, blink detection, typing behavior, human voice were also focused. From various machine learning classifiers used in previous papers, Random forest (RF) [23], [26], [38], SVM [20], [23], [26], [35]–[38], and decision trees [24], [35], [37], [38], were found to be the most effective among all due to their better results as compared to others. Also, GSR, HRV, and ST features were most useful in stress prediction.

S. Panicker and P. Gayathri [12] presented a survey on the role of machine learning in emotional and mental stress detection systems, popular feature selection methods, various measures, challenges, and applications. They also explored links between the biological features of humans with their mental stress and emotions. They briefly reviewed various machine learning algorithms used for emotion and stress detection which included the features extracted, class labels, datasets, results, advantages, and disadvantages, and also briefly studied the literature and explained the research gap very well. Another brief review is presented in [13], where authors have studied the relationship between the biosignal features used in the previous papers and their corresponding behavior during mental stress. They categorized the biosignals according to their source in the human body and made a study of the related available literature. They studied the features extracted and the significant changes in them i.e increase and decrease during stress conditions. They also listed some stress detection studies with the stressors, number of subjects, classification algorithm, biosignals, and the best accuracy achieved. However, many limitations were observed in the studied literature which are explained very well in the paper. According to their study, Stroop Colour-Word Test (SCWT) and mental arithmetic tasks were the most used stressors. Also, the analysis showed that HR and GSR which increase during stress, are the most prominent features of stress among all.

Most of the previous studies were conducted in controlled laboratory environments [17], [18] and in semi-controlled environments [19]–[21], but in daily life, it is quite difficult to detect and measure stress. Hence Yekta Said Can *et al.* [14] presented a review of the recent works on stress detection in daily life using wearable devices and smartphones. They categorized and investigated the literature according to their physiological modality and utility environments like office, campus, car, unrestricted daily life conditions, and briefly discussed and listed the promising techniques used, research challenges, and stress alleviation methods.

III. METHODOLOGY

A. SEARCH STRATEGY AND DATA COLLECTION

For this study, a literature review was carried out as a primary task which involved searching for the relevant research papers. A keyword search was conducted on papers published in IEEE Xplore, ScienceDirect, and SpringerLink till June 2020. The basic set of keywords were "mental stress", "mental stress detection", "mental stress detection using machine learning", "mental stress detection using sensors". A total of 9334 papers were retrieved and collected by all the keywords and among these 55 papers were finally selected. This systematic search aimed to provide a detailed overview of the published research papers based on machine learning and wearable sensors. The duplicate and irrelevant papers were eliminated. Some conference papers though not peer-reviewed, but still considered to be important for the broad understanding were included. Figure 2 shows the flow chart describing the search strategy used in this review paper.

B. INCLUSION CRITERIA

The inclusion criteria consisted of: i) publication date, selected papers were published between 2005 and 2020; ii) publication type, conference and journal papers were considered; iii) relevance, research paper titles, and abstracts were studied and also it was verified that the papers focused on mental stress detection where the sensors were used for data collection and machine learning techniques were used for identification and detection of stress.

C. EXCLUSION CRITERIA

Some papers were available on more than one database, hence these duplicate papers were removed. Also after screening titles and abstracts of the papers, many papers were found irrelevant. 48 papers were not available as a full-text, hence they were excluded and 168 papers either used machine learning or sensors in their methodology which was irrelevant for the review topic. Previous review papers available in the literature were also studied, hence they were also excluded in this review process. Finally, a total of 55 papers were chosen for the systematic review process.

IV. LITERATURE SURVEY

An extensive literature survey has been carried out in this paper which covers the types of devices used for data

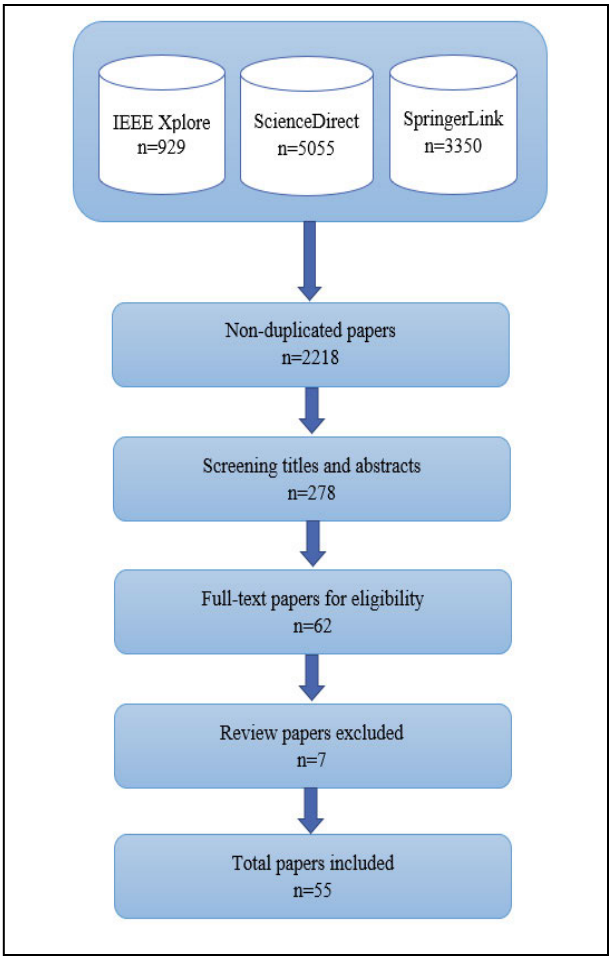

FIGURE 2. The flow chart describing the search strategy used in this review paper.

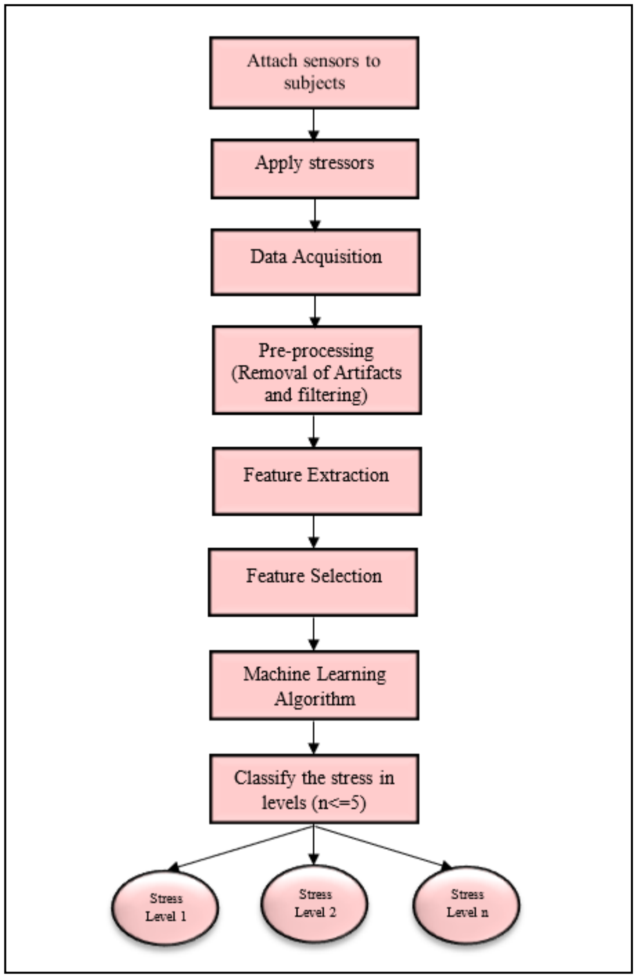

FIGURE 3. General Scheme for analysis of mental stress.

collection, the stressors, sensors, methods, and techniques used in that study with the advantages and issues present as mentioned above. Figure 3 presents the general scheme for the analysis of mental stress which was followed by many studies with varying stressors, and classification algorithms. Most of the studies identify, and classify stress in three levels i.e low, medium and high while others in two, four and maximum five levels.

A. MACHINE LEARNING TECHNIQUES

Machine learning is a system of computer algorithms that can learn from examples on their own without being explicitly coded by anyone and automatically improve their performance through experience. Using these techniques, it is convenient to develop extremely difficult or expensive systems. Machine learning is divided into supervised, unsupervised, semi-supervised, and reinforcement learning.

All the literature discussed here uses either supervised or unsupervised learning [26], [49], [54].

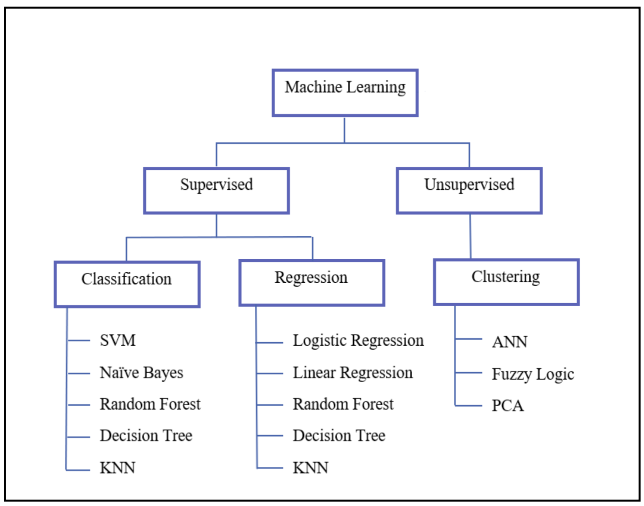

FIGURE 4. Machine learning techniques.

- Supervised learning:
  Supervised learning is an approach where a computer algorithm is trained on input data that has been labeled for a particular output. The various algorithms generate a function for mapping inputs to desired outputs. It is based on training and good at both classification

TABLE 7. Brief description of several existing machine learning techniques.

Machine Learning Technique	Advantages	Disadvantages	Applications
Fuzzy Logic Algorithm [22], [25]	No precise inputs are required, occupies a small memory space as the code is small, able to solve complex problems, constructs easily due to simple structure, helps to copy the logic of human thoughts, highly useful for uncertain or approximate reasoning.	Compromised accuracy due to inaccurate data and inputs, need a regular update of rules of a fuzzy logic control system, requires a lot of testing for validation and verification with hardware, completely dependent on human knowledge and skill, not always broadly accepted due to inaccurate results.	Medicine, Defense, Transportation systems, Industry, Naval Control, Auto transmission, Fitness management, Washing Machine
K-Nearest Neighbor (KNN) [20], [23]-[24], [26], [34], [38], [45]-[50].	Used for both regression and classification problems, effectively detects outliers, classes don't have to be linearly separable, gives high accuracy, simple to interpret and implement, no assumptions about data.	Not suitable for high dimensional data due to wide time complexity and space complexity, expensive testing of each instance, less meaningful distance numbers due to sensitiveness to noisy or irrelevant attributes.	Recommendation system, searching semantically similar documents, credit card fraud detection, banking system, political science, economic forecasting.
SVM [20], [26], [35]-[40], [42], [45]-[50], [53]-[57], [60]-[62], [64], [65]	Works well with unstructured and semi-structured data, can solve any complex problem with an appropriate kernel function, can scale high dimensional data, risk of over-fitting is less, comparatively memory efficient.	Require a long time for training large datasets, lack of transparency of results, doesn't perform very well in noise.	Handwriting and text recognition, Inverse Geosounding problem, facial expression classification, Speech recognition, stenography detection in digital images, cancer diagnosis and prognosis, intrusion detection.
Logistic regression [18], [21], [40], [47], [49], [61]-[62]	Easier to implement and interpret, make no assumptions about distributions of classes in feature space, can easily extend to multiple classes, classify unknown records fast, performs well on linearly separable datasets, less prone to overfitting and can consider regularization to avoid it, provide great training efficiency in some cases with low computation power, updated easily to reflect new data.	Constructs linear boundaries, may lead to overfitting when a number of observations are less than a number of features, can only use to predict discrete functions, requires average or no multicollinearity between independent variables, non-linear problems can't be solves due to linear decision surface, difficult to capture complex relationships, sensitive to outliers.	Online credit card transaction, detects whether the email is spam or not, credit scoring, medicine, text editing, Hotel booking, Gaming.
Naïve Bayes [23]-[24], [35], 47], [54], [59], [61]	Faster, solves multi-class prediction problems, more suitable for categorical input variables than numerical variables, requires much less training data when its assumptions of the independence of features hold true.	Faces the zero-frequency problem, estimations can be wrong in some cases which makes its probability outputs less reliable, assumes that all predictors are independent which happens rarely in real life.	Text classification, recommender systems, sentiment analysis.
Principal Component Analysis (PCA) [20], [26], [49], [65]	Removes correlated features efficiently, improves the performance of the algorithm, reduces overfitting by reducing the number of features, improves visualization by transforming high-dimensional data into low-dimensional data.	Independent variables becomes less interpretable, loss of information, before applying PCA data standardization is essential.	Facial recognition, spike-triggered covariance analysis in Neuroscience, image compression, detection and visualization of computer network attacks, quantitative finance, anomaly detection, medical data correlation.
Ensemble methods [23], [56]	Overfitting is not possible, more accurate prediction results, robust and stable model, able to capture the linear and non-linear relationships in the data allows the various needs of a difficult problem to be handled by hypothesis appropriate to those certain needs.	Due to high design and computation time not good for real-time applications, reduction in model interpret-ability due to increased complexity.	Emotion recognition, medicine, financial decision-making, computer security, remote sensing, fraud detection, face recognition.
Decision Trees [24], [35], [37]-[38], [59]	Simple and easy to understand, interpret and visualize, the output can be easily interpreted by humans, used for both classification and regression problems, can handle continuous and categorical variables, uses a rule-based approach for no feature scaling, handles missing values and outliers automatically, less training period.	Overfitting is present, not suitable for large datasets, small noise can make it unstable leading it to wrong predictions, chances of high variance in the outputs which leads to many errors in the final estimation.	Use of demographic data to find prospective clients, business management, customer relationship management, engineering, fraudulent statement detection, energy consumption, healthcare management, fault diagnosis.

TABLE 7. *(Continued.)* **Brief description of several existing machine learning techniques.**

Random Forest [23], [49], [54], [61]-[62], [66]	Provides high accuracy through cross-validation, reduces overfitting in decision trees, works fine with categorical and continuous values, used for both classification and regression problems, automatically handles missing values present in the data, uses a rule-based approach that does not require the normalizing of data, and feature scaling.	More computational power and resources required to build numerous trees to combine their outputs, require more time for training, suffer interpretability due to the ensemble of decision trees, fail to determine the consequence of each variable.	The banking industry, healthcare sectors, stock market, E-commerce.
Artificial Neural Network (ANN) [37], [53], [71]	Stored information on the entire network instead of on a database, the data may produce output even with incomplete information after training, fault-tolerant network, distributed memory, able to perform more than one job at the same time, problems are presented by attribute-value pairs, can learn by example.	Depends on hardware, unexplained functioning of the network while producing a probing solution, no specific rule for determining the structure problems firstly need to be translated into numerical values before being introduced to ANN, unknown duration of the network.	Traveling salesman problem, stock exchange prediction, image compression, handwriting recognition, speech recognition, character recognition, signature verification application, human face recognition.

and regression problems. In the classification problem, the learner is required to learn a function which maps a vector into one of the numerous classes by observing numerous input-output examples of function [75].

- Unsupervised learning:
  In this learning, models are not supervised using a training dataset. The models find the hidden patterns themselves and understand from given data. The task of unsupervised learning is to automatically develop a classification label as the algorithms are not provided with classification in it. The main goal is to find the fundamental structure of the dataset and group that data according to similarities and finally signify that dataset in a compressed format [75].

Some important and mostly used machine learning methods in this literature are described in Table 7 with their advantages, disadvantages, and applications.

Figure 4 shows how the different techniques were categorized based on these criteria.

B. STRESS DETECTION USING WEARABLE SENSORS

Nowadays, sensors play an important role in medical science and related applications. These are generally used for the detection and measurement of various diseases and their levels. The devices which use one or more sensors such as HR, ST, GSR, RR, ACC, BP sensors are considered as wearable sensors in this subsection and the studies appropriate to them are designated briefly. Stress is usually recognized as one of the major factors leading to various health problems which can be dangerous if left untreated [15]. J. Ogorevc *et al.* [2] investigated the effects of mental stress on specific psychophysiological parameters by evaluating both mental stress tasks and physical tasks on subjects. There was an increase in HR, GSR, and BP levels when subjects were introduced to stressors. Mental stress tests had weaker effects on the psychophysiological parameters as compared to physical activity.

Stress can be monitored using only one physiological signal also, but the results could be inappropriate. T. Tang [16], developed a GSR sensing system and an activity recognition system for continuous stress monitoring while considering three human activities which were sitting, standing, and walking. Only one physiological signal i.e GSR sensor was considered, and the output from the activity recognition system was fed to that sensor. The results showed that the activity information could be exploited to improve the system sensitivity in stress detection with only a GSR sensor. Table 8 tabulates the details of the studies that use wearable sensors.

C. STRESS DETECTION USING ECG

ECG measures the electrical activity of the heartbeat where mostly HRV parameters are derived from ECG signals for detecting mental stress which is further divided into Time-domain and Frequency-domain for further investigation [27], [28]. According to previous research, time-domain methods showed to be the most robust in stress detection as compared to others [32]. HRV significantly contributes to stress detection due to its close relationship with the autonomic nervous system. With the help of the combination of different HRV characteristics, it is possible to distinguish between rest, physical and mental conditions, as HRV is sensitive to any change in the mental or physical state [29]. Also, the reactivity and recovery from mental and physical stress are strongly correlated with the HRV parameters associated with parasympathetic activity [30].

Emotion recognition by facial expression was integrated with stress detection using ECG signal [31], which increased the efficiency and effectiveness of the system. A small and lightweight sensor named RF-ECG was used to record the real-time ECG signals with 204 Hz sampling rate. Stress detection was used here to address the confusion issues of facial recognition to activate the relaxation service. Negative emotions and stress were recognized with 83.33% of accuracy by combining emotion recognition and stress detection.

TABLE 8. Overview of stress detection using wearable sensors studies in chronological orders with their details.

Study	Sensors	Stressor	No. of Subject	Techniques used	Result	Advantages	Limitations/Issues
[17] (2011)	GSR, HR	Stressing Task, Relaxing Task	80	Fuzzy Decision Algorithm was used for manual and automatic implementation of the proposed approach.	Stress was detected with an accuracy of 99.5% in 10s and more than 90% by decreasing the acquisition time to 3-5s.	1. This model can easily be embedded in the current biometric systems and general accessing systems which can increase overall security. 2. The model gives Fast-oriented implementation. 3. Non-invasive and simple to use 4. Allowed adaption of behaviour of an individual by modifying the template to achieve a more accurate decision on stress degree. 5. Detected long and short-term stress.	1. Due to the lack of male subjects available at the experiment place, only female candidates were included during the collection of database. It can affect the conclusion of this approach as male and female individuals suffer different responses when stress agent endures through time. 2. Conducted in Restricted Environment
[18] (2012)	EDA, EMG, Respiration, HR	Some tests, Breathing Exercise	10	Performed a forward feature selection using the logistic regression to find a set of optimized features.	Predicted stress presence with an accuracy of 81%	1. A minimally invasive wearable sensor platform 2. Allows uninterrupted operation in excess of 13 hours. 3. A new method for the analysis of HRV which accounts for respiratory influences.	1. Several improvements to the hardware system can be possible. 2. The respiratory and EDA sensor module requires careful manual calibration at the beginning of each experimental session which is time-consuming.
[19] (2012)	GSR	Staying relaxed, Breathing deeply, Reading as fast as possible, Mathematical Operations	16	1. WEKA learning machine was used for testing Bayesian Network (BN), J48, and Sequential Minimal Optimization (SMO). 2. The data acquisition and subsequent sending of information to the computer was done by two different boards connected via ZigBee.	1. Detected different states of each user with a success rate of 76.56%. 2. This GSR device gives 90.97% accuracy in detecting whether there has been an effort or a different situation from being relaxed.	1. This device can be implemented into an application that controls different medical devices. 2. Users can use this device anywhere at home within the range of 10 meters due to the wireless communication system.	1. They have not created an algorithm that can able to differentiate between each state and also between being stressed or making an effort. 2. An improvement is required in the algorithm to establish a more reliable threshold.
[20] (2013)	ACC and skin conductance	Perceived stress scale (PSS), Pittsburgh Sleep Quality Index (PSQI) and Big Five Inventory Personality Test	18	They evaluated performance using the following six classifiers -SVM with linear kernel -SVM with Radial basis function (RBF) -KNN (k=1-4) -PCA and SVM with linear kernel -PCA and SVM with Radial basis function (RBF) -PCA and KNN (k=1-4)	1. This system gives over 75% accuracy of low and high perceived stress recognition using the combination of mobile phone usage and sensor data. 2. The research showed that mobile phone usage and wearable sensor data both include some features related to the stress levels.	This method is more general and can be useful to understand which factors influence any affective changes.	1. The study is limited to stress that participants are able to perceive and report. 2. The results are preliminary with a limited number of participants and data.

TABLE 8. *(Continued.)* **Overview of stress detection using wearable sensors studies in chronological orders with their details.**

[21] (2015)	Skin Conductance	Daily Activities like Tracking, Sleep quality etc.	12	The analysis of data was carried out using logistic regression.	The training accuracy was 91.66% and 100% with and without regularization respectively.	1. This system can monitor user's mental stress continuously and transmit the information to user's smartphones. 2. This mobile application enables users to upload data automatically on specific websites from where it can be seen by doctors and family members.	1. Only skin conductance alone cannot predict the stress level accurately in daily activities.
[22] (2016)	HR, GSR	Stroop Test	21	1. A fuzzy logic algorithm was developed and used by using MATLAB's Fuzzy Logic Toolbox. 2. The data was trained in the Adaptive Neuro-Fuzzy Interface System (AVFIS) and the C# programming language was used which has support for detecting data from serial ports used by Arduino boards.	1. An accuracy of 72% was calculated for predicting stress levels. 2. By conducting a one-tailed Spearman's Rank Correlation coefficient test, it results that this system is very capable of precisely predicting the user's level of mental stress with a high level of consistency.	This system can be used to increase awareness of stress among mouse users.	As the sensors were self-made, they have to first tested and validated by experts before using in the experiment.
[23] (2017)	HR, EDA, BVP, ST, ACC	STAI questionnaire	5	A variety of machine learning algorithms were experimented on the dataset using LOSO evaluation which is – majority classifier, J48, Naïve Bayes, KNN, SVM, Bagging, Boosting, RF, Ensemble selection.	This method detected 70% of the stress events with a precision of 95%.	1. The system recognizes the user's activity by analyzing the acceleration data from the wrist device using the machine learning method. 2. Also they have used real-life contextual information in the machine learning process to improve the performance of the method.	1. Data was collected using a costly device Empatica. 2. This method needs to be tested on a bigger population to check the robustness of the method with a higher variety in terms of gender, age, and health.
[24] (2018)	HR, Skin conductance, ST	Arithmetic problems	35	A rule-based fuzzy logic algorithm was proposed and used for stress level classification. Also, decision tree, KNN, and Naïve Bayes algorithm were used for comparison of accuracy.	The overall accuracy achieved by the system was 96.19% by using a proposed fuzzy logic algorithm.	1. The system based on GSM and GPS monitoring that can work almost everywhere including remote areas (without Bluetooth and WLAN). 2. Doctors can remotely monitor the patient and also go there using GPS location in emergencies. 3. The stress level and the physiological data are stored in the SD card for record maintenance and further analysis.	This entire data collection required a controlled environment and supervision of a medical professional.
[25] (2019)	ST, GSR, HR	Tense and calm conditions	15	Fuzzy logic was used to process data from all three sensors.	This system can work with 80% accuracy in stable conditions.	1. The reading data of sensors was transmitted wirelessly and stored in the form of digital medical record data that can be used by doctors and hospitals.	The dataset was small.

TABLE 8. *(Continued.)* **Overview of stress detection using wearable sensors studies in chronological orders with their details.**

						2. The patient's medical record stored and displayed on the website, and also results of the medical record can be accessed by a patient via an android application.	
[26] (2020)	HR, Skin Conductance, ACC, ST	NASA-TLX questionnaire, Perceived Stress Scale- 14 (PSS14) Questionnaire	32	1. The WEKA Toolkit was used for classification algorithms. 2. PCA & SVM with a linear Kernel, RF (with 100 trees), KNN (n=1), PCA & Linear Discriminant analysis (LDA), and MultiLayer Perceptron (MLP) were used for classification.	1. The maximum classification accuracy was 94.52% and minimum accuracy was 91% for 3 classes. 2. They developed a session-based stress classifier that gives a maximum of 94.44% accuracy with HR and 100% with EDA signals.	1. This system is applicable in the daily lives of people without interrupting their routines. 2. They applied stress alleviation methods which are proven effective. 3. This hybrid model can increase the accuracy of the system than the person-independent models in cases where there is not enough data of participants to develop the personalized model.	The data-gathering devices give low data quality than the medical- grade devices.

As there are many techniques available for the estimation of stress from physiological signals, its fine-grained assessment is still a challenge. Tania Pereira *et al.* [32] studied various HRV metrics for stress level assessment using a short-time window, where a sub-set of HRV metrics namely AVNN, rMSSD, SNDD and pNN20 showed consistent differences between stress, and non-stress phases. Trier Social Stress Test (TSST) with four phases was used as a stress-inducing protocol where the AVNN metric allowed a fine-grained analysis of stress effects and proved to be the most reliable metric to recognize stress level.

In [33], the authors proposed a fuzzy system that detected continuous stress situations to improve the social inclusion of people with disabilities and the quality of their life. Also, they presented some variations and enhancements in existing methods by proposing some changes in monitoring and processing physiological signals like HR, GSR, and breathing, which helped improve responses in detecting stress as compared with other previous works by using advanced signal processing.

A publicly available dataset "WESAD" [70] was used by P. Bobade and M. Vani [71], where data of sensor modalities like ACC, ECG, BVP, BT, respiration, EMG, and EDA was used. They have used KNN, LDA, RF, Decision tree, AB, kernel SVM classifiers, and achieved an accuracy of up to 81.65% and 95.20% for 3-class and binary class respectively. They have also applied a simple feed-forward deep learning technique which increased the accuracy up to 84.32% and 95.21% for that respective classes which showed that deep learning is better than the traditional machine learning classifiers and the generalization is possible with the Leave-one-subject-out evaluation scheme. The overview of stress detection using ECG studies with their details is listed below in table 9.

D. STRESS DETECTION USING EEG

The latest research in neuroscience reveals that as the awareness of the human brain determines a situation that is threatening and stressful, the primary target of mental stress is the human brain [40]. This can be identified by EEG which is an electronic record of the oscillations in the human brain which can be recorded using multiple electrodes by attaching them to the scalp. EEG uses sensors for capturing the time-varying magnitude of electric fields originating from the brain and also analyses the neutral activities occurring in the brain [41]. EEG Alpha and Theta bands are very important among all bands as the existence of stress are mainly identified through the changes occurring between them. In a state of stress, Alpha decreases and Theta increases while in a relaxed or no activity state, Alpha increases and Theta decreases [42]. The frontal brain activation has a great impact on detecting and evaluating stress levels and also gives high detection and classification rates [43].

A novel interface named CogniMeter was proposed in [44], which detected user's current emotions, level of mental workload, and stress in real-time using only EEG. The Theta band power feature was used for real-time workload recognition and FD, statistical features were used for emotion recognition. SVM was used to train the classifier model. The recognized emotions were illustrated by the facial expressions of a 3-D avatar implemented in the Haptek system. In this study stress and its levels were identified from a combination of recognized emotions and the mental workload. Table 10 shows the studies on stress detection using EEG with their details.

TABLE 9. Overview of stress detection using ECG studies in chronological orders with their details.

Study	Other Sensors	Stressor	No. of Subjects	Techniques used	Result	Advantages	Limitations/Issues
[34] (2011)	-	SCWT	10	1. The raw ECG signals were pre-processed using 4th order elliptic bandpass filter. 2. ECG bands, high frequency (HF) and low frequency (LF) were considered to extract the mental stress-related features through DWT using function, db4 wavelet, and mapped using KNN.	The maximum average accuracy of classification was 96.41% with the KNN classifier where K value varied from 1-10.	The accuracy by KNN (96.41%) higher than previous research using SVM (90.10%) on a similar Stroop colour word test.	1. The subjects were all female. 2. Only stress conditions and relax conditions were detected by the system which could further be divided into levels like low, medium, and high.
[35] (2012)	GSR, ACC	SCWT, mental arithmetic problems based on Montreal Imaging stress Task (MIST)	20	WEKA machine learning engine was used to train classifiers like the J48 Decision tree, Bayes Net, and SVM for stress inference.	1. Achieved 92.4% accuracy of mental stress classification and 80.9% accuracy for between-subjects classification. 2. Decision Tree classifier give the best performance using 10-fold cross-validation due to their low complexity.	This activity-aware system can enable the development of many effective mobile applications using physiological signals like stress management, effective tutoring, and an emotion-aware human-computer interface.	1. This study was limited to 3 specific activities which were sitting, standing, and walking. 2. The recording time of the sensor data was relatively short.
[36] (2016)	Respi ration sensor	Baseline stage, Memory task, Stress Anticipatio n, video exposition, storytelling, Arithmetic task	80	1. A SVM with a Gaussian radial basis kernel was used as a classifier. 2. A 3-fold cross-validation was applied and repeated 50 times.	The SVM discriminated stress stages from relaxing ones with an accuracy ranging from 68-89%.	1. Some features derived from Wavelet Cross-biospectrum (WCB) are useful in emotional and mental stress detection. 2. The results suggest that interactions between respiration and HRV are altered during stress.	So many stressors were applied which made the data collection procedure more time taken and complicated.
[37] (2017)	BP, GSR	Daily Routine	20	1. Zero crossing method was used for pre-processing. 2. Feature extraction was done by discrete wavelet transform. 3. SVM, ANN, BN, and decision tree were used as classifiers.	SVM gave the best results among all the classifiers.	1. Analyses the stress through real-time physiological data in different positions and moods. 2. ECG signals were pre-processed without disturbing ECG waveform characteristics.	Not properly explained the data collection procedure and accuracy of stress level detection in percentage.
[28] (2019)	-	Social expose, Stressful event recall, cognitive load, stressful videos	24	1. Minimum Redundancy Maximum Relevance (mRMR) selection algorithm was used for selecting useful features among all. 2. A 10-fold cross-validation scheme on a sample basis was used with several classifiers.	The best accuracy of stress recognition was 84.4% by using a Support vector machine with only utilizing HRV parameters.	1. The 11 stressor tasks increased the available data for each subject, helping in better results. 2. Only one ECG channel was used and can be easily used through wearable devices in daily routine.	1. A bigger dataset would enhance the generalizability of the results. 2. Only ECG signal was used for stress detection.

TABLE 9. ***(Continued.)*** **Overview of stress detection using ECG studies in chronological orders with their details.**

[38] (2020)	EDA	SCWT, light physical exercise	9	1. Applied 6 machine learning classifiers namely BN, SVM, KNN, C4.5 Decision Tree (J48 implementation), RF, and AB learning methods and also, used WEKA ML engine. 3. They applied Synthetic Minority Oversampling Technique (SMOTE) on training data for balancing the class ratio in training folds.	RF and AB algorithms showed promising stress detection results supporting the experimental analysis of the paper.	1. Proposes the m-health solution app with a novel Decision Support System (DSS) for online stress monitoring. 2. Can be used in clinical settings and in remote monitoring systems.	1. This paper inferred stimuli without a predefined stress response. 2. Fewer subjects and Fewer monitoring sessions.
[39] (2019)	-	Mental arithmetic calculations	20	1. A Convolutional Neural Network (CNN) was proposed where the stochastic gradient descent with momentum (SGDM) used for training. 2. LDA and SVM were used as classifiers with 4-fold cross-validation. 3. One-way analysis of variance (ANOVA) was used to compare the performance of detecting stress using various methods.	1. The performance of this system was better than all six conventional HRV methods ($p<0.01$) and improvement was at least 7.2% with a detection error rate of 17.3%. 2. Results proved that CNN had potential in practical applications of HRV based stress detection.	1. This CNN-based method can be very useful for acute cognitive stress detection using only 10s of ECG data and also in practical applications of real-time stress detection using HRV. 2. CNN has the automatic feature learning ability which may equally help the researchers like biologists and physiologists to acquire more insights into the physiological effects of stress.	The dataset was small and only 2 classifiers were used for validation of results.

E. STRESS DETECTION USING PPG

PPG is also known as BVP is obtained from a pulse oximeter that uses a light source and a photodetector at the skin surface. These are generally low-cost, small in size, and user-friendly devices that help in reliable monitoring of pulse rate. Table 11 shows some studies that have used wearable PPG and other sensors for data collection.

F. STRESS DETECTION IN VARIOUS ENVIRONMENTS

1) STRESS DETECTION IN DIFFERENT DRIVING CONDITIONS

There can be many stressful events that may occur while driving like maintaining the speed limit, heavy traffic, and unsafe weather conditions, etc. Driving in such conditions may lead to violations of rules and possibly car accidents. Hence the identification of the stress level of a driver while driving is an important issue for safety, security, and health purpose. In such cases, wearable devices can be helpful by alerting the driver about the elevated stress levels and advising them to take necessary precautionary measures.

A dataset was available on the PHYSIONET website (http://www.physionet.org/) which was created by Jennifer Healey and Rosalind Picard [51], wherein they used four sensors namely electrocardiogram (EKG), EMG, skin conductivity, and respiration (through chest cavity expansion) for real-time physiological data collection during real-world driving situations under normal conditions. This database contains several signals from 24 healthy volunteers while driving on a route through open roads which identified city streets as high stress, highway as medium stress, and rest as low stress around Boston. This dataset was most commonly used in many studies whose details are shown in table 12.

Hyun-Myung Cho *et al.* [52] used the Physionet dataset and mental arithmetic data set to detect stress using row ECGs and a method for training a Deep Neural Network (DNN). Some conventional machine learning classifiers namely decision tree, KNN, Logistic regression, RF, and SVM were tested. They used a transfer learning method to train a model with a small dataset which improved accuracy by 12.01% and 10.06% when 10s and 60s of ECG signal were used respectively in this model. This proposed method improved the accuracy of stress detection from 87.39% to 90.19% when compared with other DNN methods. In [53], a stress detection system was proposed where a professional dynamic driving simulator was used for an experiment. Three sensor devices were attached for recording the Skin Potential Response (SPR) from both the hands and ECG from the chest. The stressors included driving through a highway with some unforeseen events happening at some positions. SVM and ANN were used for classification, wherein ANN gave better results than SVM with a balanced accuracy of 77.59% for considered events.

TABLE 10. Overview of stress detection using EEG studies in chronological orders with their details.

Study	Stressor	No. of Subjects	Techniques used	Result	Advantages	Limitations/ Issues
[42] (2014)	Questionnaire	34	1. The four different kernels of the SVM classifier namely Linear, polynomial, Radial Basis Function (RBF), and Sigmoid were used to detect stress with 5 and 10 fold cross-validation. 2. The Power Spectral Density (PSD) and Energy Spectral Density (ESD) were the extracted features.	1. RBF kernel achieved higher accuracy than the other 3, with 50% accuracy for PSD and 83.33% for ESD while linear kernel gives lowest. 2. ESD data showed more dependable and significant data in stress determination using the RBF kernel.	1. Used a portable and reasonable device to capture raw EEG signals. 2. The results show that SVM alone can classify the stress data very well.	The result may vary if the training data set did not follow the n-fold cross-validation because it is important to avoid overfitting of the created model.
[45] (2016)	SCWT, Mental arithmetic test	10	1. The ratio of the relative difference of beta power and alpha power was used as the key parameter. 2. SVM was used as a classifier and 4-fold cross-validation to calculate accuracy. 3. C# applications were developed in Microsoft Visual Studio to interface the EEG data collection device.	1. SVM gives 75% accuracy in 3-level stress recognition. 2. For 2-level stress analysis SVM give 88% for the Stroop colour-word test and 96% for the mental arithmetic test.	They used the design of a temporal sliding window with different overlapping which increases the accuracy of the system.	1. The questions included in the Stroop colour-word test and mental arithmetic test can be modified. 2. The dataset was very small, data from more subjects are required to determine a better set of stress features.
[40] (2017)	Montreal imaging stress task	22	1. Receiver Operating characteristic curve, t-test, and Bhattacharya distance was used for feature extraction. 2. Logistic regression, SVM with linear kernel, and Naïve Bayes classification models were used with 10 fold cross-validation.	1. The proposed framework recognized stress with maximum accuracy of 94.6% between 2 levels of stress while 83.43% for multiple levels.	1. This system gives maximum accuracy while comparing with other previous stress detection methods using only EEG which shows that EEG signal alone has the potential to reliably identify the levels of stress. 2. This system could help in developing a computer-aided diagnostic tool for the identification of stress.	To identify multiple levels of stress, further analysis and validation are required.
[46] (2019)	PSS-14 Questionnaire	63	1. Features were extracted from band power of alpha, beta, delta, and theta bands. 2. Used SVM and KNN as classifiers.	1. System achieved an average classification of 74.43% using K-NN. 2. A correlation of band power ratios of different bands was observed, obtained from EEG signal from the frontal area of the brain.	1. Used EEG to predict stress levels without manual intervention and recording by a Brain-Computer Interface (BCI) instrument. 2. Proposed the design of a brain mapping-based stress recognition system using a low-cost single electrode EEG device.	1. Features were used from 4 bands. 2. The classification and results were done and compared by using only 2 classifiers.
[47] (2020)	The PSS-10 questionnaire, Interview with Psychology expert	33	1. Features were selected using a statistical significance test. 2. SVM, Naïve Bayes, KNN, logistic regression, and multi-layer perception (MLP) were used as classification models.	1. SVM was best for classify long-term human stress when used as a feature with alpha asymmetry. 2. The classification accuracy has been improved by up to 85.20% using the Expert evaluation-based labeling method.	1. Long-term stress was classified using resting-state EEG signal recordings. 2. The stress level of participants was labeled by a psychology expert which was not been explored before in previous studies. 3. Alpha asymmetry can be used as a probable bio-marker for stress classification using expert evaluation.	More instances of EEG recordings would be needed for applying deep learning-based strategies.

TABLE 11. Overview of stress detection using PPG studies in chronological orders with their details.

Study	Other sensors	Stressor	No. of Subjects	Techniques used	Result	Advantages	Limitations/Issues
[48] (2015)	EDA	Public speaking task, cognitive task, TSST, STAI Questionnaire	5	1. SVM kernel was used for classification 2. Used LIBSVM library	The results give over 82% accuracy for 2 subjects and over 80% precisions in the majority of the data from subjects.	1. The subjects can move freely while experimenting. 2. The wearable device connected through wireless to a Biopac MP150 communication station that directly sends different signals through wireless to a computer.	1. Only one type of classifier was used rather than more which may increase the accuracy of stress detection. 2. Dataset was very small.
[49] (2019)	EDA, ACC	NASA-TLX questionnaire, Algorithmic programming contest	21	1. Fast Fourier Transform (FFT) and Lomb-Scargle periodogram were applied for feature extraction. 2. PCA & LDA, PCA & SVM with the radial kernel, KNN (n=1), Logistic Regression, RF (with 100 trees), and multilevel perceptron were used as a classifier with 10-fold cross-validation.	1. For 3 class stress level detection, 90.40% accuracy was obtained by using Empatic E4 device and 84.67% with Samsung S devices. 2. Achieved maximum 97.92% accuracy with their person-specific models while 88.20% for general models. 3. RF and Multilayer Perceptron performed best among all classifiers.	1. This system was tested in real-life settings. 2. Used unobtrusive wearable devices which were easy to use in daily life which can track the stress level and intervene if the extreme level of stress detected.	The relation between perceived stress and physiological stress was not studied methodically in the literature.
[50] (2020)	PPG	Mental arithmetic task, SCWT	14	1. Quadratic discriminant analysis and SVM were used as classifiers and LOSO (leave-one-subject-out) used for evaluation of classification performance. 2. To capture the stress-related temporal information, a set of new Poincare plot features was used.	SVM gives 94.33% accuracy for the detection of five-level stress.	1. Used low-cost PPG sensor. 2. Gives temporal information extraction and accurate identification of stress with the help of ultra-short-term PPG monitoring.	Compared the accuracies of only 2 classifiers.

2) STRESS DETECTION IN ACADEMIC ENVIRONMENT

The study is one of the main sources of mental stress among adolescents especially students which generally comes from the excessive curriculum, preparation for exams, unsatisfactory academic performance, over expectations from parents, strict teachers, lack of interest in a particular subject, etc. These factors can affect the physical and mental health of students. Wearable sensors can be useful to detect stress and its level among students allowing them to perform better in their studies. Akane Sano *et al.* [58] detected stress in academics by collecting extensive subjective and objective data using wearable sensors, mobile phones, and surveys. For this, 30 days data of 66 undergraduate students were taken who were socially connected. ST, Skin Conductance, and ACC data were used as physiological signals which were captured using wrist-worn devices and 700 features were extracted

TABLE 12. Overview of stress detection using Physionet database in chronological orders with their details.

Study	Signals	No. of Subjects	Techniques used	Result	Advantages
[54] (2015)	ECG	10	1. Feature extraction was done by using WEKA software. 2. 10 classifiers namely Naïve Bayes, SMO (SVM), Logistic Regression, Multilayer Perceptron, IB1 (1-nearest neighbor), IBK(k-nearest neighbor), ZeroR, J48 (decision tree), RF, and random tree were used for classifications.	Random tree classifier identified 3 classes of stress with 88.24% accuracy and Naïve Bayes for 2 stress states with 100% accuracy.	Only ECG signals alone can detect stress in driving conditions.
[55] (2015)	Respiration, GSR hand, GSR foot, HR, EMG	7	1. KNN and SVM were used for classification using WEKA3.6. 2. 78 features were extracted for each segment of any signal signals and the best features had been found by choosing ClassifierSubsetEva and SVM classifier.	1. Respiration sensor was the most significant sensor for mental stress detection. 2. 98.42% accuracy was achieved for 100 and 200 seconds intervals and 99% for 300 second intervals.	Results of this study were more accurate and also fewer features have been used as compared to another study on the same dataset.
[56] (2019)	ECG	10	Linear Discriminant, KNN, Ensemble, and SVM classifier were used to train the model which was obtained using a backward selection algorithm and 10-fold cross-validation method.	Achieved 98.39% accuracy in detecting three classes of stress.	1. Used a small-scale (104 intervals) with only ECG signal is used to detect stress. 2. Used local Hurst Exponents.
[57] (2019)	ECG	15	1. Linear, Quadratic, and Cubic were the 3 SVM types that were used with the default kernel function and the cross-validation scheme. 2. Three features ECG-derived respiration, QT interval, and RT interval are used.	Cubic SVM with kernel function Gaussian gave an accuracy of 98.6% to detect stress with all available features.	No external sensors were used to record respiration signals as they chose EDR (ECG Derived Respiration) as an alternative for it because of the similar properties.

from the collected data. The SVM with a linear kernel and a radial basis function kernel was used as classifiers which gave accuracy ranging from 67 to 92%. They also deliberated as to how correctly the data classified the students into groups of high/low GPA, good/poor sleep quality, high/low self-reported stress, and high/low MCS with the help of collected surveys. The overview of the studies that used data from the academic environment is given in Table 13.

3) STRESS DETECTION IN OFFICE-LIKE WORKING ENVIRONMENT

The office-like environments can create mental loads which can be responsible for health issues like anxiety, stress and depression of the employees. There can be many sources of stress like long working hours, tight deadlines, work overload, job insecurity in private sectors, working in teams, and peer pressure. In [59], a model was developed to detect the stress of computer users in a working environment. ECG, EMG, EOG, and EEG signals were collected using BIOPAC software for 12 subjects doing different computer-mediated tasks. 14 features were extracted from the collected signals and a three-layer backpropagation neural network was used for classification and stress detection. This system can monitor the real-time, long-term stress of computer users and can also inform them about their stress condition and stress influencing factors continuously. Table 14 listed some studies available on stress detection in the office-like working environment and their details.

V. DISCUSSION

There are some surveys that lack exhaustive review [9]–[11] with regards to the topic of stress detection, whereas, surveys [7], [12]–[14] covers comprehensive information. However, no collective information on machine learning and wearable sensors was described in any of these reviews. To fill this lacuna this paper presents an extensive review on mental stress detection using both wearable sensors and machine learning together.

The significant observations from this review are listed below:-

- Empatica, Emotiv and SHIMMER platform have been popularly used for data collection.
- Classification accuracies obtained with specific models have been mentioned (in Tables no. 5-11) This can provide a clear guideline for fellow researchers in this field.
- Very few standards and publicly available datasets were used and most researchers built their own real-time datasets.
- SCWT, TSST, and mental arithmetic tasks appear to be the most popular and promising stressor tests.
- HR and GSR are the most distinctive and unobtrusive signals for detecting stress.

TABLE 13. Overview of stress detection in academic environment studies in chronological orders with their details.

Study	Sensor	Stressor	No. of Subjects	Techniques used	Result	Advantages	Limitations/ Issues
[59] (2016)	ECG	Ongoing verbal exam, after a vacation	42	1. Kubios software was used to perform the HRV analysis where time and frequency measures were analyzed. 2. Naïve Bayes, SVM, MLP, Adaboost M1 (AB), decision tree using C4.5 were used as a classifier and Leave-one-subject-out cross-validation technique and Weka platform was used for validation and training of the classifiers respectively.	C4.5 tree algorithm classifier was best among all achieving the following performance rates: Sensitivity=78% Specificity=80% Accuracy=79%	1. Detects mental stress via non-linear ultra-short-term HRV analysis (3 min) using advanced data mining and machine learning techniques. 2. The feature selection was performed on a separate folder than the one used for training and validating the classifier to reduce the risk of overfitting.	A large database size may be helpful to further explain the findings of the developed classifier.
[60] (2017)	ECG	Final written examination , After a long winter holiday while playing simple games	16	1. The 16 HR features were analyzed using pattern recognition methods and SVM was used as a classifier with 5-fold cross-validation. 2. To evaluate the importance of each HR features sequential backward selection (SBS) was applied.	1. Mean of RR interval series and the mean of the absolute values of the second normalized differences of RR interval series were the most effective and optimal features. 2. SVM gives 93.75% accuracy for binary classification of strong stress and 87.5% for weak stress.	The dataset was divided into strong stress and weak stress to analyze the difference between significant autonomic reactivity.	Only one classifier was used whereas more classifiers can be used for comparing results.
[61] (2017)	HR, GSR	9 mental task activity	9	1. Event Based (EB) and Minute Based (MB) approaches were used for feature extraction. 2. Naïve Bayes, SVM, Logistic Regression, RF were used as classifiers and tested using both Leave one subject out cross-validation and 10-fold cross-validation.	RF model detected stress more accurately than others with 88.8% F-measures.	This system-induced stress in a controlled environment and identified the physiological responses for accurately predict stress using only wrist-worn sensor data features.	1. Some of the activities used for inducing stress actually didn't give high accuracy, suggesting a challenge for detection of some stressful activities. 2. Performed in a controlled lab environment.
[62] (2020)	HR, ST, GSR, Pulse oximeter, Breath-rate sensor	STAI self-report Questionnaire	21	1. MATLAB software was used for processing each signal and feature extraction. 2. SVM, KNN, RF, and Logistic Regression algorithms were used to find a feature subset that provides the best accuracy for stress classification.	1. The students stress can be identified with an accuracy greater than 90% using the KNN classifier with HR, ST, oximeter signals, and four physiological features. 2. Anxiety can be identified with more than 95% accuracy using SVM with GSR signal and three physiological features.	1. This system can be used to develop a stress recognition system to help teachers to identify the stressful tasks in an academic environment which can help students to control their level of anxiety while performing academic tasks or exams. 2. The advantage is to avoid the results of diagnosis depending on student's self-perceptron.	In this experimental procedure of this study, only one type of stress task was tested.

And the identified challenges are described below.

- Improperly worn devices and the unrestricted movement of the subjects are the main significant challenges. In controlled environments, the movements and the stressors are constrained and limited, thereby, giving an opportunity to researchers to intervene with the subjects to wear the device properly and to get precise results. But in a real-time environment, movements are unrestricted and unmonitored. Also, the subjects may incline to do more than one activity at a time, making the detection process more complicated and thereby could reduce the performance of stress detection systems.

TABLE 14. Overview of stress detection in Office-like working environment studies in chronological orders with their details.

Study	Sensor	Stressor	No. of Subjects	Techniques used	Result	Advantages	Limitations/ Issues
[64] (2017)	ECG, GSR	Email Interruption, Time pressure	25	1. SVM and KNN were used to classify 17 extracted features. 2. Used 10-fold cross-validation.	The SVM classifier with RBF kernel gave high accuracy of 92.75%.	This system indicated that GSR, HR, and its variability features are very useful in stress prediction due to their immediate response.	Only 2 classifiers were used for classification.
[65] (2018)	ECG, EDA, EEG	Maastricht Acute Stress Test, Mental stress test	15	1. PCA analysis was done to calculate variance in the data. 2. SVM algorithm was used as a classifier with a 5-fold cross-validation technique.	1. A third-order polynomial kernel of the SVM algorithm was best to recognize the stress phase and relax phase. 2. SVM classifier gives 84.0 % sensitivity, specificity 86.0% and overall accuracy 86.0%.	1. A biological marker i.e salivary sample was collected to check the correlation. 2. Positive and significant results obtained from the calculated correlation of the cortisol values and physiological responses.	Improvements in feature extraction and classification algorithms are required for better accuracy.
[66] (2019)	ECG, PPG	Mental Arithmetic Task	6	1. RF classifier was used. 2. Leave-one-participant-out was used for validation.	1. Green light performed best than Infrared (IR). 2. The system achieved 80% accuracy in the PPG dataset and 79.7% in ECG.	1. HRV measures derived from wrist-based PPG have the potential to detect stress state accurately like ECG. 2. Results showed that a small window size was enough to detect the state of stress.	The wearable device gave raw RR intervals has quality issues like loose contact of the electrodes with the subject's skin due to which it was observed that green light PPG perform even slightly better than IR.

- Health issues such as those related to blood pressure, blood sugar, sleep patterns, alcohol or smoking habits, etc., are very likely to cause massive changes in subjects' physiology. Hence, it is vital to pay more attention to the said issues as they may affect the accuracy of the system.
- Collecting data in a real-time environment, removing artifacts and noise, and ensuring data accuracy are the most challenging aspects in developing any stress detection model.

VI. CONCLUSION

Stress is a psycho-physiological reaction to events or demands in day-to-day life. Stress can be induced by one or more stressors and the resulting change in bodily reactions can be detected by sensors. There are many studies available that have done experiments in controlled laboratory environments and have given a high level of accuracy for detecting stress in comparison to real-time stress detection methods which give quite less accuracy. Nowadays, many wearable devices are available in the market which can be used in physiological signal data collection. These devices are user-friendly and give less error and noise. Hence, these can be used to monitor and measure stress levels without affecting the user's daily functioning. Some researchers developed their own devices using low-cost sensors which gave promising results and good accuracies. In most of the studies, more than one physiological signal was used for stress detection and obtained using one or more wearable devices. Then the raw data was pre-processed by removing artifacts and noise using filters followed by extraction and selection of features. Various machine learning algorithms were applied to build classification models. The most common classifiers were Logistic regression, KNN, RF, and SVM. Leave-one-subject-out and k-fold cross-validation (mostly k=5 or 10) are mostly used for the validation of classification models. It is observed that HR and GSR were the most regularly used sensory signals because they gave the most promising results and high-accuracy for detecting stress and its levels. The ultimate objective in stress detection is to develop a high accuracy model that is effective and affordable. The review presented here listed important information about the previous studies with sensor names, techniques used in that model, its advantages, limitations, and issues. This review paper will help future researchers to choose the best sensors and machine learning techniques for achieving their goal of mental stress detection.

VII. FUTURE DIRECTION

The main identified lacunas in which future research work should concentrate are as following

- Developing a robust stress detection system to quantify mental stress in real-life applications.
- Identifying some specific stressors that have the capacity to determine well-being which can help better in the detection of stress.
- Developing a user-friendly, flexible, and most importantly a sturdy multimodal device comprising of sensors (HR, BP, ST, GSR) that can be used for consistent and reliable data collection.
- Developing a model compatible to detect stress in students, teachers, and office employees.
- Increasing the robustness of the system by using TSST, PSS, and STAI questionnaires.
- Increasing the efficiency and accuracy of stress detection by using deep learning.

A multimodal system capable of detecting mental stress is proposed in figure 5. The ECG and EEG devices will be commercial devices while the other physiological data (HR, BP, ST, and skin conductance) will be collected by adopting a self-made device using sensors and Arduino Uno. Furthermore machine learning and deep learning techniques will be used for the classification and detection of stress into three classes' i.e low, medium, and high. Numerical class labels shall be used for indicating levels of mental stress like class 0, 1, 2 for low, medium, and high respectively. The research will focus on the study and detection of mental stress in 2 environments, college and workplace involving analysis of stress in students, teachers, and employees. The machine learning based classifiers SVM, RF, MLPNN, KNN, and Naïve Bayes will be used to classify data. Also, a feed-forward deep learning artificial neural network and Recurrent Neural Network shall be used as deep learning tools.

Our ultimate objective in this study would be to develop a high-accuracy model based on real-time data by overcoming unresolved challenges to alleviate the stress of the users.

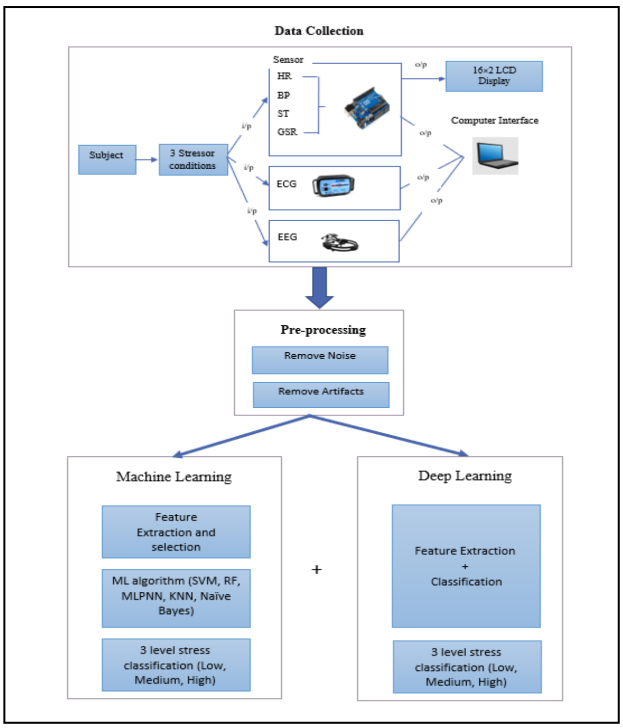

FIGURE 5. Schematic of proposed model.

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