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A Systematic Review of Computational Methods for Occupational Stress Modeling Based on Subjective and Objective Measures

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Abstract- Occupational stress is recognized as one of the major factors leads to health problems. This will lower efficiency and productivity on the job in an organization so the assessment and management of work-related stress are very crucial. Several kinds of computational techniques have been used for modeling and prediction but currently, occupational stress prediction in an early stage is still a challenge. This study is based on secondary data. In this paper, a review analysis has been carried out to analyze what has been done so far in last 26 years related to occupational stress and where there is a need to carry the further research. The paper explores occupational stress evaluation modeling techniques related to Machine Learning as well as statistical method. Occupational stress and burnout related to different kind of sector for working professional reviewed. This survey reviewed the subjective as well as objective measurement of stress evaluation. Questionnaires and physiological sensors used to measure and evaluate stress and corresponding techniques for modeling occupational stress have been reviewed. Occupational stress modeling based on Machine learning techniques such as ANN, BN, and SVM, LDA, RSM statistical methods like Regression, MLR etc. reviewed. This survey concludes with a discussion and future work, summary and finally conclusion.

Keywords- Stress, Machine Learning Techniques, Stress Questionnaire, Stress Sensor, Stress classification, Stress prediction, Computational stress model

I. INTRODUCTION

The growing complexity of stress has increased the need for early detection which may lead to a serious challenge in form of a health hazard for the effective operation [1] within an organization. Stress is a part of daily living. It is an adaptive response. Stress originates as a result of the natural reaction of an organism related to internal, external, positive as well as negative stimulation. Labor Force Survey [2] in the United Kingdom (UK), recently showed 76% employee of the UK suffering from work-related stress. Stress occurs in the workplace when there is a mismatch between the expectations of the employee and demand of the employer. Occupational stress not only for the individual but also for the organization is a major concern these days. Occupational stress can be evaluated by means of questionnaires called subjective measure and also by analyzing the physiological signals obtained from physiological sensors wore by participants called objective measures. In this survey, a systematic review of several journal articles and conference papers carried out to assess the evidence and evaluate the up-to-date progress related to occupational stress modeling and future research on this problem. Our goal is to classify studies with respect to metrics and methods that have been used in the occupational stress prediction modeling based on longitudinal data. In order to extract vital hidden information in less time from complex problems machine learning (ML) techniques are found more suitable. Many researchers used different computational approaches Such as Neural Network [89-90,92-94,96,102-104,107-108,110-111,113,115,122],Support Vector Machine [86,96-98,103,105,110,112,117-120] [55,78], Naïve Bayes Classifier [86-87,108,117-118], Fuzzy Logic [123,129,130-134], Feature Selection [96-100],KNN [97-98,112],Decision Tree [95,99], Linear Discriminant Analysis [97,121], Association rule [99,106], Ensemble method[88], Regression Analysis [100,105,113,135-157] to predict Occupational stress To the best of the authors' knowledge, this is the unique study which provides a systematic review of occupational stress prediction from different perspectives. Numerous studies have been published on the occupational stress. Unfortunately, most of the reviews are narrative in nature and thus not transparent and not as comprehensive related to ML techniques. This paper concentrates on both subjective [3,4] as well as objective[5] measures. In order to determine, analyze and monitor stress in the early stages, in this paper we reviewed all the related studies between the period of 1991 and 2017.The objective of this study is to

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systematically review evidence on subjective and objective measures of occupational stress and the associated computational techniques for prediction of stress. This survey will investigate questionnaire and sensor-based primary measures of stress and computational techniques used for "analysis, feature extraction, stress detection and recognition, and computational models" used in literature over the recent years to provide a direction for future research.

The other section of this paper is structured as follows: Section 2 presents the methodology of the review process. Section 3 discusses the stress and its classification in a brief while Section 4 has the detailed discussion related to stress response and modeling techniques. In Section 5 we try to present comprehensive discussion and future challenges along with the summarized table of the study. We mention in section 6 the limitation of the study and section 7 concludes the systematic review study.

II. METHODOLOGY

The different stages of the review planning, conducting and reporting is represented in Fig.1.In the planning stage, we identify the need for systematic review and develop the protocol .In the next stage search strategy and selection of sources described in order to identify the primary studies then in further step relevant studies based on the research questions determined. Quality assessment parameters identified in the next step for deep analysis of the studies. Further in the next stage data extraction methodology for collecting the required information mentioned. During this stage, the selected papers thoroughly read for data extraction then during the data synthesis phase data will be summarized according to the desired metrics and final stage is the reporting.

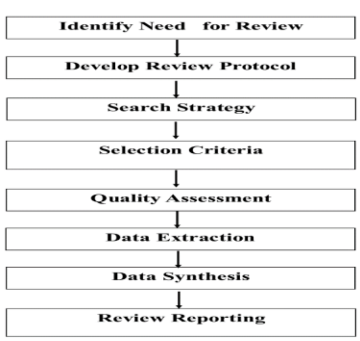

Figure 1 .Systematic Review Process

In order to review the most widely accepted measurement techniques and variety of features to measure the occupational stress of individual, we conduct a detailed literature review, with the below mention search strategy and inclusion criteria. For completing Systematic Review of Literature (SRL), total 150 papers from 1998 to 2017 studied by the authors'. We identified the search terms and then relevant digital portals selected. The data retrieval for primary study related to stress is accomplished by searching the below-mentioned databases:

S#	On Line Database
1	Science Direct
2	Springer Link
3	Web of Science
4	ACM Digital Library
5	Wiley Online Library
6	Google scholar
7	IEEE Explorer

Table1. Electronic Databases Searched

The subjective and objective measurement of stress level reviewed includes several types of features. So this feature will be helpful to measure the stress level of individual not only to the most widely acknowledged methods but also to the novel emerging methods.

2.1 *Search Strategy*

In this review, we followed the iterative process. We performed the review in an iterative way. First of all, searched the stress state of the employee and then redefined the search criteria for identifying the different prediction models related to occupational stress. This paper includes keywords based search from several kinds of online databases. Different types of keywords used are "Job Stress, Occupational Stress, employee workload, Occupational Stress, Role Overload, Fatigue, Human Emotion, Depression, Occupational Injuries, job demand and Burn out". The journals related to stress which got significant citation are listed in table 3. A total number of a search conducted for the studies is 150. Out of which only 70 studies selected which were related to stress evaluation and management using Machine learning techniques or regression techniques.

2.2. *Criteria of the Inclusion*

All the reviewed papers were innovative studies either from the Journal or conference articles written in English. In the first step, searching is done by mapping stress evaluation system for human beings. In the next step stress detection systems and responses analyzed in deep in view of the application of Machine learning techniques. In the final step of the literature search diagnostic study of stress evaluation analyzed by means of either subjective or objective techniques.

2.3 *Stress and its Classification*

This section mainly discusses stress mechanism and its different types used for stress evaluation.

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2.3.1. *Stress*

According to Dr. Hans Seyle [6], "Stress is the non-specific response of the body to any demand for change". A set of specific conditions or an event that causes some adaptive response on the part of employees is termed as a stressor. Stress is the physiological response of bodies to the stressor. Harmful physical and emotional response occurring as a result of a mismatch between the requirements of the job and employee's proficiencies leads to occupational stress [7]. It might appear due to any of the reason such as long working hours, work overload, deadline pressure, high responsibility, lack of training, conflicts, job insecurity, less social support from the colleagues, poor physical work condition and competitiveness[8,9]. In short "Occupational stress" is the form of stress so it can be described and measured accordingly in the same way as of stress.

2.3.2. *Stress Types*

In the following section we have discussed the stress classification.

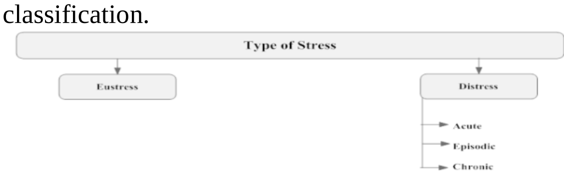

Figure 2.Stress Classification

Eustress stress and distress are the two main categories [6]. In case of distress, the stressor got specific stress reactions which are termed as negative stress. While eustress is the result of some positive changes and doesn't pose a problem to adapt to the new circumstances. Eustress is capable to meet the desired goal and increase productivity [10]. On the other hand, distress carries negative consequences. Further three levels of distress can be classified as acute, episodic and chronic stress depending on the time of exposure to stressors. When an individual facing new demands and expectations, this increases the arousal levels more than the threshold of adaptability which causes acute stress [11].The stress experienced more frequently and consistently in multiple episodes come under episodic stress. If the episodic stress persists for long times comes under chronic stress. By detecting and monitoring the work-related stress in time, a health problem can be reduced. On the other hand by recognizing a moderate level of stress appropriate working state can be maintained. Therefore detection of different levels of stress is meaningful.

2.4 *Stress Response and Modeling Techniques*

In this section, we are going to discuss different kinds of stress response used for stress evaluation. First, we will discuss Psychological Response and its Evaluation techniques. Then in the following sections, Physiological and Physical response and related modeling techniques will be discussed. There are two methods subjective as well as objective for evaluating occupational stress. If evaluated by means of questionnaires and interviews termed as a subjective method. If by evaluated by analyzing the physiological signals after collecting from physiological sensors wore by participants comes under objective methods.

2.4.1. *Psychological Response and Evaluation*

Questionnaires and interviews are the most important tools for the Psychological evaluation of stress. It is most acceptable ways to assess stress level in a human being. Several types of questionnaires used in this regard and each one has a different rating scale for the stress assessment

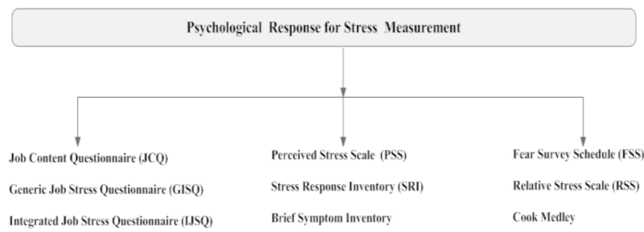

Figure 3.Psychological Response Tools

Karasek [12] illustrated psychosocial factors related to stress in JCQ. Later Henry [13] discussed psychosocial, environmental, and physical factors in GJSQ. Another researcher proposed IJSQ for evaluating job stress level by means of psychosocial, environmental, and physical as well as response factors related to job satisfaction. Further, in PSS the researcher explored how an unpredictable, uncontrollable, and overloaded respondent leads their stress full live. In another study, SRI researchers included emotional, somatic, cognitive, and behavioral stress responses. However, BRI [14, 15] tried to evaluate psychological distress by considering important factors. [16] Proposed FSS for including major fear areas while [17] proposed RSS in order to emphasize three subgroups: 'emotional distress, 'social distresses and 'negative feelings'. Later in another study, Cook-Medley Hostility Scale [18] considered six subsets for stress measurement. Human intervention is the major concern in this assessment regarding exactness of the input collected from the user. However, only current stress level information of the user can be obtained by this method. Subjective measurement by means of questionnaire needs full responsiveness from the user to avoid misleading stress level measurement.

2.4.2 *Modeling Techniques - Subjective Measurement*

In this section, we outline most commonly used algorithms used with survey-based data. Survey Questionnaire related to job stress has a large number of associated factors with high dimensionality. Researcher [19] effectively used feature selection to reduce dimensionality, and enhance the results. Response Surface Methodology (RSM) is an

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accurate approach to diminish the inherent uncertainty belongs to input under consideration and responses. To achieve this, the input-response functional form is approximated when the functional relationship is not clear or complex. [20] Successfully applied and discussed the current status and future direction of RSM related to job stress evaluation. Correlation-Based Feature Selection (CBFS) Method is a filter algorithm based on heuristic evaluation function. This method used to evaluate subset containing input factors taking consideration of the distinct prediction capability. For managing job stress, a large number of input factors are under consideration. Under these circumstances, CBFS method found very helpful [21].

A Bayesian Network (BNs) allows representing a model graphically having probabilistic relationships among variables under consideration by means of statistical techniques. Researcher [22] using BN represented a joint probabilistic model among all the variables keeping interrelationship. BNs are gaining popularity for data mining related to categorical data and found useful in the research related to safety and health [23]. Bayesian classifiers successfully applied for stress classification [24, 25], for stress modeling [26] employed Dynamic Bayesian Network in his study and found it can be used to represent the variation of stress properties with time. In order to classify stress, the divide-and-conquer approach used with decision tree classifiers [27].

2.4.3 *Physiological Responses to Objective Measurements*: The 'Autonomic Nervous System' (ANS) is responsible to maintain the body under a stable condition. ANS includes 'Sympathetic Nervous System' (SNS) and the 'Parasympathetic Nervous System' (PNS). Stress is responsible for activating the SNS [28] while PNS is responsible for bringing the body back to rest state. Naturally, heart rate increases by SNS activation, whereas PNS activation decreases it. SNS and PNS activity can be observed by means of physiological signals such as heart rate (HR), ECG, EEG etc. Recent technological advances have brought wearable biosensors e.g., ECG sensors [29], HRV sensors, GSR sensors etc. into everyday life. The SNS provokes the stress response in humans [30], which are the root cause of psychological, physiological and behavioral symptoms [31].Physiological responses are the part and parcel of a living organism [32]. Under stress state, the increased value of SNS is responsible for the change in hormonal levels. This appears in form of increased heart rate, muscle activation and excess sweating [33]. It is the Physiological signals that can represent internal affect experience [34] of individuals. The following figure shows the physiological signals and its subcategory used for stress evaluation. In the following section, we will briefly discuss the evidence used in the literature.

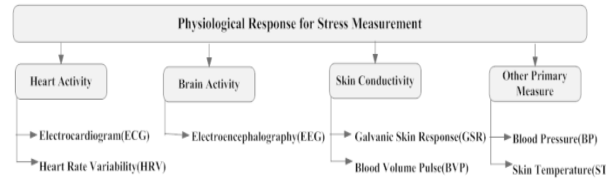

Figure 4.Physiological Responses

Many researchers used HRV to detect stress [35-36]. Short-term lower HRV represents acute stress. It is found from the study HRV negatively affected during stress [37]. ECG measurement is superior to the HRV [38] in many respects. The lower amplitude of ECG wave indicates stress [39]. EEG signal contains more useful information related to stress. Several studies proved that there is a strong relationship between brain activity and stress [40]. In a study researcher [41] explained biofeedback games by means of EEG.The study [42-45] proved that GSR is a reliable indicator of stress. Increase in GSR [46] value shows stress state while a decrease in GSR is an indication of less stressed state. Other measures of stress BP, BVP and ST can be used to detect stress more reliably [47] in conjunction with ECG, HRV, EEG, and GSR. Research showed increased Blood Pressure is an indication of an increase in stress [48]. Another researcher [49] found decrement in Blood Volume Pulse (BVP) is related to an increase in stress and vice versa. It is found from the study that ST is inversely proportional to stress [50].

2.4.4 *Physical Responses to Objective Measurements*

Humans can observe the changes in physical characteristics without the assistance of any equipment and tools. Physical signals such as 'behavior', 'gesture', 'body movement', 'facial expression', 'eye gaze', 'blinks', 'pupil dilation', and 'voice' are more sensitive to stress. A human can assess the stress states from the body language. We are going to briefly mention the evidence of the study for stress evaluation.

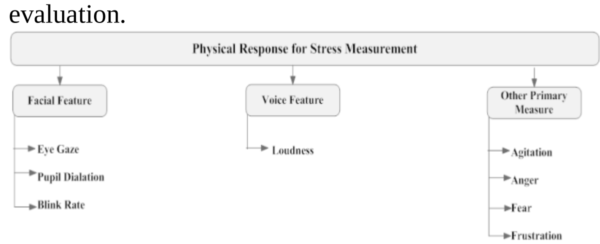

Figure5.Physical Responses

Facial features such as reduced facial muscle movements or irregular eye movements can indicate the stress level of an individual. The study revealed stress classification models [51] developed using facial feature data, collected from facial expressions. Eye gaze is the source of individual's attention which shows mental states. Researchers found eye gaze is correlated with stress levels. It is observed from the study Pupil dilation investigated for stress detection [52]. Increase in individual pupil diameter indicates stressed state.

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Several studies suggested that faster eye closure is an indication of higher stress levels. The study has shown several stress model developed by analyzing voice characteristics [53]. In a study researcher [54] model the feature across utterances by means of SVM and ANN. Researcher [55] in a study developed a stress model related to emotions by using GSR, HR, and ST. By means of Table 2, we tried to represent the ranking of primary measures used for evaluating stress as claimed in the literature

Primary Measure Ranking	
Rank	Primary Measures
1	Heart Rate Variability
2	Galvanic Skin Response
3	Electroencephalography
4	Pupil Dilation
5	Voice
6	Eye Gaze
7	Facial Expression
8	Blood Pressure
9	Skin Temperature
10	Blood Volume Pulse
11	Eye Blinks
12	Respiration
13	Electromyography

Table 2- Primary Measures Ranking

2.4.5 *Feature Extraction Techniques*

To discover the important characteristics of the data set, feature selection [56] found useful in many studies. The raw data obtained from Physiological Sensor are more complex, feature selection successfully applied for retrieving important characteristics for decision making [57]. It is found in several studies [58, 59] 'Fourier transformations (FT) and Wavelet transformations (WT)' effectively managed the noise issue available in the data set obtained from the signal in the feature extraction process.

2.5 *Modeling and Analysis Techniques– Objective Measurement of Stress*

In this section, we have discussed important algorithms used with wearable sensor data for modeling techniques.

2.5.1 *Bayesian Classification*

Naive Bayesian classifiers employed for stress classification when the classes are independent while Bayesian Networks (BN) used when classes are dependent on each other. Variation of stress properties with time well explained in stress model [26] by using Dynamic Bayesian Network (DBN).

2.5.2 *Decision Trees (DT)*

DT is a significant learning technique which is able to provide an efficient representation of rule classification [62].Using Decision trees stress classification has been implemented based on physiological measures EEG [63], as well as for the combination of measures BVP, GSR, PD and ST [60,61]. Crisp splits observed the major concern with the decision tree for stress modeling. Fuzzy techniques or some probabilistic framework can be employed in future to resolve this issue.

2.5.3 *Artificial Neural Network (ANN)*

Artificial Neural Network (ANN) is an intelligent method broadly used for classification and prediction [64]. The 'admissible predictive performance' of ANN made it most popular modeling techniques in health domain [65]. The correlation among input parameters is more complex in physiological records. In this case, ANN efficiently models highly nonlinear systems [66]. ANN employed in stress model and observed a promising result [67].

2.5.4. *Support vector machines (SVMs)*

SVM has the capability of classifying linear and non- linear primary measures of physiological signals [68]. So it is effectively used in stress modeling. The study revealed that researchers [19, 60] used SVMs to predict stress using "BVP, GSR, PD and ST" data. It is found researchers employed SVM on EEG data [69] in order to model emotions.

2.5.5 *Fuzzy Techniques*

A researcher found fuzzy techniques very helpful to model workload [70] using Heart Rate. There are several kinds of uncertainties in physiological measures of stress fuzzy filters are used for this filtering in several studies [71]. In another study based on HRV data [72], fuzzy clustering applied for stress evaluation.

III. RESULTS AND DISCUSSION

The significant advancement in the data mining techniques provides a challenging way to enhance the algorithm for a wearable sensor as well as for survey-based data. Keeping this view in mind we have reviewed the related papers and accordingly, in the following sections, we are going to discuss the important results and future problems.

3.1. *General Results and Implications*

From the analysis, it is found that combination of occupational stress and ML techniques is an interdisciplinary field and this research is in a nascent state. The main focus of this study is to concentrate on job stress prediction.

3.2. *Physiological features*

Following table presents the summary of "physiological signals and features" most commonly used in the literature for stress evaluation. These are the reliable information source for real-time stress levels of individuals. But this needs extra equipment for the measurements. Even though available in wearable format but to wear this equipment continuously is not feasible for the user. These drawbacks are being developed in future. Also for wearable sensors, experimental validation needs to be considered realistic.

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Signal	Reference	Feature
ECG	[73,74,75,76]	HRV ,HR
EEG	[76,77]	Fractral Dimension
BP	[78]	SD, No of peaks
ST	[79]	Min, Max, SD
BVP	[79]	HR,HRV

Table3. Response Signals and feature

3.3 *Behavioral Response Features*

Table 4 is the summarized representation of signals and features used for stress recognition. Behavioral measurements for stress recognition were not still enough studied as compared to physiological ones. Even though, some of them look very promising because any extra equipment is not required. Precisely, this is the added edge of the “behavioral measurements” in addition to decreased developed system’s cost.

Signal	Reference	Feature
Posture	[80-81]	Lean
Speech	[82-83]	Speech Wave Form Intensity, Pitch
PD	[84-85]	Max, SD
Blink	[84]	Blink frequency, AECS

Table 4.Summary of the behavioural measurements and features

3.4. *Modeling Techniques used for Stress Prediction*

Techniques	References	Techniques	References
Decision Tress	[95,99]	Association Rule	[99,106]
SVM	[86,96-98,103 ,105,110,112,117-120]	KNN	[97-98,112]
ANN	[89-90,92-94,96,102-104 ,107-108,110-111,113,115, 122]	Deep Learning	[91]
Ensemble Methods	[88]	Fuzzy Logic	[123,129 -134]
Naïve Bayes	[86,87,108 ,117,118]	Bayesian Network	[100-101,103]
LDA	[97,121]	Regression	[100,105, 113,135 -157]
Feature Selection	[123,124,125,126,127,128]	Text Feature	[114]

Table5. Summary of the Modeling Techniques

Decision Trees, SVM, ANN, Ensemble Methods, Naïve Bayes, LDA, Feature Selection, Association Rule, KNN, Deep Learning, Fuzzy Logic, Bayesian Network, Regression analysis and Text Feature are the applied modeling techniques for the evaluation of stress. In one hand the use of SVM and ANN modeling techniques for stress prediction is found in many studies while on the other hand other modeling techniques use is less.

Fuzzy techniques have significant contribution in the stress evaluation howsoever a combination of fuzzy techniques and other M.L Techniques can be further explored. The contribution of clustering techniques found to be least so it can be further explored in future. Multiple measurements of vital signs simultaneously are yet another challenging task in this field, particularly in sensor fusion techniques.

3.5. *Psychological Features used in the Literature*

Author	Brief Description of Study
Herrero et al., [87]	They used Bayesian Network in order to develop a stress model and indicate that emotional demands have a greater influence on raising the likelihood of stress due to workload.
Maxhuni et al., [88]	They employed ‘ensemble methods’ and ‘transfer learning’ for prediction modelling and showed an enhanced accuracy.
Lotfizade et al., [145]	They employed logistic regression for assessing significant associated factors related to occupational stress by using Socio-demographic data and stress-related variables.
Azadeh et al., [129]	They applied Adaptive Neuro-Fuzzy Inference System (ANFIS) and statistical methods for measuring job stress, and showed improved performance as compared to ‘conventional regression approaches’.
Lee et. al., [127]	They came with a new idea Response surface data mining (RSDM) and investigated the statistical relationships between the risk factors and the response of interest and provided detailed statistical inferences.
Herrero et al., [101]	They developed model to analyse how “social support reduces the occupational stress caused by work demands” Using Bayesian networks, logistic regression and conventional statistical techniques and found a good result.
Khodabakhshi et al.,[143]	The authors presented an occupational stress prediction model based on

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	regression and correlation methods.
Krishna et al., [136]	The authors presented a design of occupational stress modeling by employing classification and regression tree(CART)
Bhuvana et al., [94]	Neural network algorithm applied for faster learning of acute stressed data and then trained data used for classifying the depression by using Radial Basis Function and Hamilton acute stress rating scale.

Table 6. Psychological measurements and features

3.6. *Modeling Techniques for Subjective Measurement*

As it can be observed from above Table, several models have been proposed for improving the performance of stress prediction. However, it is difficult to predict stress well in all environments or for all time. Hence, there is a need for an effective approach to intelligently evaluate the stress. This is motivation in adopting intelligent techniques in solving occupational stress modeling problems. Some of the study employed a single method [87,145,154] while other employed combination of methods [88,101,127,129,136,143]. Most frequently employed methods for subjective measurement were found Bayesian Network, ensemble methods and transfer learning, RSM, RSDM, regression and correlation methods, classification and regression tree, logistic regression and Adaptive Neuro-Fuzzy Inference System. However, this study for stress classification and modeling using subjective measure, revealed that classification methods (i.e., decision trees, discriminant analysis, ANN and support vector machines) were investigated least number of times. This can be discussed in future work.

The regression and logistic regression applied for the evaluation of stress under subjective measurement but the analysis done in almost all cases only statistically without considering the M.L techniques implications. Therefore, elaboration of the M.L techniques for mining stress evaluation constitutes a task for future work. The rest of the methods such as KNN, Naïve Bayes, and Associative rule have not been applied to the best of the author's knowledge and they should be explored as future research.

3.7 Data-related results and implications

Text data can be collected from the documents provided by the employees. It is found from the study in almost all cases the data set has not been disclosed at all. In view of this accuracy and the reliability of the experiment cannot be justified. Unreliable data is a major concern related to the key factor of success. This fact suggests future research work must be carried out in this direction. Even if the data is available, it is not well explained. This might be root concern for unexpected patterns.

IV. Summary of the Literature Review

Table 7- Summary of Review

S.#	Author/Reference	Title	Techniques
Classifier			
1	Subhani et al.,[86]	"Machine learning framework for the detection of mental stress at multiple levels."	Support Vector Machine(SVM) and Naive Bayes classifiers
2	Herrero et al .,[87]	"The Influence of Recognition and Social Support on European Health Professionals' Occupational Stress: A Demands-Control-Social Support-Recognition Bayesian Network Model."	Bayesian Network Model
3	Maxhuniet al.,[88]	"Stress modelling and prediction in presence of scarce data."	Ensemble methods and transfer learning
4	Alic et al., [89]	"Classification of stress recognition using Artificial Neural Network."	Artificial Neural Network (ANN)
5	Pimenta et al.,[90]	"Neural network to classify fatigue from human–computer interaction approaches."	Artificial Neural Network (ANN)
6	Magana et al., [91]	" Estimating the stress for drivers and passengers using deep learning."	Deep learning algorithms
7	Sarkar et al.,[92]	"An approach to identify subject specific Human Emotions."	Artificial Neural Network (ANN)
8	Mohammadfam et al.,[93]	"Use of Artificial Neural Networks (ANNs) for the Analysis and Modeling of Factors That Affect Occupational Injuries in Large Construction Industries."	Artificial Neural Networks
9	Bhuvana et al.,[94]	"Development of combined back propagation algorithm and radial basis function for diagnosing depression patients."	ANN Algorithm

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10	Parhizi et al., [95]	"Mining the relationships between psychosocial factors and fatigue dimensions among registered nurses."	Decision Tree
11	Sharma et al., [96]	"Hybrid Genetic Algorithms for Stress Recognition in Reading".	ANN, genetic algorithms, support vector machines,
12	Cinaz et al.,[97]	"Monitoring of mental workload levels during an everyday life office-work scenario".	KNN, SVM, Linear Discriminant Analysis
13	Sano et al., [98]	"Stress Recognition Using Wearable Sensors and Mobile Phones"	SVM,KNN
14	Nenonen et al., [99]	"Analysing factors related to slipping, stumbling, and falling accidents at work: Application of data mining methods to Finnish occupational accidents and diseases statistics database".	decision tree and association rules
15	Herrero et al.,[100]	"Using Bayesian networks to analyze occupational stress caused by work demands: Preventing stress through social support".	Bayesian networks, logistic regression models,
16	Herrero et al., [101]	"Influence of task demands on occupational stress: Gender differences."	Bayesian Networks
17	Sharma et al., [102]	"Objective measures, sensors and computational techniques for stress recognition and classification: A survey,"	ANNs using a genetic algorithm
18	Sharma et al.,[103]	"Artificial Neural Network Classification Models for Stress in Reading".	Bayesian networks, artificial neural networks, and support vector machines, fuzzy logic.
19	Mehrjerdi et al., [104]	"System Dynamics and Artificial Neural Network Integration : A Tool to Evaluate the Level of Job Satisfaction in Services".	System dynamics, Artificial Neural Network
20	Saleem et al., [105]	"Automatic detection of psychological distress indicators and severity assessment from online forum posts".	Support Vector Machines, Probabilistic Logic, Markov Logic Networks.
21	Bakker et al., [106]	"Stress @ work : From Measuring Stress to its Understanding, Prediction and Handling with Personalized Coaching".	associative classification
22	Azadeh et al., [107]	"An adaptive neural network algorithm for assessment and improvement of job satisfaction with respect to HSE and ergonomics program: The case of a gas refinery".	Adaptive Neural Network
23	Chattopadhyay et al., [108]	"An automated system to diagnose the severity of adult depression".	Back Propagation Neural Network (BPNN)
24	Valle et al., [109]	"Expert Systems with Applications Job performance prediction in a call center using a naive Bayes classifier".	Naive Bayes Classifier
25	Saidatul et al., [110]	"Automated system for stress evaluation based on EEG signal: A prospective review".	ANN,SVM
26	Bakker et al., [111]	"What's your current stress level? Detection of stress patterns from GSR sensor data".	ANN
27	Santos et al., [112]	"A stress-detection system based on physiological signals and fuzzy logic".	K-Nearest Neighbor, Support Vector Machine
28	Murray et al., [113]	"The use of artificial neural networks and multiple linear regression in modelling work-health relationships: Translating theory into analytical practice".	ANN and Multiple Linear Regression.
29	Vizer et al., [114]	"Automated stress detection using keystroke and linguistic features: An exploratory study".	Text feature analysis, Classification techniques,
30	Scherer et al.,[115]	"Emotion Recognition from Speech: Stress Experiment".	ANN
31	Sahrawi et al., [116]	"Design and implementation of a human stress detection system: A biomechanics approach".	Zero Order Constant line Classification
32	Barreto et al., [117]	"Non-intrusive Physiological Monitoring for Automated Stress Detection in Human-Computer Interaction".	Naive Bayes, Decision Tree and Support Vector Machine

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33	Zhai et al., [118]	"Stress Recognition Using Non-invasive Technology",	Naive Bayes, Decision Tree and Support Vector Machine
34	Zhai et al.,[119]	"Stress detection in computer users based on digital signal processing of noninvasive physiological variables".	SVM
35	Zhai et al., [120]	"Realization of Stress Detection using Psychophysiological Signals for Improvement of Human-Computer Interaction".	Support Vector Machines
36	Healey et al., [121]	"Detecting stress during real-world driving tasks using physiological sensors".	Linear discriminant analysis (LDA) Classifier
37	Fukuoka et al., [122]	"Chronic stress evaluation using neural networks".	Recurrent ANNs
		Feature selection	
38	Ghosh et al., [123] Sensor	"Annotation and prediction of stress and workload from physiological and inertial signals".	Feature Selection, Signal Artifact Removal
39	Deng et al., [124]	"An investigation of decision analytic methodologies for stress identification".	Feature Selection
40	Deng et al., [125]	"Evaluating feature selection for stress identification".	Feature selection
41	Deng et al., [126]	"Combining Multiple Sensor Features for Stress Detection Using Combinatorial Fusion"	Feature selection (FS)
42	Lee et al., [127]	"Job stress evaluation using response surface data mining"	Feature selection (FS)
43	Liao et al., [128]	"A Real-Time Human Stress Monitoring System Using Dynamic Bayesian Network"	Feature Extraction, Dynamic Bayesian Network
		Neuro-Fuzzy	
44	Azadeh et al., [129]	"An intelligent algorithm for performance evaluation of job stress and HSE factors in petrochemical plants with noise and uncertainty".	Adaptive Neuro-Fuzzy Inference System (ANFIS)
45	Sierra et al.,[130]	"A stress-detection system based on physiological signals and fuzzy logic".	Fuzzy Logic
46	Begum et al.,[131]	"A Case-based decision support system for individual stress diagnosis using fuzzy similarity matching".	Fuzzy Logic and Feature Extraction,
47	Kumar, et al.,[132]	"Fuzzy techniques for subjective workload-score modeling under uncertainties"	Fuzzy clustering
48	Kumar et al.,[133]	"Fuzzy Evaluation of Heart Rate Signals for Mental Stress Assessment".	Fuzzy clustering,
49	Shin et al., [134]	"Estimation of stress status using Biosignal and fuzzy theory".	Fuzzy logic
		Regression	
51	Aytac et al.,[135]	"The Symptoms of Stress and Anger Styles as a Psychosocial Risk at Occupational Health and Safety: A Case Study on Turkish Police Officers".	Multiple Regression Analysis
52	Krishna et al .,[136]	"Measurement and modeling of job stress of electric overhead traveling crane operators".	Regression
53	Kalinina et al ., [137]	"Effects of Sociopsychological Factors on the Development of Occupational Stress".	Regression
54	Khaleghi et al.,[138]	"Effective Factors on Job Stress from Experts' Perception ; a Case Study in Iranian Agriculture Engineering Organization".	Regression
55	Ghani et al., [139]	"Stress among Special Education Teachers in Malaysia".	Regression
56	Bowen et al., [140]	"Occupational stress and job demand, control and support factors among construction project consultants".	Regression
57	Othman et al., [141]	"Occupational Stress Index of Malaysian University Workplace".	Regression
58	Shin et al., [142]	"Academics job satisfaction and job stress across countries in	Regression

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		the changing academic environments".	
59	Khodabakhshi et al., [143]	"Predicting Occupational Stress for Women Working in the Bank with Assessment of Their Organizational Commitment and Personality Type"	Regression and Correlation
60	Bakhtiari et al.,[144]	"An investigation on occupational stress of the operating room staffs in hospitals affiliated to Isfahan University of Medical Sciences and its association with some factors"	Regression analysis
61	Lotfizade et al.,[145]	"Occupational stress among male employees of esfahan steel company, Iran: Prevalence and associated factors".	Logistic regression
62	Muaremi et al., [146]	"Towards Measuring Stress with Smartphones and Wearable Devices During Workday and Sleep"	Multinomial Logistic Regression
63	Arshadi et al., [147]	"The Relationship of Job Stress with Turnover Intention and Job Performance: Moderating Role of OBSE".	Pearson correlation and Moderated Regression
64	Li et al.,[148]	"Research of Occupational Stress in Mine Emergency Rescuers".	Chi-square test and analysis of covariance
65	Hashim et al., [149]	"Occupational Stress And Behaviour Studies Of Other Space : Commercial Complex".	Regression
66	Cicei et al.,[150]	"Occupational stress and organizational commitment in Romanian public organizations".	Regression
67	Yang et al., [151]	"Antecedents and consequences of job satisfaction in the hotel industry".	Regression
68	Shiro et al.,[152]	"Gender, age and tenure as moderators of work-related stressors' relationships with job performance: A meta-analysis".	Regression
69	Lambert et al., [153]	"The impact of distributive and procedural justice on correctional staff job stress, job satisfaction, and organizational commitment".	Regression
70	LeRouge et al., [154]	"The impact of role stress fit and self-esteem on the job attitudes of IT professionals".	Regression
71	Isikhan et al., [155]	"Job stress and coping strategies in health care professionals working with cancer patients".	Regression
72	Armstrong et al.,[156]	"Does the job matter? Comparing correlates of stress among treatment and correctional staff in prisons".	Regression
73	Matud et al., [157]	"Gender differences in stress and coping styles"	Multivariate and univariate analyses of covariance (MANCOVA)

V. LIMITATIONS

Though we have exhaustively searched all the stated digital search libraries, there still may be a possibility that a suitable study may be left out. Also, this review does not include any unpublished research studies [19]. We have assumed that all the studies are impartial; however, if this is not the case then it poses a threat to this study.

VI. CONCLUSIONS

The aim of this study was to provide an overview of recent machine learning techniques applied to survey data as well as sensor data for stress modeling. This survey has attempted to clarify how certain ML techniques have been applied in the literature. It also has revealed trends in the selection of Physiological, Physical and Psychological responses for data processing and corresponding modeling techniques. Finally, current challenges related to stress modeling for subjective and objective measure tried to highlight. For this reason, this paper surveys several solutions by considering distinguished aspects. In particular, the review outlined the more common ML techniques that have been applied for prediction. Moreover, further details of the suitability of particular ML methods used to process the data has been described. Further study in this review paper focused on the surveys and sensors data collection techniques. Further, this survey has presented a summary of studies that discussed stressed modeling based on conventional statistical techniques and Machine Learning techniques. Finally, the paper addressed future challenges of ML techniques while analyzing the stressed data for prediction modeling.

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