An Extensive Survey on Recent Advancements in Human Stress Level Detection Systems

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Abstract— **The psychological stress has spread to harm all people in recent days. When someone is subjected to high stress continually, it can have a significant impact on their work, academic, and health aspects. To minimize the negative effects of high levels of psychological stress, it is essential to monitor and manage stress systematically. Thus, it is essential to develop reliable techniques for the quick and precise identification of human stress. Though stress detection research has gained worldwide attention by utilizing physiological and social media data, there are still a number of issues that needs to be addressed. This paper aims to discuss the need for Human Stress Level Detection System (HSLDS) focusing on the recent research utilizing human physiology, physical characteristics, social media posts, and micro-blogs. The paper explores a variety of deep learning and machine learning models deployed for stress detection, publicly available datasets based on social media posts and healthcare data, self-reporting surveys, attributes, subjected users, and levels of stress/ emotions categorized. The in-depth investigation in this research reveals new avenues for future research.**

Keywords— Social media, Deep learning, Convolutional neural networks, Microblogging, Stress detection

I. INTRODUCTION

Psychological stress became a mediaspeak in the recent years as it affects a lot of people, regardless of gender, age group, or line of work. It is because of the rapid pace of life, evolving workplace expectations, increasing pressures, and technological advancements. S. Palmer [1] defines the stress as, "the feeling of a considerable difference between the requirements imposed on an individual and their observed capacity to meet those requirements, leading to a complex psychological and behavioral situation". Although stress is typical, integral part of daily life, excessive and persistent stress can actually be detrimental to a person's physical and mental well-being [2]. The chronic stress causes depression, weakened immune system, diabetes, cardiovascular disease, cancer, and substance addiction. Hence, the development of reliable techniques for the quick detection of human stress is of greatest importance. These technologies help monitor the stress on a regular basis, enabling the medical professionals to treat illnesses brought on by stress more successfully. Thereby, the people can manage their daily activities to lower their stress levels, and avoid unnecessary health complications. The Figure 1 shows the increase in stress level among various generations as reported by American Psychological Association.

The conventional psychological stress detection relies on in-person interviews, self-report surveys, or wearable sensors. However, the conventional approaches, in contrast, are reactive, time-consuming, labor-intensive, and hysterical. Moreover, on the basis of a person's physiological parameters, numerous researches have been conducted to identify stress. A wide range of physical sensors play a significant role in capturing a person's physiological parameters, enabling the automatic detection of stress. Such techniques analyze the physiological signals obtained from sensors attached to human bodies to detect stress and categorize emotions [3].
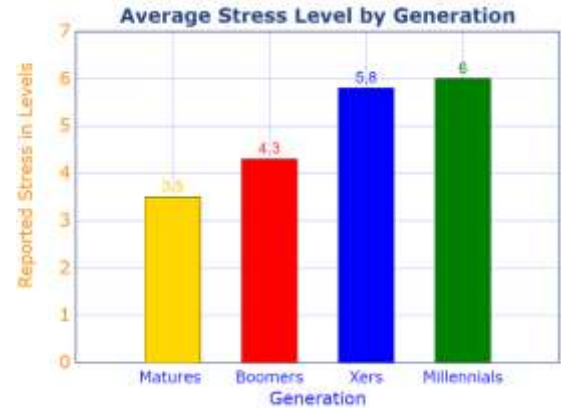

Fig. 1. An increase in the stress level among various generations

As social networks have grown, a greater number of individuals use them to connect with their friends and share their daily activities and moods. These social media data present new possibilities for expressing, measuring, modelling, and extracting user behavior patterns contributing to the theoretical foundation in psychology research [2]. The machine learning and deep learning algorithms serve a prominent role in the stress detection process through the sensor based statistics and social network contents.

This paper is structured as follows: Section 2 discusses the recent research in the domain of physiological stress detection in different taxonomies. Section 3 presents the summary of the literature from Section 2 and various attributes/parameters considered for the stress detection. Section 4 outlines the

findings of the literature which pave the path to future research improvements. Lastly, Section 5 states the conclusion.

II. RELATED WORKS

Recent years have seen a large number of research projects using ML and DL models developed using physiological responses to stress and emotional impulses. On the other hand, many researchers also focused on social media posts to extract emotions to identify the stress levels. This section presents an overview of such DL and ML based models. The Figure 2 depicts the taxonomy of the literature.
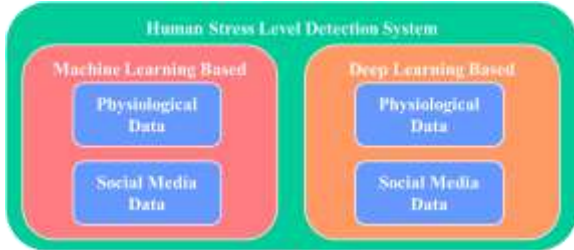

Fig. 2. Taxonomy of the literature

A. Machine learning based stress detection through physiological data

Rahee Walambe et. al. [4] proposed a multimodal Artificial Intelligence (AI) based framework to track a person's working habits and stress levels. The method identifies workload-related stress by appending diverse sensor readings like facial expressions, heart rate, posture, and computer interaction. The model also identifies the stress pattern over a period of time. The SWELL Knowledge Work (SWELL-KW) dataset is used for the demonstration. Though the model achieves a better accuracy, it requires more modalities. Further, the stress detection purely considers only the physical characteristics that arise due to workloads.

Anu Priya et.al. [5] proposed an ML based anxiety, depression, and stress detection approach. The data were collected from 348 employed and jobless people from various cultures and the communities using the Depression, Anxiety or Stress Scale questionnaire (DASS 21) through Google forms. The Decision Tree (DT), Random Forest (RF), Naïve Bayes (NB), Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) were employed to classify the stress into 5 levels as: normal, mild, moderate, severe and extremely severe. However, the stress detection relies on the variable importance (D, A, SS) having the highest number.

Vishal R. Shinde [6] et. al. invented a ML based stress detection framework for IT professional using image processing. The video captured data is fed into KNN and DL algorithms that classify user stress level based on the facial expressions as: Angry, Disgusted, Fearful, Happy, Neutral, Sad, Surprised. Yet, the work considers only the IT professionals and their related stress.

A ML based stress detection approach was introduced by Garg, P et. al. [7]. The model utilizes the data from wearable sensors, sourced from the publicly available "Wearable Stress and Affect Detection (WESAD)" dataset. The model performs binary classification (stress/ non-stress) and three-class classification as: neutral, stress, and amusement. The KNN, Linear Discriminant Analysis (LDA), RF, AdaBoost, and SVM algorithms were deployed and tested, where the RF outperformed. Though the model employs multiple

algorithms using a reliable dataset, the accuracy shall be improved.

A ML stress detection mechanism for University students was proposed by Ahuja, R et. al. [8]. It aims to detect the stress level among the students during examinations and recruitments. Four ML algorithms namely, SVM, RF, Logistic Regression (LR), and NB are employed, and were trained using the dataset (questionnaire) fetched from Jaypee Institute of Technology containing the records of 206 students. It includes data gathered one week prior to the examinations, and the stress owing to the internet usage. The SVM outperforms with highest accuracy. However, the usage of real-time data/ reliable dataset, increased data volume, and incorporating other stress factors can significantly improve the results.

B. Machine learning based stress detection through social media data

S. M. Chaware et.al. [9] proposed an ML approach to extract Facebook postings, and classify them with Transductive Support Vector Machine (TSVM), and find local hospitals with K-Nearest Neighbors (KNN). The model identifies whether a person is experiencing positive or negative stress. The approach presents a novelty of implementing a TSVM, but, the accuracy shall be improved above 90%.

In [10] G. Geetha et. al. employed ML algorithms using the social media data to determine the amount of people suffering from depression depending on early signs and social media activity. The approach is of two folds: based on the content's time and writing patterns, and based on language clues, analyzing the text or tweet posted. The research considers real-time data, however, it requires improvement in terms of data volume and accuracy.

A Bidirectional Encoder Representations from Transformers (BERT) based stress detection using Natural Language Processing (NLP) and ML using social media interactions was proposed by Tanya Nijhawan et.al. [11]. It employs massive tweets datasets for emotion analysis using BERT, and ML algorithms (DT, LR, and RF) for sentiment analysis. The models classify the emotions into 5 classes: sadness, neutral, anger, fear and joy. Nonetheless, the system needs a strong sentiment word classification algorithm.

Mohammed Mahmood Ali et. a. [12] proposed a ontology based stress detection framework utilizing probabilistic model. It uses social media Short Posts (SP) and Micro Blog (MB) messages contributing to a dataset SPDB. A Set of Pre-Defined Stress Words (SPSWDB) is used to figure out the stress words into Stress Lexicon, Negative emotion Lexicon and Negating words, Lexicon, and Emoticons. The model shall include multilingual stress detection.

In [13], Islam, M. et. al. proposed a ML based depression detection framework from social media data. The system employed the DT approach and was compared with the conventional ML approaches. The model is trained using the publicly available Facebook dataset and with the most prominent 21attributes for depression detection among the Facebook users. The framework however requires another method to fetch paraphrases from various emotional features.

Ragit, P. et. al. in [14] proposed a ML approach for stress detection using Twitter dataset sourced from Kaggle. The NB classifier is used for the training and testing. The classifier

labels 3 levels of stress: positive, negative, and neural, which is then utilized to predict whether stressed or non-stressed. However, the approach haven't considered any real-time data, and there is a room for improving the accuracy.

C. Deep learning based stress detection through physiological data

Russell Li et.al. [2] proposed two Deep Neural Networks (DNNs) for stress detection using sensor data: 1-dimensional (1D) CNN and a multilayer perceptron. The proposed model is free from fetching the hand-crafted features. The model collects data from the chest and wrist-worn sensors and performs binary stress classification, and three class emotion classification as, baseline, stressed, and amused states. Publicly available dataset was used for model training and testing. To further enhance the results, the model requires the training on huge volumes of data and diverse population.

A real-time electrocardiogram (ECG) based psychological stress detection using CNN and Bidirectional Long Short Term Memory (BiLSTM) was introduced by Zhang, P et. al. [15]. The real-time data from a group of 34 people were collected and used for training and testing. Various ML algorithms were compared and CNN produced the highest accuracy. Despite the use of a real-time dataset, the inconsideration of the personality differences among the people, and the volume of data denote a potential future research.

In the work [16], Song, S. H. et. al. proposed a Deep Belief Networks (DBNs) based stress detection approach. The model was trained using the sixth Korea National Health and Nutrition Examination Survey conducted from 2013 to 2015 (KNHANES VI). The dataset includes sleep time, body mass index, blood pressure, drinking, and smoking data. The DL based proposed model outperformed the SVM, NB, and RF algorithms. However, it requires a complete user information to identify the stress.

D. Deep learning based stress detection through social media data

In [17] Huijie Lin et.al. proposed a DL based CNN and Deep Neural Network (DNN) model to detect psychological stress in users through tweets. It considers two stress characteristics: i) low-level content attributes from single tweet (text, photos, and social interaction), and ii) user-scope statistical attributes from weekly micro blog entries (tweeting frequency, tweeting types, and linguistical styles). The CNN helps combining both the above attributes using autoencoders and the DNN helps combining two user-scope attribute to detect psychological stress amongst the users. The model could improve the accuracy by using real-time data.

Chebrolu Naga Harsha Vardhan et.al. [18] introduced a CNN based hybrid approach for stress detection using social media posts, leveraging the user-level information and tweet-level content information. The proposed model and its contributions various attributes were evaluated on an actual dataset from Sina Weibo. Yet, the classification is limited to two levels.

An ensemble learning model for stress detection was invented by Vasam Divya Mounika et.al. [19]. It aims to proactively sense the users' stress on social media. The proposed employs an ensemble learning model combined with a meta-classifier, offering higher accuracy than the other common ML approaches. The algorithms used include KNN,

RF, CNN, and SVM validating the Twitter dataset sourced from Harvard and Cornell institutions. Though various algorithms were employed to attain better results, the varying stress levels is a scope for improvement.

III. SUMMARY OF THE LITERATURE

The Table 1. outlines the summary of the literature from Section 2, highlighting the important parameters of stress detection research. It is fascinating to note that social media data contributes more to the field despite the individuals' predominate medical histories.

TABLE I.   SUMMARY OF THE LITERATURE

Ref.	Dataset	Algorithm(s)	Category/ Levels of stress	Social media data	User category	Real-time data
Rahee Walambe et. al. [4]	SWELL-KW	ANN, NASA-TLX Regression Model	Stressed/ Not-stressed	No, Body posture, Facial expressions, Keystroke dynamics	General	Yes
Anu Priya et.al. [5]	DASS 21	DT, RF, NB, SVM, KNN	5 levels of severity	No	Employed and unemployed people	Yes
Vishal R. Shinde [6]	Facial Expression	KNN (Image processing)	Angry, Disgusted, Fearful, Happy, Neutral, Sad, Surprised	No	IT Professionals	Yes
Garg, P et. al. [7]	WESAD	KNN, LDA, RF, SVM, AdaBoost	Neutral, stress, and amusement	No	General	No
Ahuja, R et. al. [8]	Jaypee Institute Survey	SVM, RF, LR, and NB	Stressed/ Not-stressed	No	University Students	Yes
S. M. Chaware et.al. [9]	Facebook	TSVM, KNN	Stressed/ Not-stressed	Yes, Facebook	General	Yes
G. Geetha et. al. [10]	Twitter	NB, RF, KR, SVM,	Stressed/ Not-stressed	Yes	General	No
Tanya Nijhawan et.al. [11].	Tweets	LR, RF, BERT	Stressed/ Not-stressed (Sentiment analysis and emotion classification)	Yes, Tweets	General	No
Mohammed Mahmood Ali et.al. [12]	SPDB	Ontology	5 levels	Yes, Tweets	General	Yes

Ref.	Dataset	Algorithm(s)	Category/ Levels of stress	Social media data	User category	Real-time data
Russell Li et.al. [2]	Sensor data	CNN	Binary stress classification, and three class emotion classification	No	General	Yes
Zhang, P. et. al. [15]	Real-time ECG	CNN, BiLSTM	Low, Medium, High	No	General, yet, closed group	Yes
Huijie Lin et.al. [17]	Sina Weibo, Tencent Weibo and Twitter	CNN, DNN	Stressed/ Non-stressed	Yes, Tweets	General	No
Chebrolu Naga Harsha Vardhan et.al. [18]	Sina Weibo	CNN	Positive/ Negative	Yes, Sina Weibo	General	Yes
Vasam Divya Mounika et.al. [19]	Twitter	KNN, RF, CNN, SVM	Positive/ Negative	Yes, Tweets	General	No
Islam, M. et. al. [13]	Facebook	DT	Yes/ No	Yes, Facebook comment	General	No
Ragit, P. et. al. in [14]	Twitter (Kaggle)	NB	Positive, Negative, and Neutral stress -> Stressed/ Non-stressed	Yes, Tweets	General	No
Song, S. H. et. al. [16]	KNHANES VI	DBN	Stressed/ Non-stressed	No	General	Yes

In addition to the summary of literature in Table. 1, the following Table 2 outlines various important parameters considered for stress detection from physiological and social media data.

TABLE II.   PARAMETERS CONSIDERED FOR STRESS DETECTION

Physiological Parameters	Social Media Parameters
Heart Rate	The post title
Galvanic Skin Response (GSR)	The post content
Body Temperature	The number of positive and negative words
Blood Pressure	The number of positive and negative emoticons
Electroencephalography (EEG)	Mean of image pixels
Photoplethysmogram (PPG)	Mean of saturation
Skin Temperature	Number of likes

IV. LITERATURE FINDINGS AND FUTURE RESEARCH DIRECTIONS

This section summarizes the potential research avenues from the literature findings. The following are some of the findings which would greatly enhance the field of research with a highest accuracy.

- Categorizing the social media user among the diverse group helps to pay customized attention to them
- Inferring the tweet's discussion topic in addition to detecting the stress
- Classifying emotion/ stress into multiple classes will help enhancing the stress remedial actions
- Extending the stress detection that supports multilingual words and multimedia data
- Capturing location, cultural, and diverse people information from the user profile would enrich the stress detection data analytics
- Hybrid/ ensemble algorithms shall help improving the model accuracy
- Defining the time period of stress observation from a single day to a couple of months will help identifying the exact stress level
- The number of attributes considered for stress detection should be optimal
- Self-report questionnaires filled by users
- Incorporating several modalities like facial expressions, audio/ video records, data from health monitoring apps
- Considering the personality differences among the users
- Taking mental and physical data in tandem

Undoubtedly, the findings from the literature would help researchers gain a better perceptive of the field.

5. CONCLUSION

Most people experience stress on various occasions throughout their daily lives. Our wellbeing will be compromised and our regular lives will be disrupted by long-term or high levels of stress. Early psychological stress detection can avoid many stress-related health issues. Thus, identifying stress and determining a person's stress pattern could help prevent serious health problems. This paper reviewed state-of-the-art DL and ML based stress detection research, figuring out the potential directions of this research. Specifically, the datasets, surveys, attributes, category of users, stress classification presented in this paper would help the budding researchers in the field to experiment further. The paper also summarized the literature findings as the potential future research.

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