A Comparative Analysis of Psychological Stress Detection Methods

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Abstract

Psychological Stress and Depression have been pinpointed repeatedly as significant issues contributing to the weakening of physical and mental health. Nowadays stress is considered as the biggest threat to individual's wellbeing. However stress can be a positive aspect in our daily life, but too much stress can rather be harmful to physical and emotional healthiness where as managing it, is a major concern for populations around the world. Hence, there is significant importance to detect stress in its early stages, before it turns into severe problem. Thus, this work analyses and brings together recent research studies carried for automatic stress detection observing over the dimensions executed along the four main modalities, viz., Psychological, Physiological, Behavioral and Social Media Interaction modalities, along with appropriate measurements, in order to give hints about the most appropriate ways and means to be used for Psychological Stress Detection.

Keywords— *Psychological Stress Detection; Social Media interaction; Physiological signals; Behavioral responses.*

Psychological stress refers to the psychological awareness of affliction and the body's response to it. Hans Selye was the first person to give definition of Psychological Stress and credited as being father of stress who defined stress in the year 1936 as "the non-specific response of the body to any demand for change"[1]. In 1979 he further expanded his definition stating, "Stress is a 'perception', it is the demands that are imposed upon us because there are too many alternatives". Further, stress exists in two forms namely *Acute stress* and *Chronic Stress Acute stress* is short-lived stress exists for time being for which human body designed to recover from it. It's an instant reaction of body to new challenge or demand that activates instantly like a fight-or-flight response. This can be seen from instances such as fight with closed relation, an accident or anxiety when meeting new people. Such stress is said to be episodic type if it happens frequently. *Chronic stress* is one, when acute stress isn't resolved and begins to increase continuously and persist for long-term. It is considered as negative. Instances of such stressful circumstances are difficulties in interpersonal relationships, bad job, abuse and poverty. The Chronic stress leads to numerous serious health problems such as heart disease, cancer, mental problems and suicide [3]. Stress and Depression have been pinpointed again and again as significant issues contributing to weakening of mental health and class of life. However, stress can be a positive aspect for motivation and achievements. At times, too much stress can be rather harmful to physical and mental health conditions. Such as depressions, insomnia and even suicide accordingly as per statistical reports of World Health Organization (WHO) over 4.5% of India's population suffer from depression as of 2015. Whereas the corporate sector in India has reported an ascending increase of stress over the last two years. Similarly, a survey by workplace solutions provider Regus in 2015 also reported 57% of corporate India is under stress. Thus, the increase of stress has become an adverse affect on human health as per survey. Concern of health is essential for growth, development and productivity of society and is vital for a happy and healthy life in the world. Thus, there is a significant necessity to predict stress in its early stages, before it turns into severe problem.

There have been many techniques developed to detect stress with the aid of data collected using physiological sensors or face-to-face interviews conducted by psychologists, which usually relies on the active individual participation hence it becomes non-trivial to detect stress timely for proactive care. With the rapid development of social networking sites (SNS), it has become a popular platform for people to express themselves. Nowadays, people are more willing to use social media as a platform to express their moods and daily life events. A Facebook's statistical report from Global social media research of 2017 shows that most popular social networks with total 1,871 million active users worldwide whereas Twitter is the fastest growing social networks with total of 317 million active users [2]. People post text, emoticons and images on social media platforms to share thoughts, express emotions, record daily habits and interconnect with friends. The observation shows that microblogs of linguistic text and visual content indicates stress related symptoms are used in social media to express their thoughts. Encoding of emotional information in text is common practice especially in online interactions. This makes the detection of user's psychological stress through their tweets, posting behavior and social interaction from micro-blog or social media feasible.

As studies suggest that the way of a person's write-up give windows into their emotional world [2], without non-verbal signs, writers become accustomed to the medium by permeating messages with emotion prompts e.g., emotion words or emojis to will allow for more natural or improved Communication (Walther, Loh, and Granka, 2005). This paper surveyed that brings together the recent research carried for automatic stress detection strategies and suggests the better strategy to improve detection of stress.

The rest of paper is organized as follows: The Section II elaborates the various techniques used for stress detection. In section III, discusses the comparison among different methods. The Section IV summarizes various techniques used for detecting stress and then suggests the better strategy to improve stress detection from social media.

I. DIFFERENT STRESS DETECTION METHODS

These days, Psychological Stress is turning into a risk to individual's wellbeing. It is of critical significance to recognize and oversee the stress before it transforms into serious issues. Figure 1 illustrates four methods for psychological Stress Detection.

Major physiological activities are controlled by Autonomic Nervous System (ANS) that includes the circulatory strain, organ emission, heart's electrical movement, and breath. The ANS has two divisions, the sympathetic nervous system (SNS) and the parasympathetic sensory system (PNS). Under unpleasant conditions, SNS is in charge of preparing the body's assets for activity. As opposed to SNS, the PNS is in charge of unwinding the body and balances out the body into unfaltering state [5, 6].

The Sympathetic Nervous System (SNS) incites the stress response in human being [5], carrying psychological, physiological and behavioral symptoms [6]. All through this paper, the accompanying definitions are considered for these gatherings of reactions. *Psychological* is comprehended as "of or identifying with the brain or mental action" [7] and they don't include the execution of an activity. *Physiological* reactions are a piece of the ordinary working of a living creature or substantial part [8], subsequently, they are non-deliberate activities or reactions, and hard or difficult to see by outer perception. *Behavioral* is interpreted as "the way of acting" [9], which are, dissimilar to physiological reactions, they include an activity that could be controlled or changed moderately and can be remotely watched. Social Interaction is defined as "a dynamic procedure of exchanging succession of acts between people or gatherings"[8]. *Social Media Interaction* is comprehended as "an online podium which individuals use to build social relations with other individuals who share similar personal or career interests, activities, backgrounds or real-life connections"[10].

1. Psychological Evaluation

Psychological responses comprises of strong increase in the negative emotions, such as rage, nervousness, Annoyanceor melancholy [11].The assessment of stress can be carried out by means of self-report questionnaire or by being interviewed by a psychologist. The first is a widely used ways amongst the most generally utilized approaches

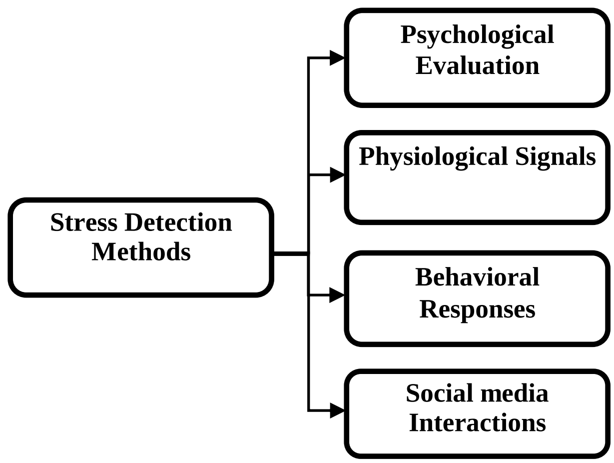

Fig. 1: Taxonomy of Stress Detection Methods

to gauge feelings of anxiety in people and it is viewed as a reliable strategy. The Stress Self Rating Scale (SSRS), the Perceived Stress Scale (PSS) or the Stress Response Inventory (SRI)[16, 17] are some instances. However, these questionnaires just offer data about current anxiety or stress levels of the client and not about the stressors nor about the development of the feelings of stress. These tests can be taken time to time, however may not be realistic for identifying the delicate changes which could indicate an early stage of a major issue. All things considered, they are just taken when the affected himself or the individuals around him understand or suspect about the seriousness of the circumstance, and this is too late in majority of the cases. Moreover, questionnaires are subjective and require the complete attention of the client. "Individuals can undergo lapses in memory about the emotional tone of a day in as little as 24 h" [30], which implies that we are not generally aware of our genuine stress levels and that techniques, such as, self-report questionnaire could sometimes lead to an erroneous stress level estimation.

2. Physiological Signals

Physiological sensors can offer data regarding the intensity and quality of a person's internal affect experience [36]. Stress also presents itself via biomarkers, it can be measured objectively and observed using wearable physiological sensors. When there is an increase in SNS activity, it changes the hormonal levels of the body and incites responses like secretion production, amplified heart rate and muscle activity because of which skin temperature drops and the Heart Rate Variability (HRV) falls [12, 36]. These changes act as cue and provide data through wearable sensors for stress detection .The physiological measures of stress and their equivalent technologies can be categorized as follows:

- Heart activity:"electrocardiography (ECG)".
- Brain activity: "electroencephalography (EEG), Functional Magnetic Resonance Imaging (fMRI)".
- Skin response:"electrodermalactivity (EDA) and galvanic skin response (GSR)".
- Muscle activity: "electromyography (EMG)".
- Respiratory response: "electromagneticgeneration".
- Pupil Diameter (PD), eye gaze and blinking: "infrared eye tracking systems".

The most prevalent techniques i.e., electrocardiogram and Electrodermal Activity are examined more closely in the following sub-section.

1.1. Electrocardiogram(ECG)

The electrocardiogram (ECG or EKG) is "the recording on the body surface of the electrical activity produced by heart" [5, 6, 21, and 22]. It is a standout amongst the most utilized measure in stress detection research because it reflects specifically the action of the heart, which is obviously influenced by ANS changes [18]. An ECG can be effortlessly estimated setting a few electrodes on particular spots of the body and estimating the potential contrast. The quantity of electrodes and their positions can differ, however a standout amongst the most straightforward and compelling ways is the Lead-II design, which comprises of putting three terminals: one on the right arm, one on the left arm and the last one on the left leg. The most classic and valuable features processed with an ECG are likely the ones identified with the Heart Rate Variability (HRV).

Many stress researches have utilized ECG sensors effectively. An illustration could be crafted by Cinaz et al. [19], who considered a 3 class characterization issue to isolate office laborers' psychological workload into low, medium and high gatherings utilizing just an ECG signal and nine HRV features (eight time area features and the LF/HF proportion), accomplishing right predictions for 6 out of 7 subjects utilizing Linear Discriminant Analysis (LDA) [20] classification. ECG has been contemplated for extracting features like the mean, standard deviation, power and vitality of the preprocessed crude information, however it is more commonly used to extract data about Heart Rate (HR) and Heart Rate Variability (HRV). HR is considered as the quantity of heartbeats every moment. HRV is the temporal difference between successions of sequential heart beats [5, 36], is likely the most regularly utilized feature in stress recognition. Nonetheless, the developed framework requires an offline study to be completed by a professional. Nonetheless, the created framework required an offline study to be completed by a professional.

1.2. Electrodermal Activity(EDA)

The Electrodermal Activity (EDA), otherwise called Galvanic Skin Response (GSR), is defined as variation in the electrical properties of the skin [5]. Under emotional stimulation, lengthened mental workload or physical activity, the level of sweat production increases changing the skin properties, i.e. increasing conductance and diminishing resistance [5, 18, 23]. EDA can be estimated placing two anodes on the skin surface near to each other and passing a weak current between them. EDA is a standout amongst other sensors in stress and emotion detection [21]. De Santos Sierra et al. [22] made individual stress formats for 80 people utilizing EDA and HR signals and a fuzzy logic algorithm. Exactness of 99.5% was accomplished for a two class classification issue, proposing that the two signals have the potential for identifying stress levels precisely.

ECG and EDA are the commonly utilized biomarkers for stress recognition. A few different less common markers can likewise be utilized to detect stress such as, Electromyogram[29],Electroencephalogram (EEG)[31], accelerometer [4], Skin temperature [18], Blood Pressure [30].It is likewise regular to utilize a mix of different biomarkers but at the same time is costly. Helawaret al. utilized GSR and BP markers [18] for identifying stress.

As it has been found in this section, there are numerous physiological signals that have been utilized as a part of stress identification and some of them have appeared to give solid data about people's real-time stress levels. Sadly, the downside of the majority of them is that additional hardware is essential for the estimations, turning into anobtrusive technique for real-life. Regardless of some researches [26] focused on making wearable physiological estimating frameworks to make them more straightforward, the user is compelled to wear continuously those equipment's, which remains being inconspicuous and even not affordable for a few individuals.

3. Behavioral Responses

Behavior is interpreted as, how an individual or a group act in a given circumstance in light of set up protocols, standards of behavior or acknowledged social practices [22]. Stress influences in people's behavior. A portion of the prompted changes are well-known, for instance, being substantially more aggressive or irritated, however these are not quantifiable effortlessly. Other plausible behavioral changes can be examined by investigating individuals' interaction with gadgets keeping in mind the end goal to confirm their association with stress and to make a dependable method to gauge it. The benefit of estimating behavioral responses in contrast with physiological estimations, they can usually be done in an absolutely unpretentious manner without the requirement of costly additional hardware. The Behavioral measures of stress and their equivalent technologies can be categorized as follows:

- Speech analysis: "Voice Stress Analysis".
- Mobile phone usage: "Information related to users".
- Facial expression: "automated facial expression analysis (AFEA)".
- Body gesture: "automated gesture analysis (leveraging AFEA)".
- Typing rhythm: "Keystroke and mouse dynamics".

The most prevalent techniques i.e., speech analysis and mobile phone usage are examined more closely in the following sub-section.

2.1. Speech analysis

The fact that stress changes human vocal production is agreed by many researchers [6, 24]. More appropriately, it has been discovered that under stressful circumstances, changes in pitch and in the speaking rate are natural, together with variation in energy and spectral qualities of the glottal heartbeat [25]. Speech analysis has caused curiosity primarily in light of the fact that it can be effortlessly estimated in an inconspicuous manner. Nevertheless, voice-based stress examination can be inadequate both in calm and noisy spaces [24], because of the absence of speech recordings and presence of too much noise. The greater part of the investigation done in stress detection from voice, has been conducted in research laboratories or in calm surroundings, however there exists exceptions and downsides.

2.2. Mobile phone usage

Nowadays, a gigantic measure of data identified with clients' behavior can be extricated from Smartphones. Call logs, SMS, messages, web perusing, application's utilization, area information and numerous other learning can be effectively gotten without the client notwithstanding seeing it. As of late, explore on stress location has assessed the likelihood of exploiting this inconspicuous data gathering strategy[18].

Muaremi et al. [26] utilized iOS Smartphone information gathered amid the day and HRV information enlisted when resting, to characterize individuals in low, medium and high business related pressure gatherings. Highlight choice methods were utilized to bring about a seven highlights' gathering where 4 had a place with HRV and 3 to Smartphone information, proposing that HRV highlights were more imperative than the extricated Smartphone includes for this situation. The best outcomes were accomplished in the client particular model case, with an exactness of 55% with just Smartphone information, 59% with just HRV information and 61% with the mix of both. This arrangement comes about likewise demonstrate that the chose HRV highlights were superior to the Smartphone highlights chose for the expressed grouping problem. Mobile telephone utilization highlights. The quantity of calls (nCalls), the total of all call term (tCalls), mean, fluctuation and middle of call length, and the proportion amongst approaching and active calls have been acquired from cell phones [26].

Behavioral estimations for stress acknowledgment are considerably less continuous than the physiological ones in the cutting edge. They have not presumably been sufficiently still contemplated, and along these lines, stress recognition results are not as precise as with physiological methods. All things considered, some of them look exceptionally encouraging, on one hand on account of their outcomes and on another, in light of the fact that they don't require any additional hardware.

4. Social media Interactions

Online networking has turned into a famous stage for individuals to convey what needs be. These days, with the quick improvement of informal communication locales, individuals are all the more eager to utilize online networking as a stage to express their inclinations and everyday life occasions. Individuals post content and pictures via web-based networking media stages to share musings, express feelings, record every day propensities and interconnect with companions. We can acquire etymological and visual substance that may demonstrate pressure related side effects. Encoding passionate data in content is a typical practice particularly in online connections. This makes the recognition of clients' mental worry through their tweets, posting conduct and social cooperation from small scale blog or online networking plausible [14, 15].

Stress recognition in text is concerned about utilizing natural language processing (NLP) strategies to perceive stress communicated in composed text message. The need is to comprehend the different feelings responsible for the stimulation of stress. As Stress is a feeling of emotional or physical strain. It can originate from any occasion or thought that makes one feel a wide range of emotions, for example, nervousness, fear, outrage, dissatisfaction, pity and misery. Feeling Theories discussion of what feelings can be distinguished in text, and how they are estimated should first begin with an investigation of the hypothetical perspectives on feeling drawn from the psychology writings.

The Darwinian Perspective characterizes feeling as being "articulations". more conspicuously his viewpoint emphasizes that there is a reliable arrangement of examples related with the expression of every one of a kind feeling (Cornelius, 1996).This infers that there is an arrangement of universal emotional articulation that people would show and could recognize regardless of culture and language [37].Advocates of the Darwinian camp, including Ekman (1971), Izard (1971) and Plutchik (1984), have based on Darwin's hypothesis of feeling by postulating a set of universal emotions, also known as basic or prototypical emotions, and Characterizing the examples related with this arrangement of feelings. Figure 2, demonstrates the degree of overlap between what (Ekman et al., 1987), (Izard, 1971, 1994) and (Plutchik, 1962) consider to be "fundamental" feelings. Ekman's six fundamental feelings are happiness, surprise, sadness, fear, disgust, and anger. Plutchik's model is an extension of Ekman's essential feelings through the expansion of trust and anticipation in his eight fundamental feelings, while Izard's ten fundamental feelings likewise incorporate guilt and shame.

The Darwinian point of view has contributed an arrangement of fundamental feeling lables to illuminate investigation on emotion detection in text, in this way making automatic detection of the fundamental emotions in text conceivable.

2.3. Cross Media Data

2.3.1. Linguistics

The way an individual composes his writing can vary depending upon his stress levels. On one hand, some pressure can upgrade the composition capacities of a man, improving works of value, utilizing a more differing vocabulary and so on. On the other hand, mood can be

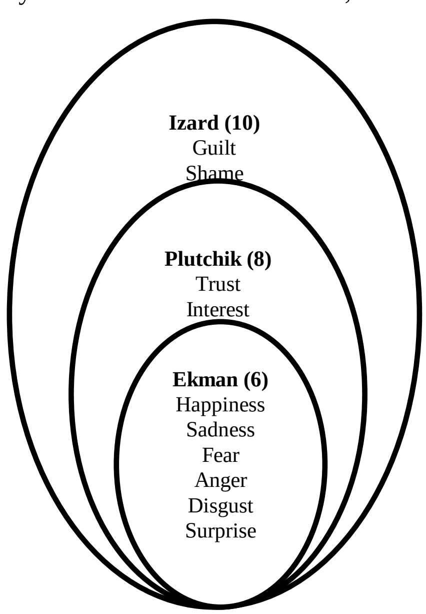

Fig. 2: Ekman, Plutchik, and Izard's basic emotions

explicitly reflected in the content being composed particularly, in free messages. Along these lines, breaking down text linguistics can be an additional incentive for a stress recognition framework.

As of now, there exist many instruments that permit to automatically analysis features of text, for instance, LIWC [32], SentiStrength [33], which can be utilized for estimating writing execution in clients by means of lexical measures, or straightforwardly examining the "emotions" of the content, which is their primary reason. Researcher [27, and 28] used this technology to analyze online posts and detect user stress levels from them.

2.3.2. Linguistics + Visual

A study says the way that an individual's compose give windows into their enthusiastic world [37]. As mention above, the way an individual composes his writing can reveal his stress levels. Incorporating visual content with textual message can increase the accuracy of stress detection model. Visual feature includes Saturation, Brightness, Warm or cool color, Clear or dull color. Low brightness and saturation makes individuals feel negative and vice versa.

Social Commitment gives the numbers of @-mentions, reposts, and replies in postings, representing individual's communal activeness with contacts. Collaborating Linguistic, visual and social attribute H. Lin, et al [14] propose an automatic method for stress detection from cross-media data. These attributes are fed into Deep Sparse Neural Network which is proposed to learn the stress categories. Testing results show that the method is effective.

But linguistic and visual attribute termed as low level attribute reflects the instant emotion expressed in a single post, which is inefficient in detecting psychological stress states are usually more changing over different time periods.

2.4. Social Behavior

2.4.1. Posting Behavior

H. Lin, et al [15] defines a set of posting behavior measures, based on the weekly tweet postings such as posting time and posting types. Posting time is average number of tweets posted in a day and posting type gives the category of the post taking a sample period of a week. Author categorizes posts of users into four types: a) Post containing images b) original post c) query posts d) Info sharing post. H. Lin, et al [15] proposes a convolution neural network (CNN) combine with deep neural network (DNN) model which incorporates posting behavior attributes with linguistic and visual attributes to detect stress. Exploratory results show that the proposed method is effective and efficient on detecting psychological stress from micro-blog data. Though its results are effective, the role that social associations' plays in individual's stress

Table 1: Summary of Literature Review

Reference	Signal	Feature	Parameters	Strategy	Acc.%	Prec. %	Rec. %
			Physiological Signal				
A. De Santos Sierra et al.[22]	EDA,ECG	$\mu\boldsymbol{\sigma^2}$,HR	$\mu,\boldsymbol{\sigma^2}$	Fuzzy Logic	98.45	97.5	99.5
J.A. Healey et al[21]	ECG,EMG,EDA	HRV, μ, Orienting responses	LF/HF, (LF + MF)/HF , Onset, peak, duration, magnitude, total no. of peaks, sum of magnitudes	LDA	97.3	97.4	97.4
X. Li et al.[35]	ECG	HRV	RMMSD, HF, entropy, complexity, pulse waveform (HR)	HMM	96.4	96.4	96.5
			Behavioral Feature				
H. Kurniawan et al.[6]	Signal	Pitch, MFCC	μ,min, max, median, SD, range, $\mu,\boldsymbol{\sigma^2}$,delta and delta-delta coefficients,	SVM	92.6	-	-
A. Sano et al. [18]	EDA,ECG	Calls, SMS, Screen use, Contacts list	nCalls, tCalls, μ, $\boldsymbol{\sigma^2}$,median of call duration, incoming/outgoing calls,μ,SD,nSMS, received/sent SMS, nsPeople	SVM,KNN	75%	-	-
			Social Media Interactions				
Y. Xue et al. [27]	Text Linguistics	Free text	Polarity, positive and negative affect rate, degree lexicon, negation lexicon.	Gaussian Process Classifier	82.4	82.8	82.5
H. Lin et al. [14]	Content Attribute(Text + Visual+ Social attributes)	Short text, image properties, count of repost	Positive and negative affect rate, degree lexicon, negation lexicon, Image Brightness, Saturation, cool and dull color, mean and variance of number of post or tweets	DNN with CAE	87.27	-	-
H. Lin et al.[15]	Content Attribute + Posting Behavior	Short text, image properties, count of repostPosting Time, Posting Type.	Positive and negative affect rate, degree lexicon, negation lexicon, Image Brightness, Saturation, cool and dull color, mean and variance of number of post or tweets, Average post per day.	CNN + DNN-4	78.49	84.4	84.3
H. Lin et al.[35]	Content Attribute + Posting Behavior + Social Interaction	Short text, image properties, count of repostPosting Time, Posting Type, social Influence, social structure.	Positive and negative affect rate, degree lexicon, negation lexicon, Image Brightness, Saturation, cool and dull color, mean and variance of number of post or tweets, Average post per day, follower count, Stressed neighbor count, count of user's interaction with friends.	CNN + FGM	91.55	96.56	90.4

states and how it can be incorporated into psychological stress detection have not been examined yet.

2.4.2. Social Interaction

Social Interaction attribute is extracted from an individual's social interactions with friends. Social Influence gives a measure to count stressed neighbor that is the number of the user's stressed neighbors. Follower Count gives the number of the user's followers. Social Structure Represents the structure distribution of the user's interacted friends. H. Lin, et al [35] proposes a model a factor graph model combined with CNN to power post content (including linguistics + visual + posting behavior) and social interaction information for psychological stress detection. Experimental results show that the proposed model achieves 91.55% of accuracy.

II. Comparison Of Different Methods

There are numerous physiological signs that have been utilized as a part of stress identification and some of them have appeared to give solid data about people realtime stress levels. Sadly, the downside of the majority of them is that additional hardware is essential for the estimations, turning into a prominent technique for the genuine living. Regardless of some researches [26] focused on making wearablephysiological assessing frameworks to make them more straightforward, the client is compelled to wear Constantly those equipment's, which remains being inconspicuous and even not affordable for a few people. Behavioral estimations for stress acknowledgment are considerably less continuous than the physiological ones in the cutting edge.

They have not presumably been sufficiently still contemplated, and along these lines, stress recognition results are not as precise as with physiological methods. All things considered, some of them look exceptionally encouraging, on one hand on account of their outcomes and on another, in light of the fact that they don't require any additional hardware.

H. Lin, et al [14], Linguistic and visual attribute termed as low level attribute reflects the instant emotion expressed in a single post, which is inefficient in detecting psychological stress states are usually more changing over different time periods.H. Lin, et al [15], its results are effective, but the role that social associations' plays in individual's stress states and how it can be incorporated into psychological stress detection have not been examined yet. Table 1 shows a summary of overall literature.

IV. CONCLUSION AND SCOPE FOR FUTURE RESEARCH

In this paper, we have presented various measures and techniques used to detect psychological stress which is an increasing problem in the world, in this day and age of job issues, including lots of assignments and necessity of adjustment to constant changes, complicates this issue. Therefore, it is essential to monitor and control individual's stress levels constantly in order to detect stress in its primary phase and avoid the harmful long-standing consequences.

Most of Psychological evaluations of stress are based on subjective Questionnaires that need individual's response which may not be accurately used for real time analysis.Numerous physiological signs that have been utilized as a part of stress identification and some of them have appeared to give solid data about people realtime stress levels. But, the drawback is,it requires additional hardware for estimating the stress which are costly and labor consuming [5, 21]. The above disadvantage is overcome by Behavioral Estimation, which reduces system development cost. It is inconspicuous to the user as no equipment's are needed [36]. But these methods compromise the accuracy of stress recognition which leads to inefficient results. Inefficiency of the above methods motivates to adopt a novel technique which is transparent and inexpensive. Thus, many researchers are focusing on leveraging social media interactions to improve the effectiveness of social media analysis for stress detection.

Capturing of contextual attributes ascend to new research opportunities that aids in decreasing of users stress. The user's stress states need to be captured daily, weekly, bi-weekly or monthly from Social Networking Sites[38], social media data are being considered more in the stress detection systems as it is inexpensive, transparent and provides primary access to new opportunities. Hence detecting user's stress levels from user's social media data or microblog content will improve the stress detection performance efficiently. Recent studies shows apart from leveraging cross-media content and social interactions, Social Structure also plays a vital role in detecting stress states of an individual, which is a useful references for future related studies[35].

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