Literature Review: Analysis of relationship between human activities and stress using machine learning

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***Abstract*—This paper is an overview of existing literature on features, machine learning techniques and classification methods used in activity recognition and stress prediction. These methods utilise data from various sources including data from sensors and surveys(sleep and personality) to analyse patterns leading to stress in an individual. The different techniques and machine learning models described in this paper have shown promising results in activity recognition and the prediction of stress. Our aim is to use activity aware sensor data to predict stress.**

I. Introduction

In today's fast-paced world, stress has become a common experience for many individuals. Whether it's due to work pressures, financial concerns, relationship issues, or other life challenges, stress can have a significant impact on both our physical and mental well-being. Understanding what stress is and learning effective strategies to manage it plays a major role in maintaining a healthy and balanced life. [1], [2] While some levels of stress can be beneficial, motivating us to take action and adapt to challenging situations, excessive or chronic stress can have detrimental effects on our health. [3] Prolonged exposure to stress can lead to a range of physical and mental health problems, including high blood pressure, anxiety, depression, and weakened immune function. [4]

Stress prediction aids stress management by offering early awareness of impending stressors, allowing individuals to intervene before stress becomes overwhelming. By analysing patterns in behaviour and physiology, predictive models can be used to provide personalised recommendations tailored to individual stress triggers and responses. [5] Continuous monitoring and prediction of stress contribute to resilience building by fostering self-awareness and facilitating the development of adaptive coping strategies. Ultimately, stress prediction may help empower individuals to take proactive steps towards self-care, leading to improved overall well-being and a greater sense of control over stress levels. [6]

It has been generally observed that activities like working, commuting, and making financial decisions can be stressful. On the other hand, activities like watching TV, engaging in a hobby or playing with your pet can help alleviate stress. Identifying such activities can help us strike a balance and manage stress in a healthy manner. Sleep plays a crucial role in regulating stress levels and promoting emotional resilience [7], better sleep quality is also observed to undo the detrimental effects of stress [8].

Our proposed project aims to provide insights into the relationship between daily activities and stress levels logged by users.Early prediction of stress allows individuals to take preventive measures to manage and reduce stress before it escalates into more serious mental health issues. We will be using the activity performed and the details associated with the activities, with sleep being a major activity, to make inferences of the stress and fatigue levels of the user. The stress and fatigue levels that will be used for training was collected from a survey that users were asked to fill twice a day during the period in which they participated in the study. [9]

II. Literature Review

Frustration, nervousness, and anxiety are the most common symptoms of stress (50%) in younger people [10]. It creates a negative impact on human lives and damages the performance of each individual [11]. Early prediction of stress and the level of stress can help to reduce its impact and different serious health issues related to this mental state.

Previous studies have primarily focused on utilizing biological and physiological sensor data for predicting stress without any contextual meaning added to it. We believe attaching activity context would add much more insight to physiological sensor data while predicting stress. However, these sensors lack inherent activity awareness, necessitating manual labelling efforts to associate sensor data with specific activities. To streamline this process, our approach aims to autonomously recognize activities from sensor data, thereby eliminating the need for manual labelling. Subsequently, we aim to leverage the recognized activities to predict the corresponding level of induced stress. In section A, we begin with examining the features that have been predominantly used for stress prediction, followed by reviewing previous research across a diverse array of daily activity recognition in section B. Ultimately, our goal in section C is to explore the most commonly employed machine learning methods for predicting stress.

A. *Features used for stress detection*

Common features utilised across various papers for predicting stress using machine learning encompass a broad spectrum of physiological, behavioural, and environmental indicators. These include biometrics such as heart rate and galvanic skin resistance, reflecting bodily responses to stressors. Activities, diet, and sleep data offer insights into lifestyle patterns, while mood, interpretation tendencies, and perceived stress scales capture psychological states. Contextual information such as time, location, and environmental factors often enhance recognition accuracy while factors like room conditions, personality traits, and even cultural preferences contribute additional dimensions. Overall, the integration of these diverse features underscores the comprehensive approach adopted in stress prediction research, aiming to capture the multifaceted nature of stress responses through machine learning techniques.

In [12] T. Yamamoto et al. used psychological features like mood experiences, cognitive and behavioural experiences, psychiatric and physical symptoms to predict happiness. Meanwhile P. Soleimaninejadian et al. [13] used biometric data, diet, historical mood data, sleep data and environment data to detect and predict the current mood of the user. The use of biological sensor data like heart rate and galvanic skin resistance and results of perceived stress scale have proven effective to predict a positive or negative change in stress levels [14]. Another study [15] also uses physiological data and other features like results from personality tests, sleep quality and music related data. S.-L. Chua et al. [16] discuss the effect of time and location on prediction of activity, they found a strong correlation between the location and activity.

We observe that most of the previous work around stress detection has dealt with data from physiological sensors i.e. features like heart rate, resting heart rate, galvanic skin resistance, skin temp. Sleep quality has also been observed to contribute largely to fatigue levels. Features relating to dietary habits surprisingly have little to no effect on an individual's mood. Very few studies in this area have considered features like activity labels and features surrounding the activities as relevant.

B. *Activity Recognition*

Activity recognition has garnered significant attention in recent years, with notable advancements in various research endeavours. The study in [17] goes beyond the low level activity recognition and analyses human behaviours at a greater level using a nonparametric approach. The experiment findings reveal that the nonparametric system learns model parameters from sensor data automatically, without needing manual selection. The study also beats traditional methods in finding human routines effectively. Wearable cameras, which are small and lightweight, have only recently started being used for recognizing activities [18]. They are everywhere and can record data on their own for a long time without needing people to do anything.

In [18] experiments were conducted using the correlation alignment (CORAL) adaptation method, showing that the model learned with their dataset can be easily and successfully transferred to other existing datasets acquired by different wearable cameras, providing competitive results with very little amount of labelled data. [19] proposes a system using deep learning to model and recognize activities from wearable sensor data, achieving a high recall rate of around 99% and offering explainable AI for understanding behaviour in various settings.

Based on the previous work on user-activity based analysis, we are attempting to predict the stress levels of people based on the activities they have performed throughout the day and previous night's sleep. This will require activity recognition as the first step - to eliminate manual labelling effort.

C. *Machine Learning Techniques Used*

Datasets on stress, unlike typical datasets, are characterised by extensive data volumes sourced from wearable devices, smartphones, electronic health records and daily activity data, offering a multifaceted perspective on stress. Machine learning models are suitable for predicting stress in individuals due to their ability to analyse large, diverse datasets and identify complex patterns indicative of stress.

P. Soleimaninejadian et al. [15] use logistic regression to predict mood and ensemble methods with weak classifiers to detect music mood and style. Being a supervised machine learning method, logistic regression predicts the likelihood of an outcome, typically for binary classification tasks by estimating probabilities based on input features. It specialises in delivering binary outcomes (Yes/No, 0/1) allowing for straightforward decisions between two possibilities.

The study [12] made use of SVM to predict happiness levels of the study subject, they achieved an accuracy of around 80%, building on this. The methodology employed a nonlinear SVM with a Gaussian kernel to predict happiness levels from various features, implemented using the "e1071" package in R. Features were preprocessed by centering, normalising, and selecting based on significant correlations with happiness and effect sizes. Fourteen features were selected as inputs for the SVM. Training involved using a radial basis function kernel, with hyperparameters (C,γ) tuned via grid search for optimal classification accuracy. Testing involved evaluating the SVM's prediction accuracy using lifelog data from a separate test dataset. P. Soleimaninejadian et al. [13] made use of C4.5 to boost the dataset to improve the accuracy of the SVM algorithm in predicting the mood of a user.

Another study [14] compared the performance of three different supervised learning algorithms like Linear Discriminant Analysis, quadratic discriminant analysis and decision tree in predicting changes in stress levels. Decision tree gave an accuracy of 70%. Validation was conducted using k-fold cross-validation ($k = 10$).

The study [20] uses machine learning algorithms for activity recognition and stress detection based on data collected from a wristband. For activity recognition, the study employs machine learning models such as Artificial Neural Network (ANN), Decision Tree (DT), K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Logistic Regression (LR). These models are trained and evaluated using 3-axis acceleration signals recorded on the wrist to distinguish daily motion activities with different levels of physical intensities. They achieved approximately 97% accuracy in recognizing physical activities using Decision trees and over 80% accuracy in detecting stress using SVM. It is observed that daily stress detection should not solely rely on physiological signals, as models based only on these signals struggle to effectively differentiate between high-intensity activities and stress conditions.

As can be seen, the machine learning methodologies usually used for activity and stress recognition tends to be SVM as it excels in adjusting to feature-based classification methods, particularly when dealing with complex relationships between features. It defines its functions by identifying a boundary in the feature space that effectively separates different classes during training. [21]

III. Conclusion

Based on the above-mentioned understanding of the state-of-the-art, we believe the gap is the lack of activity context in the sensor data, and our objective is to focus on the activities conducted rather than just the sensor data. We intend to process the raw sensor data using activity recognition algorithms to assign activity labels to the data and then investigate its relationship to stress and fatigue levels.

The existing work on predicting stress based on user activities makes several significant contributions to the field of mental health and technology integration. Firstly, it offers a novel approach to identifying and preemptively addressing stress by leveraging the data generated through user activities and other sensor data. The appropriate machine learning algorithm selection will depend on the features utilised and the models accuracy. A wide range of dataset on stress are available for us to work on. The strengths of the existing study lies in its innovative use of technology to monitor and analyse user behaviour in real-time, providing valuable insights into stress patterns and triggers. However, some weaknesses include potential privacy concerns and the need for robust validation of predictive models across diverse populations. One potential missing aspect is a comprehensive examination of the long-term effectiveness and sustainability of interventions suggested by stress prediction models. Moving forward, our research will focus on refining predictive algorithms to enhance accuracy and reliability by using not just the sensor data but the daily activities that a user performs. Addressing privacy concerns through transparent data handling protocols could also be considered for future research. Additionally, efforts should be made to validate these models across different demographic groups and socio-cultural contexts. Incorporating user feedback and iterative improvements will be crucial for the successful implementation of stress prediction systems in real-world settings.

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