**MSc In Computing**

**MCM Practicum Literature Review**

| **Project Title** | Analysis of relationship between human activities and stress using machine learning |
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**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 is essential for maintaining a healthy and balanced life. 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. 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.

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 provide personalised recommendations tailored to individual stress triggers and responses. 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 empowers individuals to take proactive steps towards self-care, leading to improved overall well-being and a greater sense of control over stress levels.

Our proposed project aims to provide valuable insights into the intricate relationship between lifestyle choices and mental health. This will allow users to avoid stressful activities and make better choices for their mental wellbeing and quality of life. We propose to find the connection between daily activities and emotions, stress levels and fatigue 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. The data we will be using was collected from a survey that users were asked to fill twice a day during the period in which they participated in the experiment.

**Literature Review**

Stress is becoming an increasingly prevalent health issue, seriously affecting people and putting their health and lives at risk. Frustration, nervousness, and anxiety are the symptoms of stress and these symptoms are becoming common (40%) in younger people. It creates a negative impact on human lives and damages the performance of each individual. 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. For this, automated systems are required so they can accurately predict stress levels.

1. **Features Used**

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 [1] the authors used psychological features like mood experiences, cognitive and behavioural experiences, psychiatric and physical symptoms to predict happiness. Meanwhile the authors used biometric data, diet, historical mood data, sleep data and environment data to detect and predict the current mood of the user in [2]. 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 [3]. [5] also uses physiological data and other features like results from personality tests, sleep quality and music related data. In [4] the authors 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.

1. **Previous work on activity Recognition**

Activity recognition has garnered significant attention in recent years, with notable advancements in various research endeavours. The study in [6] 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. It 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. They are everywhere and can record data on their own for a long time without needing people to do anything.

In [7] 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. [8] 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.

1. **Methodology**

Unlike typical datasets, datasets on stress are characterised by extensive data volumes sourced from wearables, smartphones, and electronic health records, 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.

[5] uses 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.

[3] 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), and performance evaluation utilised confusion matrix outputs to calculate various metrics including False Negative Rate (FNR), False Positive Rate (FPR), True Positive Rate (TPR), Positive Predictive Value (PPV), Accuracy, Balanced Error Rate (BER), and F1 Score. Three types of analyses were performed: utilising only heart rate data, only GSR data, and both heart rate and GSR data. Results indicated that independently using heart rate or GSR data yielded poor results, while employing the decision tree classifier with GSR data or both heart rate and GSR data significantly improved performance, as illustrated by accuracy, BER, and F1 Score results.

[1] made use of SVM to predict happiness levels of the study subject using SVM, they achieved an accuracy of around 80%, building on this [2] made use of C4.5 to boost the dataset to improve the accuracy of the SVM algorithm in predicting the mood of a user.

**Conclusion**

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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