**INTRODUCTION**

Physical or mental imbalances caused by noxious stimuli trigger stress to maintain homeostasis. Under chronic stress, the sympathetic nervous system becomes overactive, leading to physical, psychological, and behavioral abnormalities [1]. Stress levels are often measured using subjective methods to extract perceptions of stress. Stress level measurement based on collected heart rate viability (HRV) data can help to remove the presence of stress by observing its effects on the autonomic nervous system (ANS) [2].

Typically, people with anxiety disorders have chronically lower resting HRV compared with healthy people. As revealed in [2] and [3], HRV increases with relaxation and decreases with stress. Indeed, HRV is usually higher when a heart is beating slowly and vice versa. Therefore, heart rate and HRV generally have an inverse relationship [2], [3]. HRV varies over time based on activity levels and the amount of work-related stress.

Furthermore, stress is usually associated with a negative notion of a person and is considered to be a subjective feeling of human beings that might affect emotional and physical well-being. It is described as a psychological and biological reaction to internal or external stressors [4], including a biological or chemical agent and environmental stimulation that induce stress in an organism [5]. On a molecular scale, stress impacts the ANS [6], which uses sympathetic and parasympathetic components to regulate the cardiovascular system. The sympathetic component in a human body [7] works analogously to a car’s gas pedal. It activates the fight-or-flight response, giving the body a boost of energy to respond to negative influences. In contrast, the parasympathetic component is the brake for a body. It stimulates the body’s *rest and digests* reaction by relaxing the body when a threat has passed. Given the fact that the ANS regulates the mental stress level of a human being, physiological measurements such as electrocardiogram (ECG), electromyogram (EMG), galvanic skin response (GSR), HRV, heart rate, blood pressure, breath frequency, and respiration rate can be used to assess mental stress [8].

ECG signals are commonly adopted to extract HRV [9]. HRV is defined as the variation across intervals between consecutive regular RR intervals,1 and it is measured by determining the length between two successive heartbeat peaks from an ECG reading. Conventionally, HRV has been accepted as a term to describe variations of both instantaneous heart rate and RR intervals [12].

Obtaining HRV from ECG readings requires clinical settings and specialized technical knowledge for data interpretation. Thanks to the recent technological advances on the Internet of medical things (IOMT) [17], it is possible to deploy a commercially available wearable or non-wearable IOMT devices to monitor and record heart rate measurements.

Based on ECG data analysis (or HRV features, various machine learning (ML) and deep learning (DL) algorithms have been developed in recent years for stress prediction [20], [21], [22], [23], [24], [25], [26], [27] (see more details in Sec. II). Among the publicly available datasets for stress detection, SWELL−KW developed in [13] and [14] one of the two most popular ones. However, none of the existing ML and DL studies based on the SWELL−KW dataset for multi-class stress classification have achieved ultra-high accuracy, especially for multi-class stress level classification [15], [16]. Therefore, there exists a research gap on developing novel ML models which are able to achieve ultra-high accurate prediction.

Motivated by various existing applied ML and DL based studies on HRV feature processing for stress level classifications, we have designed and developed a one-dimensional convolutional neural network (1D CNN) model for multi-class stress classification and demonstrate its superiority over the state-of-the-art models based on the SWELL-KW dataset in term of prediction accuracy. More specifically, we have performed studies on stress detection using both traditional machine learning algorithms and/or multi-layer perceptron (MLP) algorithms which are inspired from the fully connected neural network (FCNN) architecture. In our work, we have developed a 1D CNN model which is based on the convolution operation. CNN reduces number of training parameters as MLP takes vector as input and CNN takes tensor as input so that CNN can understand spatial relation.

While the accuracy achieved with full features is nearly 100%, we have also introduced a feature reduction algorithm based on *analysis of variance (ANOVA)* F-test and demonstrate that it is possible to achieve an accuracy score of 96.5% with less than half of the features that are available in the SWELL−KW dataset. Such a feature extraction reduces the computational load during the model training phase.

In a nutshell, the novelty and the main contributions of this study are summarized as follows:

• We have developed a novel 1D CNN model to detect multi-class stress status with outstanding performance, achieving 99.9% accuracy with a *Precision, F1-score*, and *Recall* score of 1.0 respectively and a *Matthews correlation coefficient (MCC)* score of 99.9%. We believe this is the first study that achieves such a high score of accuracy for multi-class stress classification.

• Furthermore, we reveal that not all 34 HRV features are necessary to accurately classify multi-class stress. We have performed feature optimization to select an optimized feature set to train a 1D CNN classifier, achieving a performance score that beats the existing classification models based on the SWELL-KW dataset.

• Our model with selected top-ranked HRV features does not require resource-intensive computation and it achieves also excellent accuracy without sacrificing critical information.

The remainder of the paper is organized as follows. After summarizing related work and pointing out the distinction between our work and the existing work in Sec. II, we introduce briefly the framework for stress status classification, dataset, and data preprocessing in Sec. III. Then the developed CNN model is presented in Sec. IV. Afterwards, Sec. V defines the performance metrics to evaluate the proposed classifier and Sec. VI presents the numerical results. Further discussions are provided in Sec. VII. Finally, the paper is concluded in Sec. VIII