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MULTI CLASS STRESS DETECTION THROUGH HEART RATE VARIABILITY USING LOGISTIC REGRESSION ALGORITHM

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Abstract: This paper discuss stress as a natural human response to pressure, highlighting the risks associated with chronic stress on mental and physiological health. It also introduces the use of heart rate variability (HRV) as a measure of stress and describes a study investigating the role of HRV features in detecting stress using machine learning techniques, particularly a Long Short Term Memory(LSTM), SVM, CNN and Decision Tree Algorithms. The study claims to achieve high accuracy in multi-class stress detection (no stress, interruption stress, and time pressure stress) based on HRV features, outperforming existing methods in the literature. Additionally, it demonstrates the effectiveness of essential HRV features for stress detection using an analysis of variance technique.

1. INTRODUCTION

Stress is necessary to preserve homeostasis when unpleasant stimuli lead to physical or mental imbalances. Chronic stress causes an overactive sympathetic nervous system, which can result in abnormalities of the body, mind, and behavior [1]. Subjective approaches are frequently used to measure stress levels in order to extract perceptions of stress. Assessing stress levels using gathered heart rate viability (HRV) data can assist in eliminating stress by tracking its impact on the autonomic nervous system (ANS) [2]. Anxiety disorder sufferers typically have a persistently lower resting heart rate than healthy individuals. HRV rises with relaxation and falls with stress, as [2] and [3] have shown. In fact, a slowing heart beats with a greater HRV, and vice versa. Consequently, there is typically an inverse relationship between heart rate and HRV [2], [3]. HRV changes throughout time in response to activity levels and the degree of stress associated with one's job.

Additionally, stress is typically linked to a negative perception of an individual and is thought to be a subjective human emotion that may have an impact on one's physical and emotional health. It is defined as a biological and psychological response to environmental stimuli and biological or chemical agents that cause stress in an organism [5], as well as internal or external stressors [4]. Stress affects the ANS on a molecular level [6], which controls the cardiovascular system using both sympathetic and parasympathetic components. The sympathetic nervous system in humans [7] functions similarly to the gas pedal in an automobile. It triggers the fight-or-flight reaction, which gives the body more energy to react to harmful stimuli. On the other hand, the parasympathetic nervous system acts as the body's brake. When a threat has passed, it relaxes the body, which promotes slumber and digestion. Physiological measures including electrocardiogram (ECG), electromyogram (EMG), galvanic skin response (GSR), heart rate, blood pressure, breath frequency, and respiration rate can be used to measure mental stress because the ANS controls an individual's level of mental stress [8]. HRV is often extracted from ECG signals [9]. HRV is assessed by taking the difference in time between two successive heartbeat peaks from an ECG signal. It is defined as the variance across periods between consecutive regular RR intervals, 1. Traditionally, fluctuations in both RR intervals and instantaneous heart rate have been referred to as HRVs [12]. Clinical circumstances and specialist technological skills for data interpretation are necessary in order to extract HRV from ECG measurements. Heart rate readings can now be monitored and recorded using commercially accessible wearable or non-wearable Internet of medical things (IOMT) devices, thanks to recent technological advancements in this field [17].

Many machine learning (ML) and deep learning (DL) algorithms have been created in recent years for stress prediction based on the analysis of ECG data (or HRV features) [20], [21], [22], [23], [24], [25], [26], [27] (see more details in Sec. II). SWELL−KW is one of the two most widely used publically available datasets for stress detection, having been developed in [13] and [14]. Nevertheless, no ML or DL study has yet attained ultra-high accuracy for multi-class stress classification using the SWELL−KW dataset, particularly when it comes to multi-class stress level classification [15], [16]. Consequently, there is a research void in the area of creating innovative machine learning models that can reach incredibly high prediction accuracy. We have designed and developed a one-dimensional convolution neural network (1D CNN) model for multi-class stress classification, and we show its superiority over the state-of-the-art models based on the SWELL-KW dataset in terms of prediction accuracy. This model is motivated by various existing applied ML and DL based studies on HRV feature processing for stress level classifications. More precisely, we have conducted research on stress detection with multi-layer perceptron (MLP) methods, which draw inspiration from the fully connected neural network (FCNN) architecture, as well as conventional machine learning algorithms. We have created a 1D CNN model in our work that is predicated on the convolution technique. Because MLP accepts vectors as input and CNN accepts tensors in order to comprehend spatial relationships, CNN minimizes the number of training parameters. We have also introduced a feature reduction algorithm based on analysis of variance (ANOVA) F-test, and while the accuracy achieved with full features is nearly 100%, we show that it is possible to achieve an accuracy score of 96.5% with less than half of the features available in the SWELL−KW dataset. During the model training phase, this kind of feature extraction lessens the computational strain. The primary contributions and innovation of this work can be summed up as follows:

With exceptional performance, we have created a novel 1D CNN model that can detect multi-class stress state with 99.9% accuracy, a Precision, F1-score, and Recall score of 1.0, respectively, and a 99.9% Matthews correlation coefficient (MCC) score. We think this is the first study to obtain such a high accuracy score for classifying stress into many classes.

Moreover, we disclose that the precise classification of multi-class stress does not require the use of all 34 HRV variables. Our model with selected top-ranked HRV features achieves excellent accuracy without sacrificing critical information, and it does so without requiring resource-intensive computation, outperforming existing classification models based on the SWELL-KW dataset. We have performed feature optimization to select an optimized feature set to train a 1D CNN classifier, and we have achieved a performance score that beats them. This is how the rest of the paper is structured. We briefly explain the framework for stress state categorization, dataset, and data preprocessing in Sec. III after summarizing previous work and highlighting the differences between our work and the current work in Sec. II. In Section IV, the created CNN model is then given. The performance measures to assess the suggested classifier are then defined in Sec. V, and the numerical results are shown in Sec. VI. Section VII provides more discussion. In Sec. VIII, the paper is finally ended.

2. LITERATURE SURVEY

1) A Deep Learning-Based Platform for Minimally Invasive Multisensory Device Stress Detection in Workers

Summary: When it comes to assessing the stress levels of employees who work in increasingly complex work environments, Industry 4.0's requirement for significant human-machine interaction poses new difficulties. Without a question, stress at work has a big impact on people's overall stress levels, which can have negative effects on people's quality of life and long-term health problems. Psychological questionnaires have been used for stress assessment for a long time, but they are not able to track stress levels over time or in real time, which makes it difficult to pinpoint the causes and stressful components of the job. An efficient way around this restriction is to analyze physiological signals, which are continuously measurable using ambient or wearable sensors. Prior research in this area has mostly concentrated on stress assessment using invasive wearable systems that are prone to noise and performance-degrading aberrations. A wearable and ambient hardware-software platform that can detect human stress without interfering with regular work tasks is described in one of our recently published publications. It is also slightly prone to artifacts caused by motions. The system's low accuracy in identifying various stress levels is one of its limitations. For this reason, the study focused on enhancing the platform's software performance through the application of deep learning techniques. Three neural networks were used for this purpose; the 1D-convolutional neural network performed the best, identifying two degrees of stress with an accuracy of 95.38%, which is a significant improvement over the results reported earlier.

2) Stress Detection via Multimodal Machine Learning

Summary: The modern information age has made people more knowledge-focused in their lifestyles, which has resulted in sedentary jobs. Numerous medical conditions and mental illnesses have resulted from this. One of the most important yet often overlooked components of the fast-paced environment we live in today is mental wellbeing. A person's daily activities and performance might be hindered by mental health problems, which can also have a direct or indirect impact on other areas of human physiology. Finding a person's stress level and stress pattern, which could result in major mental illnesses, can be difficult and entail a number of variables. Accurate identification can be accomplished by combining these several modalities that result from an individual's behavioral patterns, which can be caused by a variety of causes. For this objective, certain methodologies are recognized in the literature; nonetheless, for such multimodal fusion problems, very few machine learning-based solutions are provided. This paper proposes a multimodal AI-based system to track an individual's stress levels and work habits. We provide a technique that combines heterogeneous raw sensor data streams (e.g., posture, heart rate, computer interaction, and facial expressions) to effectively identify stress brought on by workload. This information can be safely kept and examined to identify and comprehend individual behavioral patterns that cause weariness and mental strain. This work makes two contributions: first, it suggests a multimodal AI-based fusion technique to detect stress and its degree; second, it identifies a pattern of stress over time. On the test set, we were able to detect and classify stress with 96.09% accuracy. Furthermore, by employing these modalities, we were able to lower the stress scale prediction model loss to 0.036. The general public, in particular those with sedentary professions, may find it useful to monitor and diagnose stress levels, particularly in light of the COVID-19 pandemic.

3) Wearable devices as feasible physiological markers for stress detection through HRV features

Summary: One of the main factors contributing to car crashes, which in turn cause a significant number of fatalities and injuries annually, has been identified as stress. Physiological measures can be used to quantify stress, and in this study, the aspects that are often derived by wearable technology will be the main focus. As a result, heart rate variability will be the primary focus of the investigation (HRV). The purpose of this work is to examine the function of features obtained from HRV as stress markers. This is accomplished by trying various machine learning techniques, such as K-Nearest Neighbor, and creating a strong predictive model that can precisely categorize stress levels from ECG-derived HRV data, collected from drivers of motor vehicles. In addition, a machine learning model that classifies stress using HRV features generated from heart rate measurements received from wearable devices will be developed using the models that yielded the highest prediction power as a guide. We show that HRV characteristics are useful indicators for stress detection because the best machine learning model that was created had an 80% recall rate. Additionally, this study shows that HRV measures were significant for stress detection, including the Root mean square differences of successive NN intervals (RMSSD), Standard deviation of the average NN intervals (SDNN), and Average of normal-to-normal (AVNN) intervals (AVNN). The suggested approach can also be applied to any application where it's critical to track stress levels in a non-intrusive way, such as mental health, anxiety management, or physical rehabilitation.

4) In an office setting, thermal comfort and stress recognition

Summary: Among the challenges that office workers deal with on a daily basis are work-related stress and discomfort from the heat. Office workers may feel stressed out at work since their jobs require a lot of mental effort and are lengthy. In addition, the methods used to provide thermal comfort today are energy-intensive and inefficient. In earlier research, we suggested a technique for providing effective thermal comfort based on an individual's heart rate variability (HRV). However, because a person's HRV can also be impacted by work stress, this study looks into the feasibility of differentiating between changes in HRV that result from work stress and changes that are caused by thermal discomfort. We tested this on participants performing the Advanced Trail Making Test (ATMT) and found that stress changes heart rate variability (HRV) and that there is a 100% accuracy difference between stressed and non-stressed respondents. Using the multimodal SWELL knowledge work (SWELL-KW) stress dataset, we verified our technique and obtained comparable results (average recall of 99.75% and accuracy of 99.25%). Additional research indicates that although occupational stress and thermal comfort have an impact on HRV, their effects may not overlap and that they can be differentiated almost exactly from one another. These findings suggest that an autonomous, non-intrusive system that provides thermal comfort and forecasts work stress based on individuals' heart rate variability may be feasible to create.

3. EXISTING SYSTEM

A thorough analysis of the HRV data quality pertaining to data obtained from ECG and IoMT devices, including the Motorola Droid, Elite HRV, H7, and Polar, can be found in [18]. When comparing the HRV values derived from commercially available IoMT devices with measurements based on an ECG instrument, 23 studies found small inaccuracies. Such a small-scale inaccuracy in HRV measurements is appropriate in practice because obtaining HRVs using portable IoMT devices is more convenient, economical, and doesn't require any laboratory or clinical equipment [18], [19]. However, there have been numerous recent studies on the use of ML and DL algorithms to categorize stress using ECG data analysis [20], [21], [22], and [23]. Prioritizing binary (stress versus nonstress) and multi-class stress classifications has been the main focus of existing algorithms. For example, the authors in [4] distinguished between physiological states that are normal and stressed based on HRV data. The authors examined many machine learning (ML) techniques, including naive Bayes, random forest, knearest neighbor (KNN), support vector machine (SVM), MLP, and gradient boosting, for the purpose of identifying stress. Their highest recall rating was eighty percent. Using the time-domain and frequency-domain properties of HRV, the authors of a comparable comparison study [27] shown that SVM with radial basis function (RBF) produced an accuracy score of 83.33% and 66.66%, respectively. Moreover, the optimal temporal and frequency domain components in HRV have been chosen using dimension reduction approaches [24]. In [25], the authors used CNN to do binary classification, or stressed versus not stressed, and they were able to acquire an accuracy score of 98.4%.

In a different study called StressClick [26], mouse-click events—that is, the gaze-click pattern obtained from a commercial computer webcam and mouse—were used to identify subjects as stressed or not stressed using a random forest method. In [14], SVM based on the SWELL−KW dataset was used to accomplish tasks for multi-class stress classification (e.g., no stress, interruption stress, and time pressure stress). They were 90% accurate at their best. Additionally, for multi-class (amusement versus baseline versus stress) and binary (stress versus non-stress) classifications, another publicly accessible dataset, WESAD, was employed in [27]. ML algorithms were able to reach up to 81.65% accuracy for three-class categorization in their investigations. The three-class stress classification task was completed with an accuracy level of 84.32% by the authors, who also evaluated the

effectiveness of deep learning algorithms. In addition, it is noteworthy to mention that newer deep learning methods have emerged as effective tools for two-dimensional data categorization tasks, such as genetic deep learning convolutional neural networks (GDCNNs) [38], [39]. However, further alterations or adaptations are needed in order to apply GDCNN to 1D data, and this subject is outside the purview of this work.
A novel double-check mapping function called DCMF, which is utilized to offer early attack detection at the switch level, is never proposed by the system. This is one of its disadvantages.The following issues plague an existing system: Three steps: 1) replace missing values; 2) encode categorical data; and 3) scale features.

Furthermore, it is worth mentioning that novel deep learning techniques, such as genetic deep learning convolutional neural networks (GDCNNs) [38], [39], have appeared as a powerful tool for two-dimensional data classification tasks. To apply GDCNN to 1D data, however, comprehensive modifications or adaptations are required and such a topic is beyond the scope of this paper.

DISADVANTAGES
The system never proposes a new double-check mapping function called DCMF, which is used to provide early attack detection at the switch level.
An existing system has the following problems
1) missing values replacement
2) encoding categorical data and
3) feature scaling.

4. PROPOSED SYSTEM
With exceptional performance, we have created a novel 1D CNN model that can detect multi-class stress state with 99.9% accuracy, a Precision, F1-score, and Recall score of 1.0, respectively, and a 99.9% Matthews correlation coefficient (MCC) score. We think this is the first study to obtain such a high accuracy score for classifying stress into many classes. Moreover, we disclose that the precise classification of multi-class stress does not require the use of all 34 HRV variables. In order to train a 1D CNN classifier, we undertake feature optimization. By doing so, we were able to choose an improved feature set and outperform the competition in terms of performance, using the SWELL-KW dataset as our base. Our model, which uses a subset of the highest-ranked HRV features, provides exceptional accuracy without requiring computationally demanding processes.

ADVANTAGES
- Medical professionals label important features and annotations (such as no stress, interruption situation, and time pressure) to train, test, and validate the developed DL-based multi-class classifier.
- To make the data fit the feature ranking algorithm, preprocessing is done. For feature ranking and selection in this work, ANOVA F-tests and forward sequential feature selection are utilized, respectively.
- A DL-based multi-class classifier that has been constructed is subjected to training, testing, and validation using important features and annotations labeled by medical specialists, such as no stress, interruption condition, and time constraint.

SYSTEM ARCHITECTURE

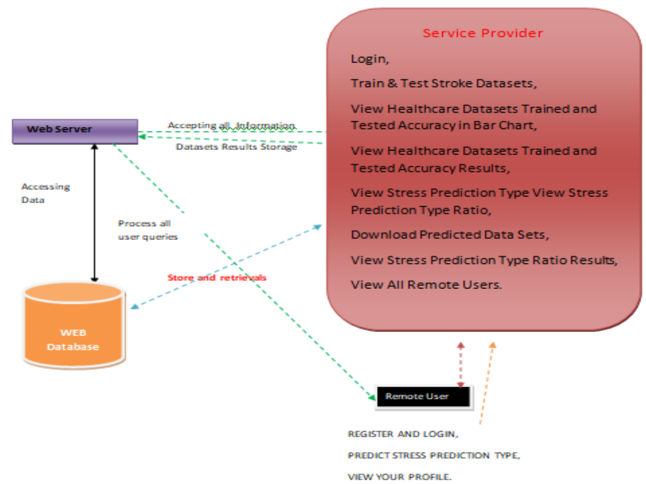

Fig 1: System Architecture

5. ALGORITHMS

5.1 DECISION TREE CLASSIFIERS
Decision tree classifiers have proven effective in a wide range of applications. The ability to extract descriptive decision-making knowledge from the provided data is their key characteristic. Training sets can be used to create decision trees. The following is the process for creating such a generation based on the set of objects (S), each of which is a member of one of the classes C1, C2,..., Ck:
Step 1: The decision tree for S has a leaf labeled with this class if every item in S is a member of the same class, such as Ci.
Step 2: If not, let T represent a test with the possible results O1, O2,... On. The test divides S into subsets S1, S2,..., Sn where each object in Si has result Oi for T. This is because each object in S has a single outcome for T. T becomes the decision tree's root, and we create a subsidiary decision tree for each outcome Oi by applying the same process recursively to the set Si.

5.2 CLASSIFIER OF LOGISTIC REGRESSION
The relationship between a set of independent (explanatory) variables and a categorical dependent variable is examined using logistic regression analysis.

When the dependent variable simply has two values, such as 0 and 1, or Yes and No, the term logistic regression is employed. When the dependent variable, such as married, single, divorced, or widowed, has three or more distinct values, the term multinomial logistic regression is typically reserved for that situation. While the dependent variable's data type differs from multiple regression's, the procedure's practical application is comparable. When it comes to examining categorical response variables, discriminant analysis and logistic regression are rivals. Compared to discriminating analysis, many statisticians believe that logistic regression is more adaptable and suitable for predicting the majority of scenarios. This is so because, unlike discriminant analysis, logistic regression does not make the assumption that the independent variables are normally distributed. On both categorical and numeric independent variables, this program computes binary and multinomial logistic regression. Together with the regression equation, quality of fit, odds ratios, confidence intervals, probability, and deviance are also reported. Complete residual analysis is carried out, including with diagnostic residual reports and charts. It has the ability to search for the optimal regression model with the fewest independent variables using an independent variable subset selection search. It offers ROC curves and confidence intervals on expected values to assist in figuring out the ideal cutoff point for categorization. It does this by automatically categorizing rows that are not utilized in the study, allowing you to verify your results.

5.3 SVM

A discriminate machine learning approach is used in classification problems to create a discriminate function that can properly predict labels for newly acquired instances, based on an independent and identically distributed (iid) training dataset. A discriminating classification function takes a data point x and assigns it to one of the several classes that are part of the classification job, in contrast to generative machine learning techniques that need calculations of conditional probability distributions. Discriminate procedures are less effective than generative approaches, which are typically employed when prediction requires outlier identification. This is especially true for multidimensional feature spaces and situations where just posterior probabilities are required. Discriminate approaches also need fewer training data and processing resources. Finding the equation for a multidimensional surface that optimally divides the various classes in the feature space is the geometric equivalent of learning a classifier. Because SVM solves the convex optimization issue analytically, it is a discriminating approach that consistently yields the same optimum hyper plane parameter—in this case, in contrast to perceptions or genetic algorithms (GAs), which are both often employed in machine learning for categorization. The commencement and termination criteria have a significant influence on the solutions for perceptions. Training yields precisely specified SVM model parameters for a given training set for a certain kernel that converts the data from the input space to the feature space; in contrast, the perception and GA classifier models vary with each training set. Only minimizing mistake during training is the goal of GAs and perceptions, which translates into several hyper planes fulfilling this need.

5.4 RANDOM FOREST

Random forests, also known as random decision forests, are an ensemble learning technique that builds a large number of decision trees during the training phase for problems including regression, classification, and other applications. The class that the majority of the trees choose is the random forest's output for classification problems. The mean or average prediction made by each individual tree is returned for regression tasks. The tendency of decision trees to overfit to their training set is compensated for by random decision forests. Although they are less accurate than gradient enhanced trees, random forests still perform better than choice trees in most cases. Their performance, however, may be impacted by the peculiarities of the data. Tin Kam Ho[1] developed the first random decision forest algorithm in 1995 by utilizing the random subspace technique, which is a means of putting Eugene Kleinberg's "stochastic discrimination" approach to classification into practice. Leo Breiman and Adele Cutler created an expansion of the algorithm and filed for a trademark for "Random Forests" in 2006; as of 2019, Minitab, Inc. is the owner of this trademark.In order to create a set of decision trees with controlled variance, the extension combines Breiman's "bagging" concept with random feature selection, which was initially presented by Ho[1] and then separately by Amit and Geman[13]. Businesses commonly utilize random forests as "blackbox" models because they produce good predictions across a wide variety of data with minimal processing power.

6. RESULTS

6.1 Output Screens

Fig 6.1 Comparison of Accuracy graph in bar chart

In above screen is the Comparison of Accuracy graph in bar chart for different ml algorithms

Fig 6.2 Comparison of Accuracy graph in line chart

In above screen is the Comparison of Accuracy graph in line chart for different ml algorithms

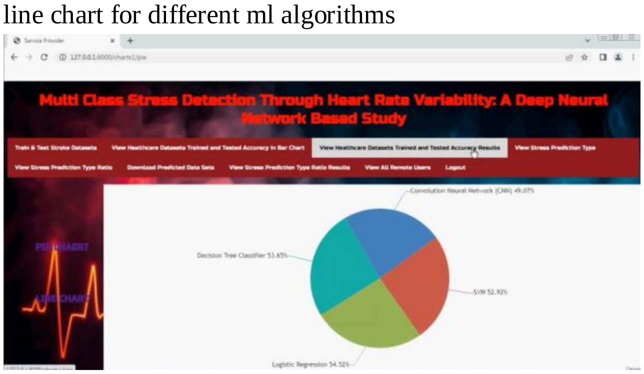

Fig 6.3 Comparison of Accuracy graph in pie chart

In above screen is the Comparison of Accuracy graph in pie chart for different ml algorithms

Fig 6.4 Prediction Result

In above screen shows the prediction result for the stress detection.

7. CONCLUSION

Using HRV signals, we have created a novel 1D CNN model for stress level categorization in this work. The proposed model has been verified using the publically available SWELL−KW dataset. We also used an ANOVA feature selection method for dimension reduction in our model. We show, by comprehensive training and validation, that our model outperforms the state-of-the-art models when all features are used in terms of key performance measures, such as Accuracy, Precision, Recall, F1-score, and MCC. Additionally, our method with ANOVA feature reduction performs exceptionally well. In order to make real-time stress detection a reality, we intend to continue researching the viability of refining the model to fit it into edge devices in future work.

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