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Classifying Multiple Stress Levels from Heart Rate Variability via Deep Neural Networks

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Abstract - Heart rate variability (HRV) is an arguably valuable parameter, acting as a stress biomarker in this review that dwells upon the finer points of chronic stress and its likely physiological effects. Many types of chronic stress deteriorate mental health. Relevant conditions include depression, anxiety, and insomnia, which may arise from stress. To measure stress formally with HRV, which is variability in time between heartbeats, a lot of work needs to advance.

The review experimented with many recent machine learning techniques towards the realization of a multi-class stress recognition framework: 1D CNN, 3D CNN, LSTM, GRU, and hybrid models such as LSTM + GRU + RNN. These methods intend to augment efficacy and applications in the detection of stress through studying HRV features, with probable stress-related markers. The idea underlying physiological responses to stress must be borne in mind for heart rate and HRV, in particular, regarding changes in RR intervals. Hopefully, in the future, the output of this work may benefit the interpretation of stress recognition and provide avenues for potentially better interventions for mental health issues stemming from anxiety.

***"Keywords: -** Heart rate variability (HRV), stress biomarkers, gloom, nervousness, sleeping disorder One-Layered Convolutional Neural Network, Three-Layered Convolutional Brain Organization, Long Momentary Memory, Gated Intermittent Unit, RR spans."*

I. INTRODUCTION

This study scrutinizes the complex relationship of chronic stress and its probable effects on physical health, emphasizing the role of "heart rate variability (HRV)" as a stress biomarker. Stress is the very internal response of an organism to an adverse situation; however, when stress is no longer recent or acute in nature, it could possibly ravage one's mental health; resulting in psychiatric disorders such as depressive illness, anxiety, or sleep disturbances. This research intends to develop a multi-class stress recognition model employing advanced machine-learning methods for the conceptualization of stress where accurate detection of stress becomes of primary centrality.

This work concentrates on the improvements on the effectiveness of stress-detection methods by looking at the HRV traits as potential stress markers. To increase the efficiency of stress-detection models, a variety of advanced scientific approaches were employed: 1-dimensional CNN, 3-dimensional CNN, LSTM, GRU, and many combinations of LSTM + GRU + RNN. Further, we intend to shed more light on understanding the convoluted nature of heart rate and HRV, focusing mainly on measuring changes in RR-intervals. The main goal would provide HRV Stress Recognition, whereas learning specifically how the body reacts to stressors would be an additional aim. Most likely, these expected results will improve the understanding of stress recognition and, thereby, help in the further development of efficient techniques in relieving the mental-health issues caused by ongoing stressors. Hence, it is expected that this project shall lay the platform for newly evolved methods of knowing stress and consequently providing remedies for stress-related mental health afflictions.

II. LITERATURE SURVEY

The above research delineates a study on the relationship between stress and heart rate variability (HRV), studied through physiological techniques, mobile applications, and machine learning techniques. Insights from these analyses constitute stress detection, its physiological manifestations, and possible application areas.

In-depth analysis of stress and pulse fluctuation usually called heart rate variability analysis is given by Kim et al. [1]. The paper offers a good review of existing literature and clearly defines the complicated relationship in stress and HRV. Going further, Muhajir et al. [2] design and develop an Android application that measures stress levels by HRV methods, bringing forward practical applications that could use mobile technologies in stress monitoring.

As for other researchers, they study the relation of stress and the variability in the heart rate related to mental tasks. Held et al. [3] published a paper dealing with heart rate fluctuations in anxious subjects subjected to mentally demanding tests, thus shedding some light on the physiological responses to stress both in and outside populations. Dalmeida and Masala [4] point at the possibility of using wearable sensors to acquire HRV estimates as physiological parameters for stress recognition, thus opening doors for continuous monitoring.

The dataset provided by Miranda-Correa et al. [5] stands as a major research resource in respect of influence, personality, and mood. Deep states are understood more in correlation with physiological signals (such as heart rate variability) on behalf of this dataset. Won and Kim [6] studied the causality of depression with stress, the autonomic nervous system, and the immune kynurenine pathway so that it can broadly view the long-term consequences of stress upon mental health.

Thus, in researches of Olshansky et al. [7], Goel et al. [8] and Hegde et al. [9], there are aspects pertaining to analysis of cardiovascular system, extraction of ECG features for stress detection, and processing ECG signals with HRV analysis, respectively. These works further contribute to the understanding of physiological parameters and their signal processing techniques in stress research.

Malik et al. [12] propose a general standard for HRV measurement concerning its definition, physiological basis, and clinical relevance. This standardization forms the basis for consistency and reproducibility of the HRV studies. The explored literature concerned the potential of machine learning for stress detection. Albaladejo-González et al. [15] discuss different machine-learning models for pressure detection based

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on the subject heart rate and emphasize model organization. Walambe et al. [16] and Ibaida et al. [17] study protection-aware stress models and multimodal machine learning, respectively-agents of progression upon stress identification methods.

Dobbs et al. [18] discusses at great length the validity of obtaining heart rate variability from the mobile devices, stressing impartially the importance that utmost reliability in wearable technologies has to be maintained for accurate stress assessment. Chen et al. [19] state that the combined method of wearable and adaptable sensors for stress evaluation is the newly found way for acquiring their physiological data.

Studies of Rahman et al. [20], Jambukia et al. [21], and Padha et al. [23] talk about the responsibility of machine learning in the detection of mental health disorders and lay emphasis on the versatility of such techniques to varying areas. Various other works, in the meantime, of [24], Sarkar and Etemad [25], and Huang et al. [26] show examples of machine learning being used toward stress detection through physiological indicators and expressions.

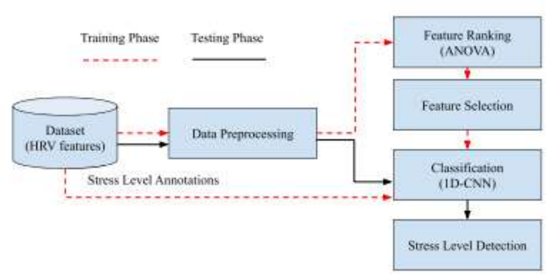
The reviewed literature emphasizes a multidisciplinary methodology in the design of stress detection, interweaving physiological signals, mobile applications, and machine-learning techniques. The coupling of wearable technology and complex analytics results in the nurturing of research which yields innovations in stress monitoring with a vast implication for real-world applications.

III. METHODOLOGY

Modules:

- Import Kinda libraries which are dependent on the dataset and perception.
- Import the HVR dataset for exploratory data analysis.
- A totally illegal attribute, displaying data, and performing PCA for feature extraction.
- Normalization done by scaling for better performance of the model.
- Data splitting: This module splits the data into training and testing subsets.
- Model building: Generating models-"1D CNN, 3D CNN, LSTM, GRU, LSTM+GRU+RNN."
- User Registration and Authentication: This module deals with transferring user data and logins.
- User Information: This is the inputs for predictive analysis.
- Prediction: Final projection shown.

A) System Architecture



"Fig 1: System Architecture"

Proposed work

The above system uses advanced classification techniques, such as 1-D CNN, 3-D CNN, LSTM, GRU, and several combinations such as LSTM + GRU + RNN, to build a general tool for multi-class pressure recognition. The method focuses on using heart rate variability (HRV) as a biomarker for stress, by attempting to discriminate stress levels via monitoring variations in RR intervals. This work attempts at improving the effectiveness and applicability of stress-classification approaches through the study of changes in HRV parameters. The very purpose is to account for real-life stress effects and promote a better diagnosis and treatment of mental disorders that surface through chronic stress.

B) Dataset Collection

The dataset selected for the designed stress detection system has been created with the goal of affronting those biological responses to stress, with heart rate variability (HRV) being the primary biomarker. Therefore, this dataset contains a heterogeneous group of subjects drawn from diverse demographics to provide a representative testing base for successful model training and validation.

Demographic Information:

Age: It covers all age groups since responses to stress may vary with age.

Gender: Both males and females are included to allow studies on gender differences in stress detection models.

Ethnicity: The dataset includes individuals belonging to multiple ethnic groups to check for any inter-ethnic variations in stress responses.

C) Pre-processing

Importing all the relevant Python libraries would include Pandas, NumPy, Matplotlib, and Seaborn. Once the imports are done, the next step entails loading the HRV dataset with Pandas, usually via pd.read_csv(). For conducting Exploratory Data Analysis (EDA), checking for null values by means of df.isnull().sum() is essential for identifying missing values and treating them accordingly. This perception shall go a long way in helping to understand the dataset, while the Matplotlib and Seaborn packages may be able to provide the necessary plots, histograms, and heatmaps. Principal Component Analysis (PCA) can then be done by scrutiny feature extraction. This would aid in reducing the dimensions of a dataset and extracting only the prominent features at ease. Preprocessing involving Min-Max scaling or Standard Scaling through scikit-learn MinMaxScaler or StandardScaler classes can aid in the standardization by scaling, which is a general approach to enhance model efficiency. The complete data processing phase would include library importation, dataset loading, null value assessment, carrying out visualization for exploratory data analysis (EDA), feature extraction being conducted using principal component analysis (PCA), and finally data scaling for normalizations to maximize performance.

D) Training & Testing

There are some crucial jobs to do for regular processes on the prescient model. With the aid of the machine learning library that is usually termed scikit-learn, one sets training and testing by calling the "train_test_split," in essence ensuring that a portion of the data is used to train the model and the rest is set aside for evaluation. Model establishment thus involved the building of several architectures related to brain networks, including 1D CNN, 3D CNN,

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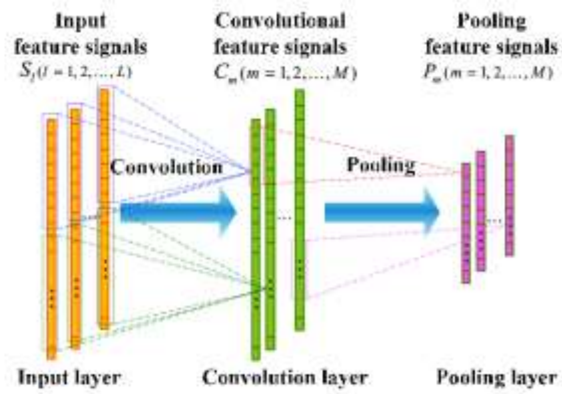
LSTM, GRU, and combinations thereof such as LSTM + GRU + RNN. For such purposes, the use of libraries such as TensorFlow or PyTorch exists. Each design suits particular data or activities more or less. Client registration and authentication should be developed using some web development frameworks, such as Django or Flask, for authentication security and management. An interface may be created to collect input data required for prediction. It can be created using web technologies like HTML and JavaScript or a GUI with Tkinter-like tools. The prediction module analyzes the last inputs from the user with a learned model to provide the final predicted output. This is achieved by combining the learned model with the application program and input from the user interface. Therefore, data partitioning, model development, user registration and authentication, user input collection, and forecasting should represent a whole structure able to incorporate each element of a powerful predictive application.

E) Algorithms.

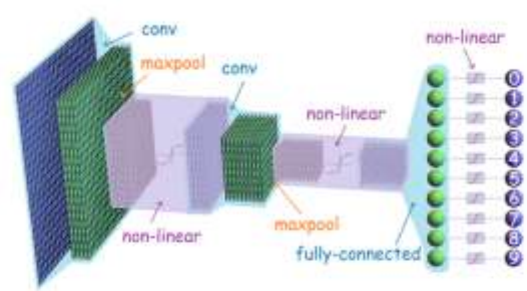
1D CNN (Convolutional Neural Network):

The 1D CNN was originally designed for analyzing one-dimensional data groups encompassing time series or sequential problems. It utilizes convolutional layers to identify local patterns and more abstract features in an arrangement of data. The design thus finds fitting applications in speech recognition, natural language processing, and signal processing. With the convolution axes, the model gains the ability to mask out unimportant aspects independently, highly suitable for situations where spatial correlation between observations in the data plays a major role.



3D CNN (Convolutional Neural Network):

In essence, a 3D CNN is the consideration of extending convolutional layers to three dimensions concerning the analysis of volumetric data, for example, video sequence or medical imaging. The framework simultaneously accounts for the geographic and the temporal element while capturing spatiotemporal features. Up to now, 3D CNNs have demonstrated the ability in video analysis, activity recognition figures, and medical image study wherein understanding both spatial arrangement and temporal evolution of the data is paramount.



LSTM (Long Short-Term Memory):

Characterized, in essence, as an LSTM, a recurrent neural-network architecture exists to overcome the

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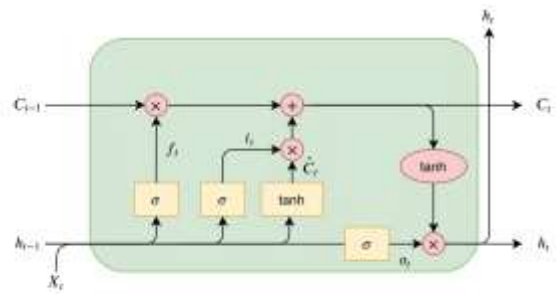
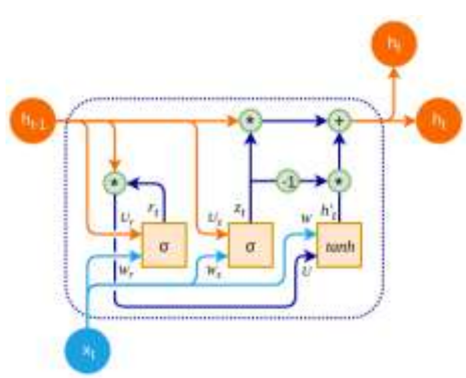
vanishing gradient problem, which had plagued the ordinary RNN. An LSTM leverages memory cells and gates to capture long-range dependencies in sequential data. Such networks are well-suited for various tasks of natural-language processing (NLP), automatic speech recognition (ASR), and time-series applications



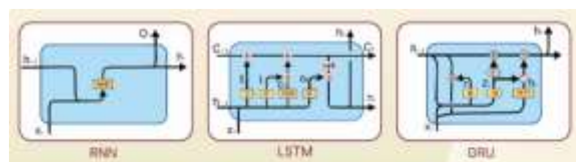
GRU (Gated Recurrent Unit):

Another approach of the dictionary category RNNs that have been developed to overcome the limitations of standard RNNs is GRU. Essentially, in GRUs, both memory cell and hidden state operations are combined, allowing for a simpler architecture with fewer parameters to train faster. These systems along with LSTMs are working more efficiently and have, inter alia, been used in machine translation, speech synthesis, and sentiment analysis.



LSTM + GRU + RNN:

LSTMs, GRUs, and standard RNNs, when merged into a hybrid model, have complementary strengths of the individual systems. The hybrid modeling attempts to predict the short-term and long-term dependence in diverse sequential data, drawing from both approaches and thus attaining the best of both worlds. This hybrid modeling enhanced by the LSTMs for long-term memory, GRUs for computational efficiency, and RNNs for simplicity, would benefit several applications, thereby negotiating memory, computation, and training speed.



IV. EXPERIMENTAL RESULTS

A) "Comparison Graphs → Accuracy, Precision, Recall, f1 score"

Accuracy: Any test with the highest discriminatory power that can distinguish between strong and weak models perfectly. A test of its accuracy should contain an insignificant number of false positives and false negatives among the fully focused-on studies. This can be mathematically stated as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

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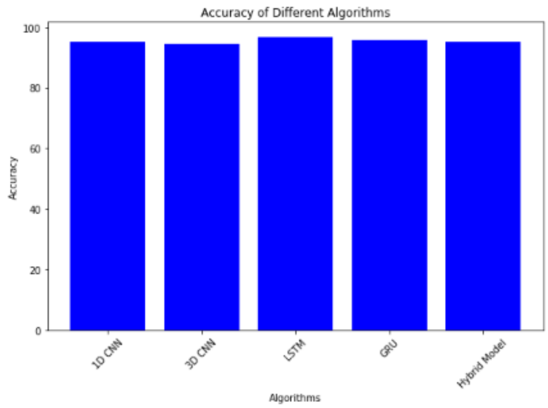
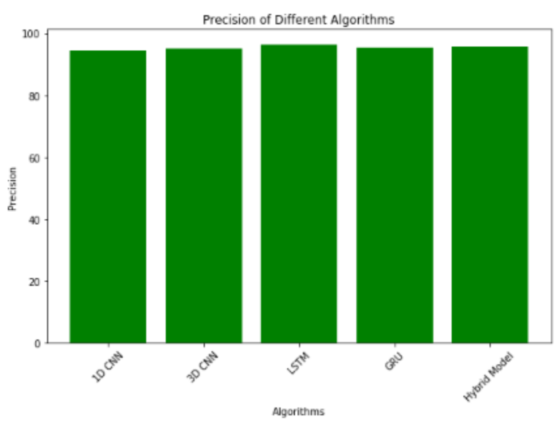


"Fig 2: Accuracy Graph"

Precision: Accuracy calculates the smallest fraction of events or tests accurately identified as positives and can be calculated using the following equation:

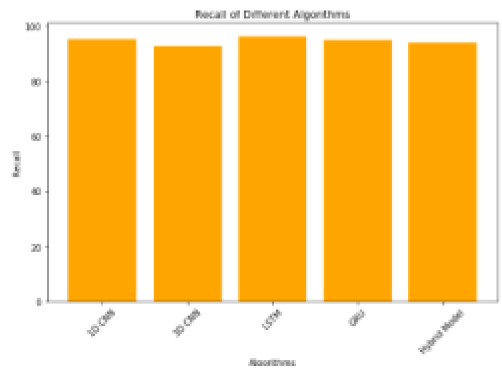
$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$



"Fig 3: Precision Score Graph"

Recall: Recall is an essential evaluation metric for lacking machine learning algorithms as it serves to determine whether all instances of a class have been captured by a model. It is the ratio of the model prediction for class occurrence in actuality to the total actual positives; hence it establishes key performance at capturing instances of a class actually realized by the system.

$$Recall = \frac{TP}{TP + FN}$$



"Fig 4: Recall Score Graph"

F1-Score: The F1 score is used to measure the precision and accuracy of machine learning models. It is a kind of harmonic mean between the model's precision and recall. The metric for accuracy is almost the frequency with which the model below study predicts reasonably for the whole dataset.

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

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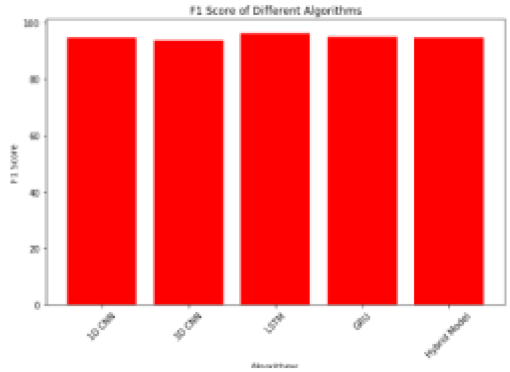
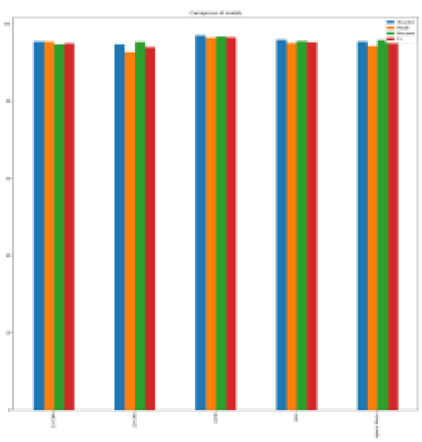


“Fig 5: F1 Score Graph”

B) Performance Evaluation table.



“Fig 6: Performance Evaluation Table”

C) Frontend

“Fig 7: Home page”

“Fig 8: User Signup page”

“Fig 9: User Sign in Page”

“Fig 10: User Sign in Page”

“Fig 11: Enter Data”

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“Fig 12: No Stress Detected”

V. CONCLUSION

The notion uses machine learning systems of one-dimensional CNN, 3D CNN, LSTM, GRU, and some hybrid types such as LSTM + GRU + RNN to develop the multi-class stress identification system from HRV signals. It thus sheds light on the multifaceted relationship between chronic stress and its physiological outcomes, stressing the urgency of correctly identifying stress in order to manage mental well-being adequately.

Indicating that anxiety arises in response to extreme situations, the negative influence of chronic stress has been considered on the mental health side of common syndromes such as Depression, Anxiety, and Sleep Disorders. The study thus explores the ability of changes in HRV to act as biomarkers of stress, with an aim to bring more precision and applicability to the measurement of reliability in recognizing stress.

Having a physiological understanding of stress learns the central aspect that there is a differential reaction of heart rate and heart rate variability, especially while analyzing the fluctuations of R-R intervals. The study proposes the use of several machine learning techniques in stress recognition with caution while opening exciting avenues toward furthering our understanding of stress and paving a way to the development of newer methods to managing stress-related mental health problems. The results, thus, are expected to make significant contributions to the paradigm of stress recognition and hence pave the way for developing better treatment options for stress-related mental health issues.

VI. FUTURE SCOPE

The future potential bounds of this examination are ongoing improvement and use of the pressure recognition model that was set up in its practicality. Further investigation would include coupling actual-time information streams for dynamic stress The future potential bounds of this examination would be the continuing development and use of the pressure recognition model as set up in its practicality. Further exploration would involve the coupling of real-time data streams for dynamic stress monitoring, the enhancement of model transparency, and modification of architecture for customized interventions in stress management. Collaborations with medical experts and technical engineers would help in embedding this perspective into wearable devices for widespread access. Furthermore, a cross-sectional understanding of the context applicability of this model across different demographic groups and sociocultural settings might increase its applicability. It might be worth investigating longitudinal studies for continuous updating and validation so as to maintain the model's relevance and reliability in evolving settings of mental health.

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