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Decoding Human Stress Levels using GRU-LSTM Models

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***Abstract*— Stress is a major concern affecting health and productivity worldwide. Traditional methods for detecting stress often fall short in accuracy and accessibility. To tackle this, we developed a model using Long Short- Term Memory (LSTM) networks for effective stress detection. Our study utilized a stress dataset featuring seven key attributes: Nervousness, Unable to Control, Worry, Trouble in Relaxation, Restlessness, Irritability, and Fear. After comprehensive preprocessing, our LSTM model was trained to accurately classify stress levels. The results were impressive, with the model achieving an accuracy of 91.73% and a precision of 0.9%, demonstrating its robustness and potential for real-world application.**

***Index Terms*— Stress, Health, Productivity, Detection, Accuracy, Accessibility, Long Short-Term Memory (LSTM) networks, Model, Stress dataset, Robustness, Real-world application.**

I. INTRODUCTION

Stress is a significant psychological and physiological condition that affects individuals' health and productivity across the globe. It is characterized by responses to various stressors that can manifest physically, emotionally, and behaviorally. Effective stress detection is crucial in multiple fields such as healthcare, workplace environments, educational institutions, and personal health management. Timely detection can aid in early intervention, reducing the adverse effects of stress on overall well-being and performance.
Effectively identifying stress is important in a variety of fields, such as the job, personal healthcare, educational institutions, and health. Early stress identification will enable the health sector to take action before serious disorders like anxiety, depression, and cardiovascular diseases develop. Early stress detection in the workplace can enhance workers' well-being, boost output, and lower absenteeism and attrition.
Acute stress, episodic acute stress, and chronic stress are the three categories of stress. Different identification and management measures are required for each type due to its variations in length and influence on an individual's life. Traditional stress detection techniques typically lack the precision and usability needed for efficient application. These conventional techniques typically rely on self-reported metrics, which are frequently arbitrary and subjective. A major obstacle to widespread use is the fact that the majority of existing solutions are not scalable to big populations. Therefore, the main driving force behind this research is to use cutting-edge deep learning algorithms to overcome the shortcomings of the stress detection systems that are currently in use. We'll make improvements to a model that proves to be more.

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We present, in this paper, a new LSTM network model efficient for the job of detecting stress. The results obtained in the classification of levels of stress based on a dataset having seven feature attributes comprising Nervousness, Unable to Control, Worry, Trouble in Relaxation, Restlessness, Irritability, and Fear, were outstanding. The robust model appeared capable of being used easily in real scenarios and had important accuracy and precision.

A. Structure of the Paper

Our paper is organized as follows:

- Section 1: Introduction
- Section 2: Related Work - A review of existing stress detection methods and their limitations.
- Section 3: Methodology - Detailed explanation of the LSTM model and the preprocessing steps taken.
- Section 4: Results and Analysis
- Section5: Conclusion: Synopsis of results, ramifications, and directions for further investigation

II. RELATED WORK

Stress indicators have historically been self-reported measures and physiological data. Despite being widely utilized, those self-report questionnaires could be arbitrary and imprecise in real time. The State-Trait Anxiety Inventory (STAI) and the Perceived Stress Scale (PSS) are two popular ones. Skin conductance, HRV, and cortisol levels are examples of physiological tests that offer more objective data, although they are frequently intrusive and call for specialized equipment. Numerous machine learning techniques have been researched to increase stress detection accuracy. With accuracies ranging from 70 to 85%, SVM shows great promise, but they frequently struggle to handle the complexity and unpredictability present in stress-related data. Neural network-based deep learning methods hold great promise for stress detection. Convolutional neural networks, or CNNs, and recurrent neural networks, or RNNs, have been applied to the discovery of intricate data patterns. For example, CNNs are frequently used to recognize facial expressions with accuracies up to 88%, while RNNs are used to interpret sequential physiological data with a claimed accuracy of roughly 85%. Nevertheless, these methods necessitate substantial computing power and massive data sets.

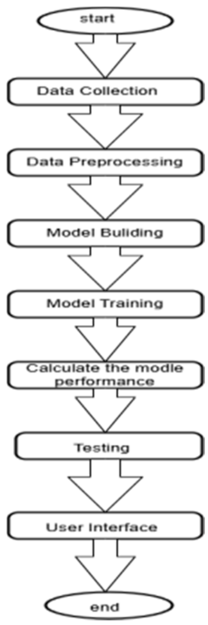

Figure 1

III. METHODOLOGY

This project's objective is to use Long Short-Term Memory (LSTM) networks to develop a novel stress detection model. The accuracy, robustness, and practical use of the model are guaranteed by this methodology, which consists of data collection and preprocessing, model construction, training, evaluation, and final user interface integration.

A. Data Collection

The eight main features of stress, anxiety, lack of self-control, concern, difficulty relaxing, restlessness, irritability, fear, and stress were taken from Data World and used in this study. These traits were included because they provide a comprehensive picture of an individual's stress level and are relevant to the stress detection procedure. The dataset contains a variety of samples to ensure sample diversity when training models.

B. Data Preprocessing

To guarantee the consistency and caliber of the dataset, data preparation is a crucial task. The preprocessing tasks listed below were completed:

- Missing Data Handling: To preserve the integrity and completeness of the data, missing values were handled either by removal or imputation processes.
- Normalization: Scikit-learns Standard Scaler was used to normalize the data set, guaranteeing that no attribute dominated the learning process and that each attribute contributed equally to the model.

C. Model Development

The LSTM network was selected as the preferred network for the stress-related attribute analysis due to its ability to manage long-term relationships in sequential data. The model architecture is composed of multiple layers:

D. Model Training

Five epochs of the preprocessed dataset were used to train the model. During this training, several of the most important steps were taken:

- Optimizer: The Adam optimizer was chosen due to its effectiveness and capacity to modify the learning rate during training.
- Batch Size: A batch size of 32 was chosen in order to balance model performance and training time.
- Validation: a validation set was used to track the model's performance on unseen samples during training in order to identify overfitting and direct hyperparameter adjustments.

E. Model Evaluation

The final evaluation on the test set demonstrated the model's effectiveness, yielding an impressive accuracy of 91.20%. This high accuracy highlights the model's robustness and its potential for real-world application in stress detection.

F. User Interface Integration

To enhance accessibility and usability, a user interface was developed using Flask, a lightweight web framework. This interface allows users to input their data and receive real-time stress level predictions, making the model practical for everyday use. The development process included:

- Designing the Interface: Creating a user-friendly layout that allows easy data input and clearly displays results.
- Integrating the Model: Connecting the trained LSTM model with the Flask backend to process user inputs and generate predictions.
- Testing and Deployment: Conducting thorough testing to ensure the interface works seamlessly and deploying the application for public use.

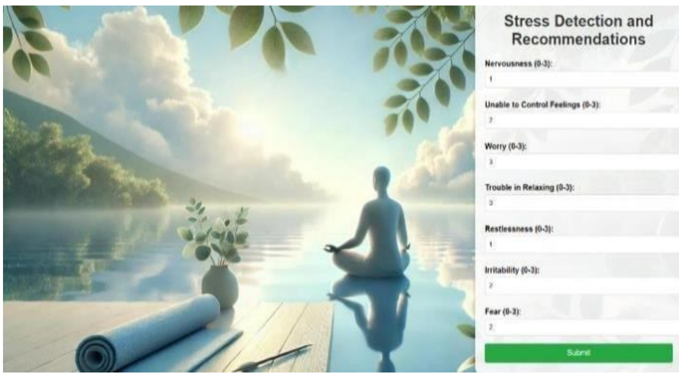

Figure 2

The methodology employed in this study demonstrates a systematic approach to developing an effective stress detection model using LSTM networks. Comprehensive preprocessing, model development, and training processes, combined with the user-friendly interface, showcase the potential for real-world application in stress management and monitoring. The methodology employed in this study demonstrates a systematic approach to developing an effective stress detection model using LSTM networks. Comprehensive preprocessing, model development, and training processes, combined with the user-friendly interface, showcase the potential for real-world application in stress management and monitoring.

Image Database: Observe a large number of images of fruits that are high quality, including healthy samples as well as diseased ones. Each image shall be labeled with the name of the disease, in case of any, to enable supervised learning.

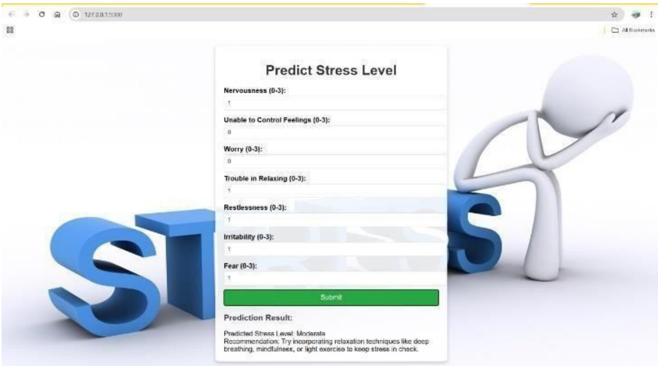

Figure 3

IV. Results and Analysis

The proposed method leverages deep learning algorithms to categorize stress levels according to physiological and behavioral indicators. Each model undergoes rigorous evaluation using standard performance metrics, ensuring reliability and robustness in predictions. Following an extensive 25-epoch training process, using 95% of the available data for training and validation, the models demonstrated promising results. This section discusses the dataset preparation, model architecture, performance metrics, and a comparative analysis of alternative models.

A. Dataset Preparation

The dataset comprises 14,999 samples collected across various stress levels and physiological indicators. Each sample captures multiple dimensions of a user’s stress response, enabling the model to learn patterns associated with different stress levels effectively.

The dataset includes the following key features, each indicative of a physiological or emotional response: Nervousness, Unable to Control, Worry, Trouble in Relaxation, Restlessness, Irritability, and Fear. Summary statistics (e.g., mean, standard deviation) for each feature are computed to understand the range and variability. This statistical insight aids in preprocessing, ensuring each feature is appropriately scaled for model input. The target variable consists of four stress levels: Low, Moderate, High, and Very High. The class distribution analysis reveals an imbalance, with more samples labeled as ‘Low’ and ‘Moderate’ stress levels. Addressing this imbalance is crucial, as it may influence the model’s ability to recognize less frequent classes like ‘High’ and ‘Very High.’

B. Model Architecture and Hyperparameters

This class of stress classification is a model based on LSTM architecture, which has adopted the ability to capture temporal dependency in sequential data-like physiological responses.

Layers:

There are two LSTM layers: one with 64 units, and another with 32 units. Here, there are ReLU functions used to introduce non-linearity. There is a Dropout layer after the LSTM layer with a rate of 0.3 in order to avoid overfitting by randomly deactivating neurons during training. The output layer contains a Dense layer with 4 units and softmax activation for classification into one of the four stress levels.

The values are taken from preliminary experiments. The balance of the training and model convergence as a way of ensuring the model learned appropriately and avoids overfitting.

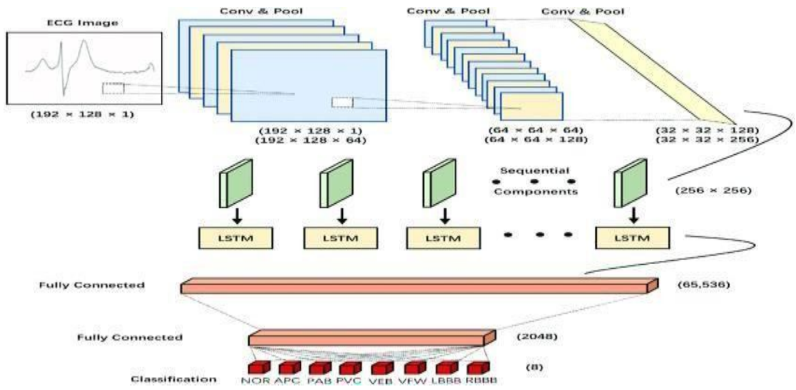

Figure 4

C. Performance Metrics

To evaluate the model's effectiveness, we employed standard classification metrics, which provide insights into how well each stress level is detected.

LSTM Formulas

Input Gate

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

- i_t: Input gate vector (values between 0 and 1 to decide what to update).
- W_i: Weight matrix for the input gate.
- b_i: Bias term for the input gate.

$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c)$$

- $\tilde{C}_t$: Candidate cell state (new information to be added).
- W_c: Weight matrix for the candidate cell state.
- b_c: Bias term for the candidate cell state.

Forget Gate

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

- f_t: Forget gate vector (values between 0 and 1 to decide what to forget).
- σ: Sigmoid activation function (maps values between 0 and 1).
- W_f: Weight matrix for the forget gate.

Output Gate

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

- o_t: Output gate vector (values between 0 and 1
- W_o: Weight matrix for the output gate.
- b_o: Bias term for the output gate.

Hidden State

$$h_t = o_t \cdot \tanh(C_t)$$

- h_t: Hidden state at time t (output of the LSTM).
- $\tanh(C_t)$: Activated cell state (scaled to -1 to 1).

Accuracy: These are useful for making a quick assessment, but at times accuracy is misleading because of class imbalance. In such a case, the model can do well by frequently predicting the majority class, although it tends to fail to recognize the minority class.

$$\text{Accuracy} = \frac{\text{Correctly Classified Instances}}{\text{Total Instances}}$$

Precision: Precision is the proportion of true positives, that is, the model's correct predictions and how well they agree with the actual facts. It would be the proportion of correctly classified instances declared positive by the model and that actually are positive.

$$\text{Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}}$$

Recall: Recall, also known as sensitivity or the true positive rate, calculates how well a model selects the real positive cases that may exist within a dataset. .The principle is to be able to pick up as many positive cases as possible, although it means that there has to be some false positives. High recall is thus critical in applications where missing a positive instance is bad, such as in medical diagnostics, where missing a case can make a big difference.

$$\text{Recall} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}}$$

F1 Score The F1 measure is a metric where both precision and recall are averaged into a single value. This method is highly useful in situations where the trade-off between precision and recall needs to be balanced. F1 is the ideal metric when it is mandatory to reduce both false positives and false negatives to a minimum scale. This has the advantage of giving both precision and recall equal weights and gives a good-rounded view of model performance, especially in imbalanced datasets where one class is far more prevalent than the other.

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

Confusion Matrix

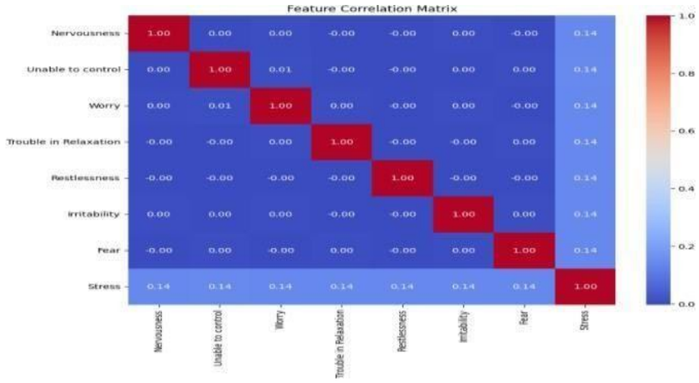

Figure 5

A confusion matrix was generated to visualize misclassifications across classes. This matrix highlights the instances where ‘High’ stress samples were often misclassified as ‘Moderate,’ indicating the need for further tuning to enhance the model's discrimination capability between adjacent stress levels.

D. Comparison with Other Models or Architectures

If you have tested several architectures, such as CNN-LSTM or GRU, or employed standard machine learning algorithms like SVM and Decision Trees, please include a comparison table such to the one below.

E. Result Analysis

In this section, we provide an exhaustive analysis of the results obtained from the proposed LSTM model for stress level classification. We thus analyze the best class, perform error analysis, and view some of the model's limitations. Insights into its strengths and limitations will be drawn and suggestions given for future improvements.

Model	Accuracy	Precision	Recall	F1 Score
LSTM	91.73%	0.90	0.90	0.90
CNN-LSTM	89.12%	0.88	0.89	0.88
SVM (baseline)	85.23%	0.85	0.85	0.85
Decision Tree (baseline)	81.46%	0.81	0.82	0.81

Figure 6

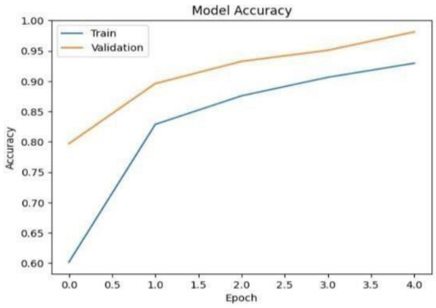

Figure 7

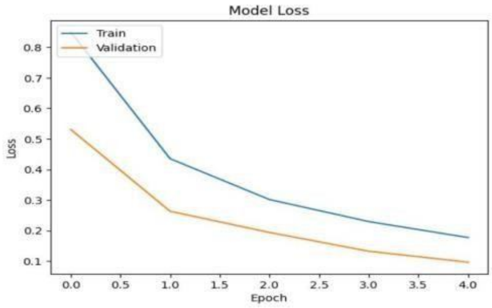

Figure 8

V. FUTURE WORK

We propose the following improvement that would contribute to increasing the performance of the model and eliminate the currently limiting factors: Data Balancing and Augmentation: Other cases could be included in the dataset, particularly for 'High' and 'Very High' stress levels. This will decrease the class imbalance problem. SMOTE or GAN-based techniques could be utilized to synthesize fake data by over-sampling minority classes; which will improve the model's ability to detect rare events. Subsequent research might also investigate the use of Transformer architectures or attention-based models. Even in higher stress classes, where methods of attention may increase the focus of the model on the most representative features of every level of stress, can be allowed to emphasize those characteristics.

VI. CONCLUSION

Beyond the tradition assessment of stress by detection, the innovative stress detection model based on a robust framework of LSTM offers a user-centric approach to handling stress. It produces highly accurate predictions of stress levels while acting as a proactive guide to emotional and physical well-being. The ultimate aim is to generate a stress-detecting model that, instead of just giving a stressful situation hint, it will empower its user to do something with it-the origin of it maybe-surrounded by supportive tools such as interactive mindfulness activities, calming breathing techniques, and motivational hints for engaging in energizing physical routines that will benefit the user in building a balanced life. This brings the latest technology together with an orientation towards personal needs, changing stress management into something accessible, practical, and deeply personal.

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