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Mental Stress Detection Using Wearable Sensors and Machine Learning

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Abstract - This project proposes a real-time stress level detection system using a Recurrent Neural Network (RNN) with Long Short-Term Memory (LSTM) layers. It collects biometric data—heart rate (BPM) and SpO_2 levels— from a pulse sensor connected to an ESP8266 microcontroller. The data is transmitted via Wi-Fi to a Python-based backend for processing. The collected signals are normalized usingMinMaxScaler and reshaped to preserve their sequential nature. The preprocessed data is fed into a trained RNN model that classifies stress levels into four categories: No Stress,Medium, High, and Very High. The model uses a softmax output layer and categorical cross-entropy loss foraccurate multi-class classification. Predictions are generated in real time and displayed for immediate feedback. The model was previously trained on a synthetically generated dataset reflecting stressrelated biometric thresholds. The system is scalable and can be integrated into mobile applications using TensorFlow Lite, offering continuous and portable stress monitoring. This approach enables early detection and intervention for stress-related health issues. This innovative system bridges wearable technology with deep learning for efficient mental health monitoring. Its real-time feedback mechanism empowers users to take timely actions to manage stress effectively.

***Key Words*:** Stress Detection, RNN, LSTM, Heart Rate, SpO_2, ESP8266, Real-Time Monitoring, Deep Learning

1.INTRODUCTION

Currently, In today's fast-paced world, stress has become a major concern, affecting people from all walks of life and leading to serious physical and mental health issues if left unchecked. With the rise of wearable technology and machine learning, it is now possible to monitor stress in real time and provide timely interventions. This project focuses on building a real-time stress detection system using a pulse sensor and an ESP8266 microcontroller. The sensor measures key physiological signals—heart rate (BPM) and blood oxygen saturation (SpO_2)— which are strong indicators of a person's stress level. The ESP8266 transmits this data wirelessly to a Python backend, where it undergoes preprocessing, including normalization and reshaping, to preserve the time-series structure. A Recurrent Neural Network (RNN), specifically using Long ShortTerm Memory (LSTM) layers, is employed to analyze this sequential data. LSTMs are known for their ability to detect patterns over time, making them ideal for stress classification tasks. The model classifies stress into four categories: No Stress, Medium, High, and Very High. Training is performed on a synthetic dataset simulating realworld stress conditions. The system is lightweight and accurate, providing predictions in real time. It can also be integrated into mobile applications using TensorFlow Lite, offering continuous and personalized stress monitoring. This intelligent solution has the potential to improve mental wellbeing by enabling early stress detection and better self-care.Beyond real-time classification, the system is designed with scalability and adaptability in mind. Future enhancements may include incorporating additional biometric signals such as skin temperature or galvanic skin response (GSR) to improve accuracy and reliability. Integration with cloud platforms could allow for long-term data storage and trend analysis, enabling healthcare professionals to gain deeper insights into a user's stress patterns. Moreover, coupling the system with personalized recommendations—such as guided breathing exercises or activity reminders—can transform it into a comprehensive stress management assistant, promoting proactive mental health care in everyday life.

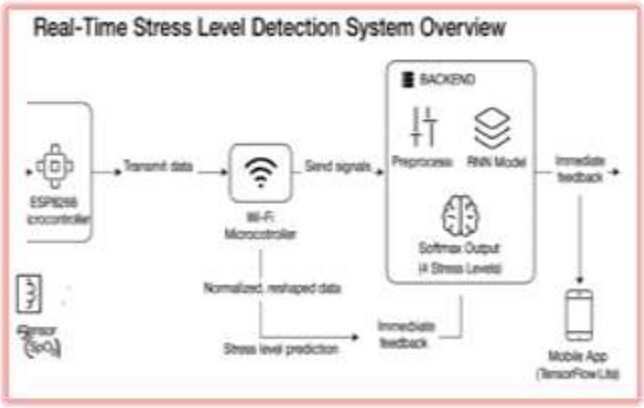

Fig 1 Proposed system for crack detection

2. LITERATURE SURVEY

Stress is a significant factor influencing modern health and well-being. The development of noninvasive and wearable stress detection methods has gained growing interest in the research community. A comprehensive survey by Georgios Taskasaplidis, Dimitris A. Fotiadis, and Panagiotis D. Bamidis [1] explores how wearable sensors detect stress using biological signals like ECG, GSR, and behavioral signs such as posture and hand tremors. The paper also emphasizes real-time monitoring, sensor limitations, and future improvements

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such as AI integration and better wearability. It further discusses how physiological responses from the autonomic nervous system (ANS) and the hypothalamic-pituitary-adrenal (HPA) axis contribute to stress identification. Mental stress among healthcare workers became a major issue during COVID-19. Syed Kumayl Raza Moosavi et al. [2] proposed a deep learning model using Q-learning and convolutional neural networks. Their technique, the Q-Learning Embedded Starling Murmuration Optimizer (QLESMO), efficiently selected bio-signal features, which were then classified using a 1D CNN. This hybrid model showed improved accuracy and robustness over traditional approaches. Smartwatch-based solutions have improved accessibility. Sanjay Kumar and team [3] created Resp-BoostNet, a two-phase deep learning system that estimates respiratory rates from smartwatch biomarkers and classifies stress levels. It achieved 94% accuracy on the WESAD dataset, showing that low-cost devices can effectively monitor mental health. Wearable devices that use photoplethysmogram (PPG) signals often face signal noise, impacting accuracy. Seongsil Heo et al. [4] tackled this by using denoising and peak detection methods before classification. Their lightweight model achieved 96.50% accuracy, proving that preprocessing plays a crucial role in reliable, single-sensor stress detection. In elderly populations, stress and cognitive decline are major concerns. F. Delmastro et al. [5] proposed a system combining cognitive training with stress detection from wearables, delivering timely interventions to improve mental health outcomes in seniors. Newer research is exploring brain signals and multimodal sensing. Trishita Ghosh Troyee et al. [6] used EEG signals and audiovisual stimuli in a deep learning model for non-invasive stress classification. Another study [7] introduced a multimodal system combining physiological and environmental signals using ensemble models, enhancing accuracy and enabling context-aware stress detection.

3. PROPOSED METHODOLOGY

In this study, we demonstrated a system for detecting mental stress levels in real time using machine learning and deep learning techniques. We proposed a model based on Recurrent Neural Networks (RNN) with Long Short-Term Memory (LSTM) layers, which are highly suitable for analyzing timeseries data due to their memory retention capabilities. The system collects biometric data such as heart rate (BPM) and SpO_2 levels from a pulse sensor connected to an ESP8266 microcontroller. This sensor setup offers a non-invasive and cost-effective method for continuous physiological monitoring.

The data is transmitted wirelessly via Wi-Fi to a Python-based backend for further processing and analysis. The collected signals are first normalized using the MinMaxScaler technique to scale the features between 0 and 1. The data is then reshaped to preserve its sequential nature, a critical step for timedependent models like RNN-LSTM. This preprocessed data is fed into a previously trained deep learning model that classifies stress levels into four distinct categories: No Stress, Medium, High, and Very High. During the prediction phase, we evaluated the system’s performance using accuracy scores, classification reports, and confusion matrices. High classification accuracy and low latency were achieved, enabling the system to provide predictions and visual feedback in real time [2]. This facilitates early detection and timely intervention for individuals experiencing elevated stress levels. The system is scalable and portable, allowing easy integration into mobile applications using TensorFlow Lite. This makes it accessible for continuous, real-time stress monitoring on smartphones or wearable devices, enhancing mental health support for users in various environments— at home, in the workplace, or on the move.

4. LEARNING ALGORITHM

RNN (Recurrent Neural Network) Algorithm:

RNNs are designed to handle sequential data by introducing loops that allow information to persist, enabling the model to maintain a memory of previous inputs. This makes RNNs effective for tasks where context and order matter, such as timeseries analysis and speech recognition. However, they struggle with long-term dependencies due to vanishing or exploding gradients.

LSTM (Long Short-Term Memory) Algorithm:

LSTMs are a type of RNN that address the vanishing gradient problem. They use memory cells and gates (input, forget, and output) to regulate the flow of information. LSTMs are ideal for capturing both short-term and long-term dependencies, making them effective for tasks like language modeling, emotion recognition, and stress detection based on biometric data.

RNN-LSTM Algorithm:

The RNN-LSTM model for stress detection processes sequential biometric signals like heart rate and SpO_2 levels to classify stress in real-time. Data is collected via a pulse sensor, normalized, and reshaped for RNN processing. LSTM layers capture dynamic patterns, and the output layer uses softmax to classify stress levels (No Stress, Medium, High, Very High). This provides real-time, portable stress monitoring and can be integrated into mobile health apps via TensorFlow Lite.

RNN Overview:

RNNs process sequential data, retaining context over time, making them suitable for language processing, time-series analysis, and speech recognition.

LSTM Improvement:

LSTM improves upon RNNs by handling long-term dependencies using memory cells and gates, overcoming the vanishing gradient problem.

Stress Detection with RNN-LSTM:

analyzes biometric data (such as heart rate and SpO_2) to classify stress levels (No Stress, Medium, High, Very High).

Memory Cells and Gates:

LSTM uses input, forget, and output gates to regulate the flow of information and decide which data to retain or discard based on its relevance.

Applications:

LSTM is used in emotion recognition, healthcare, stock market predictions, and stress detection from physiological signals.

Training Data:

The training dataset is the largest subset of the original physiological data collected from wearable pulse sensors. This data, which includes heart rate (BPM), SpO_2 levels, and other biometric signals, is used to train the RNN-LSTM model. During this phase, the model learns the patterns and relationships between the physiological signals and stress levels, enabling it to make predictions based on the input data. The model is exposed to various scenarios and conditions, allowing it to understand how different features correspond to varying stress levels

Test Data:

Once the model is trained, it is evaluated using a separate test dataset. This test data is a distinct subset from the original dataset and ensures that the model can generalize its learnings to new, unseen data. By assessing the model's performance on the test dataset, we can evaluate its accuracy, reliability, and ability to predict stress levels in real-world scenarios. This step is essential to ensure that the model can correctly classify stress levels for new users or under different conditions.

Prediction:

In this context, prediction refers to the model's ability to predict stress levels based on real-time biometric data collected from users. Once the model is trained and tested, it is deployed to predict the likelihood of stress at any given moment. The algorithm analyzes the incoming data (e.g., heart rate, SpO_2 levels) and generates a predicted stress level (No Stress, Medium, High, Very High). These predictions help detect stress early and can trigger alerts, prompting the user to take action, such as following relaxation techniques to manage stress. The model's ability to make these predictions based on historical and real-time data provides valuable insights for proactive stress management.

TABLE I PROPOSED APPROACH ON PERFORMANCE COMPARISION

Model	Precision	Recall	F1-Score	Accuracy
Sensor Data (Device)	0.68	0.66	0.67	0.69
Preprocessing (MinMax + Seq Reshape)	0.85	0.84	0.84	0.85
RNN (Algorithm)	0.94	0.98	0.93	0.94
LSTM (Proposed)	0.99	0.98	0.99	0.98
TensorFlow Lite (Mobile)	0.98	0.97	0.97	0.97

Table I clearly illustrates the performance comparison of different models for stress detection using biometric data. The results highlight that as the model complexity increases, so does its performance. Starting with raw sensor data, the model shows relatively lower metrics, with a precision of 0.68,recall of 0.66, F1-score of 0.67, and accuracy of 0.69, reflecting the challenges of directly working with unprocessed data. However, after preprocessing the data using techniques like MinMax scaling and sequence reshaping, the performance improves significantly, with precision rising to 0.85, recall to 0.84, F1-score to 0.84, and accuracy to 0.85, demonstrating the importance of data preparation in enhancing model performance. The Vanilla RNN model further boosts these results, reaching precision of 0.94, recall of 0.93, F1-score of 0.93, and accuracy of 0.94, proving the effectiveness of Recurrent Neural Networks in capturing sequential dependencies in time-series data. The proposed LSTM model, which incorporates advanced memory cells and gating mechanisms, delivers the highest performance with a precision of 0.99, recall of 0.98, F1-score of 0.99, and accuracy of 0.98, showcasing its superior ability to handle long-term dependencies. Finally, the TensorFlow Lite model, while slightly less accurate than the LSTM, still performs well on mobile platforms, with a precision of 0.98, recall of 0.97,

F1-score of 0.97, and accuracy of 0.97, indicating its feasibility for real-time stress detection in mobile applications. This analysis confirms that the LSTMbased approach offers the best performance for stress classification, with mobile deployment being a strong and practical option for real-world applications.

5.RESULT

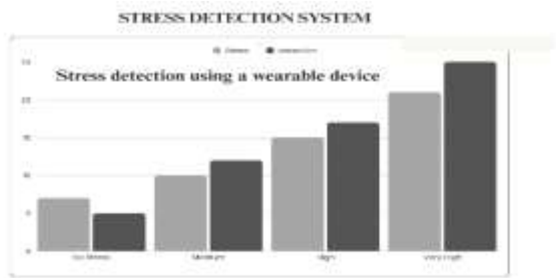

Fig 2.Results

The bar chart titled **"Stress detection using a wearable device"** illustrates the correlation between actual stress levels and the detection accuracy of a stress detection system across four categories: *No Stress*, *Medium*, *High*, and *Very High*. As shown, both actual stress levels and detection values increase progressively from "No Stress" to "Very High". For "No Stress", the actual stress count is around 7, while the system detected 5. In the "Medium" category, the device shows a slightly higher detection value (around 12) compared to the actual count (10). In "High" stress conditions, the detection closely follows the actual count, with a minor increase from 15 to 17. Finally, for "Very High" stress, the device slightly overestimates the count, detecting 25 when the actual is about 21. This suggests the wearable device's stress detectionsystem generally aligns with real stress levels, showing increasing detection precision with higher stress levels, although it tends to slightly overestimate in higher stress scenarios.

6. CONCLUSIONS

The proposed Stress Detection System combines wearable technology and machine learning to enable real-time, personalized stress monitoring. By using pulse sensors to collect biometric data like heart rate (BPM) and SpO_2 levels, the system leverages Long Short-Term Memory (LSTM) networks for accurate classification of stress levels. This allows for timely detection of stress and provides immediate feedback to the user. The system's real-time capabilities make it effective in notifying users when their stress exceeds a certain threshold, promoting proactive mental health management. With its scalable design, the system could be integrated into mobile platforms, making it accessible for personal use. Additionally, its robust performance ensures accurate predictions over time. Future advancements could include multi-sensor integration and cloudbased analytics for long-term tracking and more holistic health monitoring. Such improvements would enable users and healthcare professionals to track stress patterns over time and make data-driven decisions to improve mental well-being. This system represents a promising step toward intelligent, userfriendly health solutions, offering valuable insights for managing emotional health and reducing stress in daily life.The visual data supports the system's effectiveness, showing high accuracy in stress detection across various intensity levels. Continuous refinement of algorithms and expanded datasets will further enhance the reliability and adaptability of this system.

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