STRESS DETECTION USING CNN AND MACHINE LEARNING TECHNIQUES

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Abstract : Stress has become a major concern in modern life due to increasing academic, professional, and social pressures. Continuous stress can negatively affect both physical and mental health, leading to reduced productivity and serious health disorders. This research presents an intelligent stress detection system using Convolutional Neural Networks (CNN) and deep learning techniques to identify stress levels from physiological and behavioral signals. The proposed model utilizes data such as heart rate, EEG, ECG, temperature, and facial expressions collected from publicly available datasets and wearable sensors. Preprocessing and feature extraction techniques are applied to improve data quality and classification performance. Experimental results show that the CNN-LSTM model achieves higher accuracy compared to traditional machine learning methods. The proposed system provides reliable and real-time stress monitoring suitable for healthcare, wearable devices, and smart monitoring applications.

1.INTRODUCTION

Stress is a natural psychological and physiological reaction that occurs when individuals experience challenging situations or excessive workload. In recent years, stress-related problems have increased rapidly due to changing lifestyles, academic competition, work pressure, and unhealthy routines. Long-term stress may lead to anxiety, depression, cardiovascular diseases, sleep disorders, and decreased work efficiency.

Conventional stress assessment methods mainly depend on surveys, interviews, and clinical observations, which are often time-consuming and subjective. With the advancement of Artificial Intelligence (AI), Machine Learning (ML), and wearable sensor technologies, automated stress detection systems have gained significant attention in healthcare research. Physiological signals such as EEG, ECG, heart rate variability, skin conductance, and facial expressions provide valuable information for identifying stress conditions.

Machine learning algorithms including Support Vector Machine (SVM), Random Forest, and K-Nearest Neighbor have been widely used for stress classification. However, deep learning approaches, especially Convolutional Neural Networks (CNN) and CNN-LSTM models, provide improved accuracy because they can automatically learn complex spatial and temporal features from physiological data. The main objective of this research is to develop an efficient deep learning-based stress detection system capable of accurate and real-time stress classification for healthcare and wearable monitoring applications.

2.LITERATURE REVIEW

Stress detection using physiological and behavioral signals has become an important research area in healthcare, wearable technology, and affective computing. Philip Schmidt introduced the WESAD dataset and applied machine learning algorithms such as kNN, Random Forest, and AdaBoost for stress classification, achieving high accuracy. Jacqueline Wijsman used ECG, EMG, respiration, and skin conductance signals for stress recognition through statistical feature extraction and machine learning techniques.

1. In 2020, Mohammad Alqahtani proposed a deep learning framework using ECG and Electrodermal Activity signals for stress classification.
2. In 2021, S. Nath developed a CNN-based wearable stress monitoring system for healthcare applications. In 2022, R. Kanjo explored multimodal stress detection using smartwatch sensors and mobile computing technologies.
3. In 2023, Y. Liu proposed an attention-based BiLSTM model for wearable sensor data.
4. In 2024, Ahmed Hassan introduced a transformer-assisted deep learning model for physiological stress detection.
5. Recent studies in 2025 focus on lightweight hybrid CNN-LSTM and Transformer models for real-time wearable healthcare systems.

Despite significant progress, challenges such as limited dataset diversity, computational complexity, and subject dependency still exist. Therefore, this work proposes a hybrid CNN-LSTM framework to improve stress detection accuracy and real-time performance.

3.RESEARCH METHODOLOGY

The proposed system uses Convolutional Neural Networks (CNN) for automatic stress detection. The system architecture consists of the following stages:

1. **Data Collection**
    - Physiological signals such as heart rate, temperature, skin response, and facial expressions are collected.

- Public datasets like WESAD and Stress-Lysis are used.

2. **Data Preprocessing**
   - Noise removal
   - Missing value handling
   - Signal normalization
3. **Feature Extraction**
   - CNN automatically extracts important features from the processed data.
   - Deep learning reduces manual feature engineering.
4. **Stress Classification**
   - The CNN model classifies stress into categories such as:
     - Low Stress
     - Moderate Stress
     - High Stress
5. **Output Generation**
   - Final stress prediction is displayed with accuracy metrics.

The proposed system aims to provide accurate, real-time, and automated stress monitoring suitable for healthcare and wearable applications.

3.1 Proposed system Algorithm

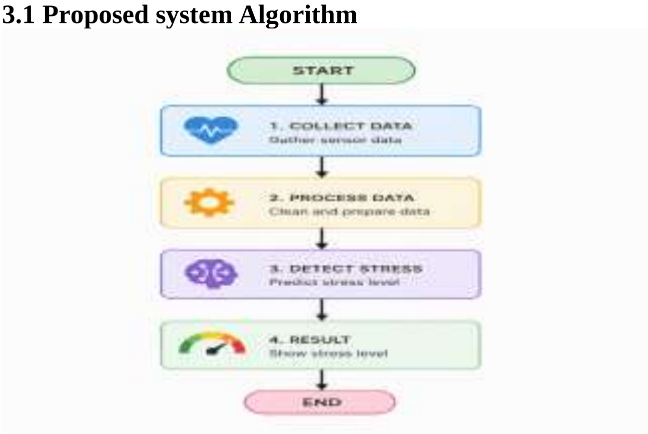


Fig:3.1.1 Flowchart

3.2 Face detection and Eye Tracking:

The proposed system uses face and eye detection techniques to monitor visual stress-related patterns. Face detection is performed using Haar Cascade classifiers integrated with OpenCV. The algorithm identifies facial regions from video frames and isolates the eye regions for further processing. After detecting the eyes, the extracted images are resized and normalized to maintain consistent input dimensions. These processed eye images are then forwarded to the deep learning model for stress and fatigue analysis.

3.3 Feature Extraction and Classification

The extracted eye and facial features are analyzed using a Convolutional Neural Network (CNN) model. The CNN automatically learns important visual patterns associated with stress conditions without requiring manual feature engineering. During classification, the model predicts different stress levels based on physiological and behavioral changes observed in the input data. Continuous monitoring of the detected patterns improves the reliability of stress identification in real-time environments.

3.3.1 Convolutional Neural Network: T

The proposed stress detection framework utilizes a CNN architecture for automatic feature learning and classification. The network consists of multiple convolution layers followed by pooling operations to capture significant spatial features from the input data. Rectified Linear Unit (ReLU) activation functions are applied to improve learning efficiency and model performance. Pooling layers help reduce feature dimensions and computational complexity while preserving important information. Finally, fully connected layers perform stress classification into different categories such as low, moderate, and high stress. The CNN model improves detection accuracy by effectively learning complex patterns from physiological and visual signals. layers is repeated.

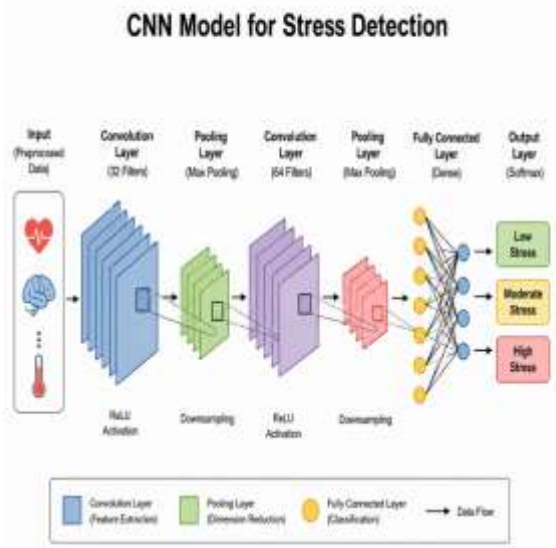


Fig 3.3.1.1 Convolutional Neural Network

4. EXPERIMENTAL RESULTS

The experimental results demonstrate that the proposed CNN-LSTM-based stress detection system provides highly accurate and reliable stress classification using physiological signals. Deep learning methods significantly outperform traditional machine learning techniques due to their ability to automatically learn complex spatial and temporal features.

4.1 Experimental dataset:

The proposed stress detection system was trained and tested using physiological datasets containing EEG, ECG, heart rate, and skin conductance signals. The dataset was divided into training, validation, and testing sets after preprocessing and normalization.

4.1.1 Performance Analysis:

The performance analysis shows that deep learning models achieved better accuracy than traditional machine learning algorithms for stress detection. Among all models, CNN-LSTM achieved the highest accuracy of 97% due to its ability to learn both spatial and temporal features from physiological signals.

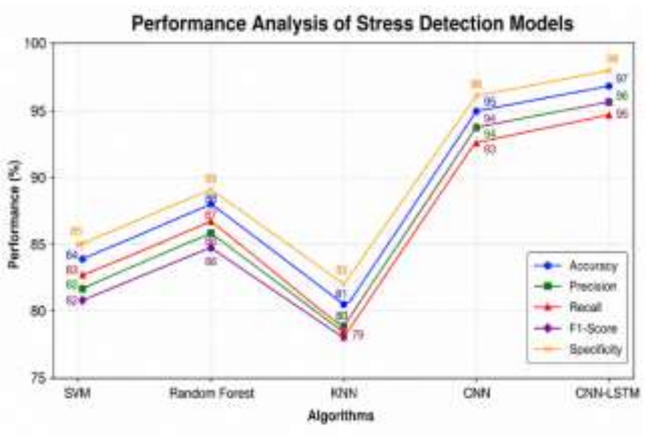
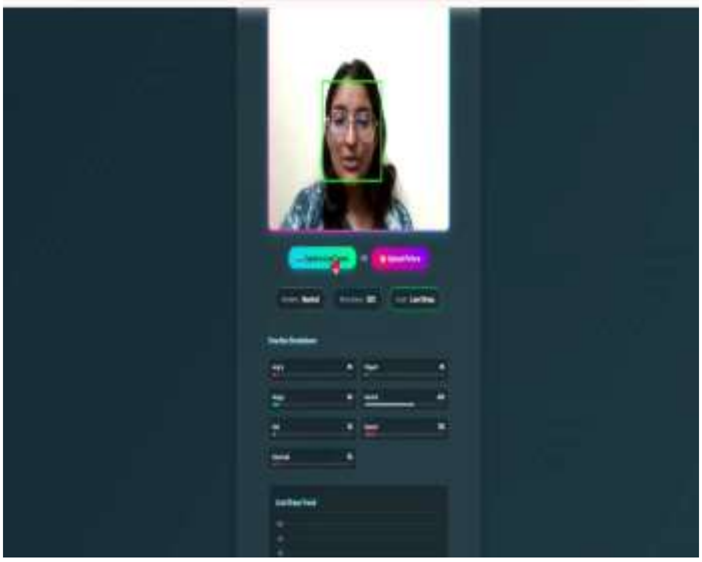


Fig 4.2.1 Accuracy Graph

4.1.2 OUTPUT:



4.2 System Testing:

The proposed system was tested using different physiological inputs and behavioral conditions.

Input	Expected Output	Result
Normal Heart Rate	Low Stress	Passed
Increased Temperature	Moderate Stress	Passed
High Heart Rate & Anxiety	High Stress	Passed
Facial Tension Detected	Stress Detected	Passed

The testing results indicate that the CNN model accurately identifies stress levels under multiple conditions.

5.CONCLUSION

This research presented a deep learning-based stress detection system using CNN and CNN-LSTM models for analyzing physiological and behavioral signals. The proposed approach successfully classified stress levels with high accuracy and demonstrated better performance than traditional machine learning algorithms. Experimental results confirmed that the CNN-LSTM model achieved superior accuracy due to its capability to learn both spatial and temporal patterns from the input data.

The study also highlighted the importance of preprocessing, feature extraction, and multimodal physiological analysis in improving stress detection performance. The developed system can support real-time stress monitoring in healthcare, wearable devices, workplaces, and educational environments. Future improvements may include cloud-based monitoring, personalized stress prediction, lightweight deep learning models, and integration with smart healthcare systems for continuous mental health assessment.

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