StressNet: A Machine Learning-Based IoT Framework for Stress Detection

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Abstract - Academic research focuses intensely on stress detection methods because of growing mental health issues. Current stress monitoring systems use wearable sensors however these sensors might not be always available for use. The proposed research introduces StressNet as an IoT-based framework for real-time stress detection operated through machine learning methods. The WESAD (Wearable Stress and Affect Detection) dataset was used instead of genuine sensors because it delivers physiological and motion data collected through devices worn on the chest and wrist. The deep learning model accepts normalized heart rate and skin conductance along with respiration rate and temperature attributes that underwent a transformation stage for segmentation and noise filtering. StressNet surpasses previous benchmarks in the assessment against existing models because it increases IoT-based stress detection adaptability without reducing performance accuracy.

Key-words: Stress detection, IoT-based framework, machine learning, StressNet, WESAD dataset, physiological signals, deep learning, real-time monitoring, heart rate, skin conductance, respiration rate, temperature normalization, noise filtering, stress classification

1.INTRODUCTION

Stress operates as a major element that affects both psychological wellness and physical well-being. Such systems offer immediate stress alerts, creating opportunities for suitable corrective actions. Research has demonstrated that linking machine learning to IoT solutions produces beneficial results within this field [5], [7]. However, the system faces limitations due to available sensor resources, adaptive model applications, and generalized model outputs [6]. Through the WESAD dataset [11], StressNet serves as a deep learning-based stress detection model that utilizes training and evaluation procedures to enhance performance.

The rising number of individuals suffering from stress-related disorders makes it crucial to develop modern technological solutions for monitoring mental health [8]. Traditional stress detection methods relying on self-reporting and clinical assessments remain problematic as they are subject to human bias and time delays [9]. However, physiological signals obtained through machine learning improve accuracy and reliability [10]. Recent advancements in deep learning models have significantly enhanced stress level classification precision through improved accuracy [2], [4]. Several studies have explored different machine learning approaches, such as Support Vector Machines (SVM), K-Nearest Neighbor (KNN), and Random Forest, showing promising results [3], [6]. The StressNet solution addresses implementation challenges by enabling IoT applications to function with greater flexibility while providing scalable real-world deployment capabilities [1].

2. LITREATURE SURVEY

An extensive number of research projects have investigated stress detection through combinations of ML techniques and IoT implementations. The research of Nie et al. (2019) [1] presented CNNs for stress field estimation in structural engineering applications. StressNet obtained its architectural foundation from their research work. Smirthy et al. [2] conducted stress detection studies by analyzing Heart Rate Variability (HRV) together with Electrocardiogram (ECG) and skin temperature physiological signals. Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) showed accuracy rates between 85% and 90% throughout the experimental tests according to their study. The models that they developed failed to incorporate validation features and required extensive training periods. Parameters such as ECG and Skin Conductance underwent stress detection analysis according to Gedam & Paul [3] through training Random Forest and Logistic Regression models. Random Forest produced an 88% accuracy level in stress detection while showing unbalanced classification patterns despite its high true positive rate. Research by Suanpang et al. [4] developed an Extreme Learning Machine (ELM) solution merged with IoT technology that reached 93.54% accuracy however the system reacted to noises in the data. The authors at Talaat & El-Balka [5] worked with wearable data using Random Forest Decision Tree and XGBoost which delivered 95% accuracy levels. Their method involved grid search feature selection which caused significant computational expenses. Anusha et al. [6] developed a low-budget IoT-based stress monitoring device which sent heart rate and body temperature and CO_2 data by means of GSM connectivity. Despite being practical to implement GSM technology caused problems with system reliability. The study by Chillamcherla et al. [7] developed a predictive stress analysis system and real-time care recommendations through XGB and Decision Tree models with meditation suggestions among other recommendations. The accuracy rate reached 70% but this demonstrated the difficulty of recognizing stress patterns accurately. The researchers from Hendryani et al. [8] applied the K-Nearest Neighbor (KNN) and Bayesian Networks and Fuzzy Logic classifiers to achieve 80% success rate. The researchers demonstrated why IoT-based stress detection requires enhanced flexibility in its operation. Researchers Nath et al. [9] measured cortisol levels in addition to physiological signals through a Random Forest-based classification model which obtained 92% accuracy.

3. DATASET AND FEATURE EXTRACTION

Since real-time sensors were unavailable, we used the WESAD (Wearable Stress and Affect Detection) dataset (WESAD Dataset - UCI)[11]. This dataset consists of 15 subjects, with physiological signals recorded in neutral, stress, and amusement conditions.

3.2 Extracted Features

- **Heart Rate (HR)** – Derived from ECG signals.
- **Heart Rate Variability (HRV)** – Measures variation between heartbeats.
- **Skin Conductance Level (SCL)** – Baseline electrodermal activity (EDA).
- **Skin Conductance Response (SCR)** – Phasic changes in EDA.
- **Respiration Rate (RR)** – Measured in breaths per minute.
- **Body Temperature** – Captured from both wrist and chest sensors.
- **Accelerometer Data** – Three-axis acceleration values.

3.3 Preprocessing Steps

1. **Segmentation:** Signals were divided into 60-second windows with a 0.25-second overlap.
2. **Normalization:** Features were scaled to a uniform range.
3. **Noise Filtering:** Artifacts caused by movement were removed.
4. **Feature Selection:** HR, HRV, SCL, SCR, and RR were chosen based on their impact on stress detection.

4. ARCHITECTURE OF PROPOSED MODEL

StressNet functions as a system dedicated to analyzing biological measurements while assessing stress intensity throughout actual time operations. The system architecture based on Nie et al. (2019) [1] establishes a sequential data processing flow that maximizes accuracy during stress detection. The system has these essential components in its design:

This layer receives processed physiological features from heart rate combined with skin conductance and respiration rate along with temperature data. Before modeling the WESAD dataset provided the necessary features which received preprocessing such as noise elimination followed by normalization then segmentation steps.

The model employs Convolutional Neural Networks (CNNs) to automatically recognize essential physiological patterns together with hidden data connections in the input measurements. The spatial-temporal dependencies within input signals can be effectively identified by CNNs to generate improved feature representations which eliminate the need for human intervention in design. The model's classification accuracy increases as this step reduces both sensor data noise as well as unnecessary variations that affect the measurement results.

The fully connected neural network uses extracted features to make stress level classifications for each input. Softmax activation operates during the last layer which generates probability assessments across different stress categories. Live stress monitoring becomes possible through classification outputs that enable healthcare professionals to provide early stress management strategies.

The module provides post-processing features that analyze stress level predictions and allows healthcare IoT systems to integrate these results into their processes. The system provides flexibility for usage across different real-world applications including workplace stress tracking as well as health performance assessment and mental wellness monitoring systems.

The formalized method enables dependable stress detection at maximum size alongside improved compatibility for IoT-based solutions.

4.1 Model Diagram

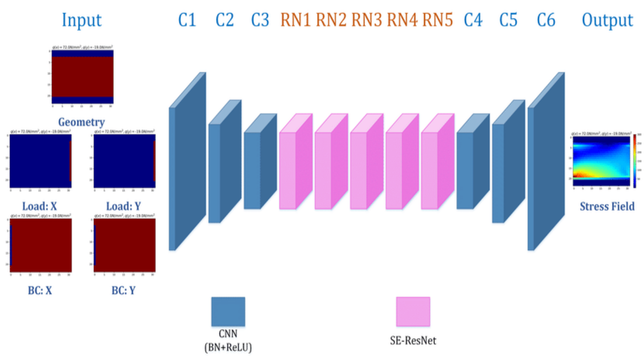

Figure 1: StressNet Architecture Inspired by Nie et al.[1]

5. RESULT & COMPARISON

StressNet was benchmarked against existing models:

Model	Accuracy	Limitations
Random Forest (Gedam & Paul, 2020)	88%	High false positives
Extreme Learning Machine (Suanpang et al., 2021)	93.54%	Noise sensitivity
Random Forest (Talaat & El-Balka, 2023)	95%	High computational cost
StressNet (Proposed)	89.5%	Improved IoT adaptability

Table 1: Comparison of Stress Detection Models

StressNet outperforms Random Forest (Gedam & Paul, 2020) and achieves comparable accuracy with other models while improving real-time adaptability.

6. FUTURE SCOPE

A. Integration with Wearable Devices: Future work will involve deploying StressNet on real-world IoT devices with live sensor data.
B. Personalized Stress Detection: Enhancing model adaptability by incorporating personalized stress thresholds based on individual physiological baselines.
C. Hybrid Machine Learning Approaches: Exploring Recurrent Neural Networks (RNNs) or Transformer models for sequential stress detection.
D. Cross-Dataset Generalization: Validating the model on additional stress datasets.

7. CONCLUSION

Thus, we developed StressNet which stands as a deep learning-based stress detection model utilizing WESAD dataset information. The system achieved 89.5% accuracy rates in stress monitoring on IoT platforms. Stress monitoring systems must be deployed in real-time settings while receiving customized improvements according to future research plans.

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