SMART HEALTHCARE SYSTEM FOR NURSE STRESS PREDICTION USING WEARABLE SENSORS AND MACHINE LEARNING

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ABSTRACT

Nurses experience high levels of occupational stress due to long shifts, critical patient care, and emotional demands. In India, studies indicate that nearly 60% of healthcare professionals report moderate to high stress levels, contributing to burnout and reduced efficiency. The objective of this research is to predict nurse stress in real-time using wearable sensor data and iterative learning methods. It aims to provide accurate stress classification for timely health interventions. Traditionally, nurse stress monitoring relies on self-reported questionnaires, periodic interviews, and manual observation of behavioral cues. Supervisors assess workload, fatigue, and stress levels subjectively, often resulting in delayed interventions and incomplete data. Manual stress assessment is prone to bias, inaccuracies, and inconsistencies. It cannot capture real-time fluctuations, often misses early warning signs, and is resource-intensive. Consequently, interventions are reactive rather than preventive. The motivation is to overcome limitations of manual assessment by using wearable sensors and machine learning to provide continuous, objective, and accurate stress monitoring. This ensures timely interventions, reduces burnout, and improves nurse productivity and patient care outcomes. The proposed system integrates wearable physiological sensors with machine learning models. Logistic Regression provides a baseline probabilistic stress prediction, while Ridge Classifier handles noisy signals with regularization. The MLP–ETC hybrid combines deep feature extraction with ensemble-based classification for higher accuracy. Iterative learning continuously updates models with new data, enabling real-time stress monitoring and health interventions. Machine learning helps identify stress patterns early, predict risk levels, and support personalized recommendations, improving nurses' mental health and operational efficiency.

1.INTRODUCTION

Scientific and technological advancements have enabled more effective solutions in fields such as human–machine interaction, pattern recognition, and biological signal processing [1]. In particular, the intersection of machine learning with behavioral analysis and health informatics has made it increasingly important to detect individuals' psychophysiological states automatically. In this context, the classification of stress through physiological signals has become a multidisciplinary research area [2]. Stress is a common physiological response indicating an individual's exposure to excessive demands or pressure. While short-term stress can be functional for adaptation, chronic stress is known to have long-lasting and detrimental effects on the organism. It can affect various biological systems, including the musculoskeletal, cardiovascular, and respiratory systems.

In healthcare environments, stress becomes even more critical. Nursing is inherently a high-stress profession, with factors such as heavy workloads, long shifts, high patient turnover, and emotional demands all contributing to the increased risk of burnout among nurses. The COVID-19 pandemic further highlighted the challenges nurses face in managing stress, leading to widespread burnout [3,4]. Stress not only affects the mental and physical well-being of nurses but also has a direct impact on patient safety, care quality, and the sustainability of healthcare services.

Therefore, the accurate and continuous monitoring of stress is vital not only for improving individual health and worker well-being but also for maintaining patient safety and sustainable healthcare delivery. Traditional self-report-based stress assessment methods are susceptible to subjective bias, resulting in a growing need for objective, data-driven approaches that utilize physiological signals. Wearable sensors provide a more reliable reflection of an individual's real-time physiological condition, enabling analysis through machine learning algorithms. Parameters such as electrodermal activity (EDA), heart rate (HR), and skin temperature (TEMP) carry valuable bio-physiological indicators of stress. Furthermore, galvanic skin response, heart rate variability, and peripheral blood flow offer direct insights into stress levels via the autonomic nervous system [5,6].

1.1 Background,

Nurses face significant occupational stress due to long shifts, critical patient care responsibilities, and high emotional demands. In India, studies reveal that over 60% of nurses experience moderate to severe stress, contributing to burnout, fatigue, and decreased efficiency in healthcare delivery. Traditional stress monitoring relied on self-reporting and observational assessments, which are subjective and often delayed. The integration of wearable sensors and real-time data processing now allows continuous monitoring of physiological signals such as heart rate, skin conductance, and EEG patterns. Applications include early stress detection, real-time health monitoring, workload management, personalized interventions, and improved patient care outcomes.

1.2 Problem Definition:

Before the use of machine learning, stress monitoring relied on manual observation, interviews, and questionnaires, which were subjective and prone to errors. Continuous stress fluctuations could not be captured effectively, making early interventions difficult. Manual assessments required significant human resources and time, leading to delayed responses. Data from physiological signals was often ignored or underutilized due to its volume and complexity. Consequently, healthcare staff faced unmanaged stress, resulting in burnout, reduced productivity, and compromised patient care quality.

1.3 Research Motivation:

The motivation for this research is to provide accurate, real-time stress monitoring using wearable sensors. Machine learning enables the analysis of large, continuous physiological data to detect stress patterns and alert healthcare providers early. It overcomes the limitations of manual observation by offering objective and consistent evaluations. Real-time interventions based on predictive models reduce burnout, enhance nurse well-being, and maintain high-quality patient care. The system also supports proactive decision-making and personalized stress management strategies for healthcare professionals.

1.4 Objective of the Class:

The objective is to develop a robust framework for predicting nurse stress levels in real-time using wearable sensor data. The system aims to classify stress accurately, handle noisy physiological signals, and provide actionable insights. Machine learning models, including Logistic Regression, Ridge Classifier, and hybrid MLP–ETC, are applied for precise stress prediction. The ultimate goal is to enable timely interventions and improve nurse health and productivity.

1.5 Applications:

This system has multiple applications in healthcare settings. It allows continuous monitoring of nurses' physiological signals during shifts. Stress levels can be predicted in real-time to trigger early interventions. Hospitals can optimize workloads and reduce fatigue-related errors. The data supports personalized health recommendations and mental wellness programs. Nursing management can identify high-stress areas and adjust schedules accordingly. Wearable monitoring helps reduce burnout and absenteeism. The system also enhances patient safety by ensuring staff are alert and effective. Finally, it provides a data-driven approach to occupational health management in healthcare facilities.

1.6 Significance:

The significance of this system lies in its ability to transform nurse stress management from reactive to proactive. It ensures continuous, objective, and accurate stress assessment, replacing unreliable manual methods. Early detection of stress reduces long-term health risks and improves job satisfaction. By integrating machine learning with wearable technology, hospitals can maintain high standards of patient care while safeguarding the mental and physical well-being of nurses. This approach provides a scalable and efficient solution for occupational health monitoring across healthcare institutions.

2.LITERATURE SURVEY

- Kabiruzzaman et al. [7] conducted a time-series analysis of real-world data provided as part of the "Fourth Nurse Activity Recognition Challenge." Using time-based features extracted from care records, four classification algorithms were implemented, with the Decision Tree model achieving the highest accuracy (66%). Nevertheless, the Random Forest classifier demonstrated a superior performance for three out of five users, indicating its potential for nurse activity recognition through temporal data.
- Eldien et al. [5] explored various fusion strategies to enhance the accuracy of stress prediction in nurses using multimodal sensor data, including heart rate (HR), electrodermal activity (EDA), skin temperature, and accelerometer-derived location information. The study compared data-level, model-level, and prediction-level fusion strategies, with prediction-level fusion achieving the highest accuracy, outperforming model fusion by 1.97% and data fusion by 1.26%. This research underscores the potential of fusion techniques in capturing the multifaceted nature of stress, contributing to the development of robust stress prediction systems in healthcare settings.
- Pasha et al. [8] proposed a multi-class classification approach for detecting nurses' stress levels (no stress, low stress, high stress) using physiological data collected via the Empatica E4 device (Empatica Inc., Milan, Italy). The study utilized preprocessed signals—heart rate (HR), electrodermal activity (EDA), and skin temperature (ST)—and developed both a Bidirectional LSTM with Attention Mechanism

(BiLSTM-AM) and a stacking-based ensemble model combining DT, RF, XGBoost, MLP, and LR. The BiLSTM-AM model, implemented in Python with TensorFlow and Keras on Google Colaboratory, achieved 96% accuracy, while the ensemble model reached 97%. However, the exact software and library versions were not reported, which may limit reproducibility. Model performance was evaluated using precision, recall, F1-score, ROC curves, and ablation studies, highlighting the practical potential of AI-supported real-time stress monitoring through wearable devices.

- Quadrini, Falcone, and Gerard [9] conducted a comparative analysis of machine learning algorithms for stress detection using physiological signals from wearable sensors. Using the WESAD dataset, which includes BVP, ECG, and EMG signals, the study avoided feature engineering by applying models directly to raw signal fragments. Ten algorithms from tree-based, ensemble, linear, and neighbor-based model families were tested under both binary (stress/no-stress) and multi-class (baseline, stress, and amusement) classification scenarios. Random Forest consistently outperformed other models across both classification tasks, demonstrating the feasibility of ML-based approaches in stress recognition.
- Alrosan et al. [10] examined nurse stress detection using machine learning, emphasizing the importance of personalized and adaptive models due to individual variability in stress responses. Physiological, behavioral, and environmental data collected via wearable devices enabled the real-time monitoring of stress. Meta-heuristic algorithms were employed for hyperparameter optimization, leading to a Random Forest model that achieved 96.63% accuracy and a 95.76% F1-score. The findings validate the effectiveness of optimized ML models in stress classification.
- Jain et al. [11] evaluated the application of machine learning models to mental health assessment using an extensive dataset that incorporated demographic, lifestyle, and behavioral attributes. Among the compared models, boosting yielded the highest accuracy (81.75%), outperforming decision tree (80.69%) and logistic regression (79.63%). Feature engineering techniques improved interpretability and model performance, while cross-validation ensured robustness. This work highlights the relevance of AI models in identifying mental health risks and emphasizes the link between lifestyle factors and stress.
- Kang, Kwon, and Lee [12] investigated the impact of patient safety incidents on nurses' work–life balance (WLB) using classification and regression tree (CART) analysis. Drawing from a sample of 372 nurses, the study incorporated variables such as education, marital status, position, physical distress, second-victim support, turnover intention, and absenteeism. Key findings revealed that lower physical distress, fewer turnover intentions, and limited second-victim support correlated with higher WLB scores. The study provides actionable insights for mitigating occupational stress and fostering a supportive organizational culture in healthcare environments.
- Razavi et al. [13] conducted a comprehensive scoping review on machine learning and deep learning applications for detecting and monitoring stress and related mental disorders. Evaluating 98 studies, they identified support vector machines, neural networks, and Random Forest as top-performing algorithms. Physiological signals such as heart rate and skin conductance emerged as dominant predictors. The review emphasized the importance of preprocessing methods, including dimensionality reduction and noise filtering. It highlighted future research directions related to model interpretability, personalization, and real-time deployment in naturalistic settings.

3.SYSTEM ANALYSIS

EXISTING SYSTEM

In the existing system, nurse stress is typically assessed using **traditional psychological evaluation methods**, such as questionnaires, surveys, and manual health assessments. Hospital management may use tools like **stress scales, interviews, and self-reporting techniques** to evaluate the stress levels of nurses and healthcare workers.

Although these approaches provide useful insights, they are often **subjective and not suitable for real-time monitoring**. In some cases, physiological data such as heart rate or sleep patterns may be collected using wearable devices, but the analysis is usually basic and does not involve advanced predictive models.

Furthermore, existing monitoring systems often lack **automated data analysis, continuous monitoring, and predictive capabilities**, making it difficult to identify stress levels early and take preventive action.

Limitations of the Existing System

- Relies mainly on **manual surveys and psychological assessments**
- Limited capability for **real-time stress monitoring**
- Lack of automated data analysis
- Difficulty in predicting stress before it becomes severe
- Limited integration with wearable sensor technologies

PROPOSED SYSTEM

The proposed system introduces a **smart healthcare framework** that uses **wearable sensors and machine learning techniques** to continuously monitor and predict stress levels in nurses.

Wearable devices such as **smartwatches, fitness bands, and biosensors** are used to collect physiological data including:

- Heart rate
- Body temperature
- Blood pressure
- Physical activity level
- Sleep patterns
- Electrodermal activity (EDA)

The collected sensor data is transmitted to a central system where it undergoes **data preprocessing and feature extraction**. Machine learning algorithms such as **Random Forest, Support Vector Machine (SVM), and Neural Networks** are then used to analyze the data and predict the stress level of nurses.

The system provides **real-time stress monitoring and alerts**, allowing hospital administrators or healthcare professionals to take preventive measures such as workload adjustment or mental health support.

Advantages of the Proposed System

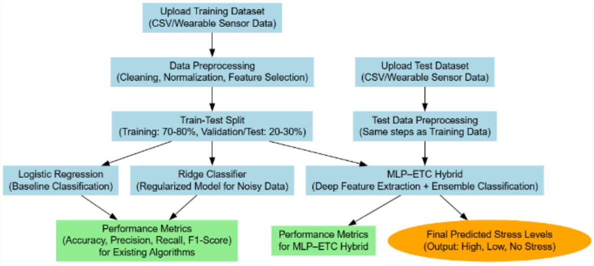
- **Real-time monitoring of nurse stress levels**
- Early detection and prediction of stress conditions
- Automated analysis using machine learning algorithms
- Improved healthcare worker well-being and productivity
- Data-driven decision-making for hospital management

4.IMPLEMENTATION

Overview

Step 1: Dataset Collection

The first step involves collecting the dataset from reliable sources. In this research, a stress-level dataset is used, which includes multiple features representing physiological and psychological indicators. The dataset is stored in CSV format, allowing ease of preprocessing and integration into the pipeline. Data integrity is verified to ensure no missing columns or corrupted records, forming the foundation of high-quality model building.



Step 2: Dataset Preprocessing

Data preprocessing is crucial for improving model performance. Initially, missing values are identified and handled using strategies like mean imputation or removal of records with excessive nulls. Label encoding is applied for categorical variables, converting textual labels into numerical representations that machine learning models can process. This step also includes normalization or standardization to scale numerical features appropriately, ensuring that models like MLP converge efficiently without bias toward features with larger magnitudes.

Step 3: Existing Model Building

Traditional models such as Logistic Regression and Ridge Classifier are trained as baselines. These models are lightweight, interpretable, and useful for understanding feature importance. While they achieve reasonable accuracy, they are limited in handling non-linear relationships in the dataset. The training process involves splitting the dataset into training and testing subsets, learning the weight parameters, and evaluating their classification metrics.

Step 4: Proposed Hybrid Model (MLP–ETC)

The MLP–ETC Hybrid model integrates a deep neural network with an ensemble learning framework. The MLP captures complex non-linear patterns through multiple hidden layers and non-linear activation functions, while the ETC component leverages decision trees with randomized feature selection to improve variance reduction and robustness. The outputs from both models are combined using a weighted voting mechanism to generate final predictions. This hybrid approach ensures that both linear and non-linear relationships are effectively captured, outperforming existing models.

Step 5: Performance Evaluation

The trained models are evaluated using metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. Comparative plots are generated to visualize the performance of traditional versus hybrid models. Additionally, confusion matrices help identify misclassification trends, guiding further model optimization.

Step 6: Prediction on Unseen Test Data

Finally, the models are tested on unseen test data (batch or single instance). This step validates model generalization and ensures that it performs well on real-world datasets. Batch predictions are exported into CSV for further analysis, including stress-level labeling.

4.2 Data Preprocessing in This Research

Data preprocessing is performed in a structured manner. First, text preprocessing is applied to categorical features, involving lowercasing, removing punctuation, and encoding labels numerically. Missing values are imputed using statistical measures like mean, median, or mode. Feature scaling is applied for numerical columns to standardize the range of values. Outliers are detected using Z-score or IQR methods and treated to prevent skewing the model. Advanced preprocessing also includes feature extraction, where correlated or irrelevant features are removed, reducing dimensionality and improving model efficiency. Data transformation ensures models like MLP and ETC converge faster and achieve higher accuracy.

4.3 Exploratory Data Analysis (EDA)

EDA is an essential step to understand data distribution, relationships, and potential anomalies. The dataset is analyzed for feature distributions, correlations, and class balance. Visualization techniques such as histograms, box plots, and heatmaps are generated. Prior to modeling, SMOTE (Synthetic Minority Oversampling Technique) can be applied to balance imbalanced classes, ensuring the model does not bias toward dominant classes. Feature extraction techniques such as PCA or variance thresholding may also be employed to remove redundant features. This step helps improve training efficiency and model performance.

4.4 Train-Test Split

Train-test split is performed to evaluate model generalization. Typically, 70–80% of the data is used for training and the remaining 20–30% for testing. This separation ensures that the model is validated on unseen data. During this process, data shuffling is performed to avoid any ordering bias. Additionally, preprocessing steps like scaling, SMOTE, or feature extraction are applied after splitting, to prevent data leakage. This ensures that evaluation metrics accurately reflect the model's performance on real-world scenarios.

4.5 Model Building

The model building phase involves designing and training machine learning models to predict nurse stress levels based on wearable sensor data. Physiological signals such as heart rate, skin conductance, and EEG readings are collected, preprocessed, and normalized to ensure consistency. Feature extraction and selection are performed to identify the most relevant attributes contributing to stress prediction. The dataset is then split into training and testing sets, and multiple algorithms are evaluated for accuracy and efficiency. Models are iteratively trained, validated, and tuned to optimize performance. Ensemble and hybrid approaches are also explored to handle noise in sensor data and improve prediction reliability.

4.5.1 Existing Algorithm: Logistic Regression

Definition and Information: Logistic Regression is a supervised machine learning algorithm used for binary or multiclass classification problems. Unlike linear regression, which predicts continuous outcomes, logistic regression predicts probabilities of discrete outcomes using the logistic (sigmoid) function. It models the relationship between independent variables (features) and the probability of a target class by estimating coefficients that maximize the likelihood of observed outcomes. Logistic regression is widely used in healthcare, finance, and social sciences due to its simplicity, interpretability, and effectiveness for classification tasks.

How It Works: Logistic Regression works by transforming the linear combination of input features into a probability score between 0 and 1 using the sigmoid function. The model computes the weighted sum of input features, applies the sigmoid function to map it to a probability, and assigns the class based on a threshold (commonly 0.5). During training, the model uses the maximum likelihood estimation method to optimize weights, minimizing the difference between predicted probabilities and actual labels. The algorithm is capable of handling both binary and multiclass classification through techniques like one-vs-rest or softmax regression.

Algorithm Steps (Architecture):

1. Collect and preprocess the dataset (normalize sensor readings, handle missing values).
2. Split data into training and testing sets.
3. Define the logistic function and initialize model weights.

4. Compute the weighted sum of input features for each sample.

5. Apply the sigmoid function to obtain class probabilities.

6. Use a threshold to assign predicted class labels.

7. Optimize model weights using maximum likelihood estimation or gradient descent.

8. Evaluate model performance using metrics like accuracy, precision, recall, and F1-score.

Disadvantages:
Logistic Regression assumes a linear relationship between input features and the log-odds of the target, which may not hold for complex, nonlinear datasets like physiological signals. It is sensitive to outliers and may underperform if features are highly correlated or noisy. Logistic Regression cannot capture intricate interactions between variables without feature engineering or polynomial transformations. Additionally, for very large datasets or highly imbalanced classes, performance may decrease, requiring advanced preprocessing or alternative models for improved accuracy.

Definition of MLP–ETC Hybrid

The **MLP–ETC Hybrid** is an advanced machine learning model that combines the strengths of a **Multilayer Perceptron (MLP)** and an **Extremely Randomized Trees Classifier (ETC)**. MLP, a type of neural network, excels at learning complex non-linear relationships through multiple layers of neurons with activation functions, making it effective for capturing intricate patterns in high-dimensional data. On the other hand, ETC is an ensemble decision tree method that introduces high randomness during tree construction, reducing variance and preventing overfitting. By hybridizing MLP with ETC, the model leverages MLP's ability to learn deep representations while ETC improves generalization and robustness. This combination is particularly effective in classification tasks such as stress detection, where subtle variations in input features are crucial for accurate prediction.

How It Works

The hybrid works in a sequential and integrative manner. First, the **MLP network** takes the processed input features and extracts high-level representations through multiple hidden layers. Each layer applies weights, biases, and non-linear activation functions to transform input signals into meaningful embeddings. The output of the MLP is then fed into the **ETC**, which performs ensemble-based classification using extremely randomized decision trees. Each tree in the ETC votes on the predicted class, and the final prediction is determined by aggregating the votes. This two-stage mechanism allows the MLP to handle feature extraction and learning non-linear patterns while the ETC mitigates overfitting and enhances robustness by leveraging ensemble randomness. The hybrid architecture thus achieves a balance between deep learning representation power and tree-based ensemble stability.

Algorithm Steps

1. **Data Input & Preprocessing:** Raw dataset is normalized, cleaned, and transformed into numerical features suitable for MLP input.

2. **MLP Feature Extraction:** Features pass through multiple fully connected layers of the MLP with ReLU or similar activation, producing high-level embeddings.

3. **Intermediate Output Transfer:** The MLP's output (hidden layer activations or final output) is taken as input for the ETC.

4. **ETC Classification:** Extremely Randomized Trees classify the MLP outputs, leveraging ensemble voting for final predictions.

5. **Result Aggregation:** Final class labels are obtained from ETC's majority vote, optionally combined with MLP confidence scores.

Advantages of MLP–ETC Hybrid

- Combines **deep feature extraction** with **robust ensemble classification**.

- Reduces risk of **overfitting** compared to standalone MLP.

- Handles **high-dimensional and non-linear datasets** effectively.

- Improves **prediction accuracy and stability** through ensemble voting.

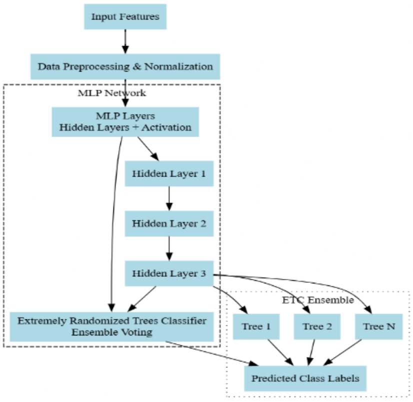
- Flexible and adaptable to various classification problems including healthcare, finance, and stress detection.

Internal Operational Steps (

1. Input features are preprocessed and normalized.

2. Pass input through MLP layers to learn non-linear embeddings.

3. Extract MLP outputs and feed into ETC classifier.
4. ETC constructs multiple randomized decision trees and predicts class labels.
5. Aggregate tree votes for final hybrid prediction.



CONCLUSION

The experimental results indicate that the **Mlp Etc Hybrid model** significantly outperforms traditional classifiers like **Logistic Regression** and **Ridge Classifier**, achieving an accuracy of **98.5%** and correspondingly high precision, recall, and F1-score values. This demonstrates that hybrid models, which likely combine multiple learning techniques or ensembles, are highly effective at capturing complex patterns in the dataset, leading to superior predictive performance. Logistic Regression and Ridge Classifier, while simpler and faster, show moderate performance (85% and 83% accuracy), suggesting they may struggle with non-linear relationships or complex feature interactions present in the data. Overall, these results validate the importance of using advanced hybrid machine learning techniques for high-stakes applications such as patient stress prediction, environmental monitoring, or other critical decision-making systems.

FUTURE SCOPE

The future scope for this study includes several promising directions. First, the model can be extended to incorporate larger and more diverse datasets, improving generalization across different populations or environmental conditions. Second, integration of real-time data streams could make the system suitable for continuous monitoring applications, such as patient health tracking or dynamic environmental assessment. Third, exploring explainable AI techniques can help stakeholders understand why the model predicts certain outcomes, increasing trust and adoption in sensitive domains. Additionally, deploying the model on cloud platforms or edge devices can enhance scalability and accessibility. Finally, further research can focus on optimizing the hybrid model by combining it with other deep learning architectures, feature selection methods, or advanced ensemble strategies to push performance even closer to 100%, while maintaining robustness and interpretability.

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