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Smart Stress Monitoring and Personalized Music Recommendation Using IoT and Machine Learning

Varad U. Deshpande, Rushikesh Tapsale, Dheeraj Borse, Jay Gajare
Department of Artificial Intelligence and Data Science Vishwakarma Institute of Information Technology, Pune, India

Abstract: Mental health has emerged as a prime area of concern over the last few years, particularly among the youth and corporate professionals. The current research formulates a framework that applies machine learning to label stress levels and then suggests music according to the age group of the user. Based on the analysis of physiological and survey-based inputs, the model classifies stress as Low, Moderate, and High and maps results against age for recommending personalized music. Methods like SMOTE-Tomek resampling, PCA, and Random Forest Classifier were applied for accuracy improvement. Results indicate high accuracy in stress classification and validate age-based music therapy as a complementary method for stress alleviation.
Keywords: IoT, Stress Classification, Machine Learning, GSR Sensor, Heart Rate Monitor, Random Forest, PCA, SMOTE-Tomek, Music Recommendation.

I. INTRODUCTION

Mental health has become a major issue worldwide, with stress, anxiety, and depression impacting more and more people. Although conventional treatments are available, there is a growing interest in non-pharmacological treatments, including music therapy. With the introduction of the Internet of Things (IoT), real-time physiological monitoring has become more convenient and effective. This.study suggests an end-to-end solution that employs IoT-based sensors along with ML algorithms to measure stress levels prior to and subsequent to music therapy sessions.

The suggested model employs biometric sensors like Heart Rate Sensors and Galvanic Skin Response (GSR) sensors to capture physiological signals from the individuals. These signals are markers of autonomic nervous system activity and offer objective measures for stress level measurement. To provide personalized therapeutic intervention, the system has an age-based music recommendation engine that plays soothing or era-specific music depending on the age group of the user.

The data processing pipeline of the system combines supervised learning methods, specifically Random Forest Classifiers, following data pre-processing operations such as Label Encoding, Standardization, PCA for Dimensionality Reduction, and SMOTE-Tomek class balancing. Stress levels are categorized into three combined categories: Low, Moderate, and High. Comparative analysis is done by parameters such as precision, recall, F1-score, and confusion matrix. Also, visualizations are produced to examine stress level distributions and the effect of music therapy for various age groups.

II. LITERATURE SURVEY

Music therapy has become increasingly popular as a non-invasive technique for stress management. IoT advancements have made it possible to come up with automated music therapy systems that offer personalized therapies. This literature review discusses research on IoT-based music therapy, where stress detection, automation, and system performance are the areas of interest.

IoT-based systems use sensors, cloud computing, and machine learning to track physiological markers of stress, including heart rate variability (HRV), galvanic skin response (GSR), and blood pressure. Research has proven that real-time monitoring of stress, combined with an adaptive music recommendation system, can improve emotional well-being markedly. Music therapy has been used more and more to address benefits in mental well-being and regulation of hypertension. With the introduction of the Internet of Things (IoT), intelligent health monitoring systems using personalized music therapy are now possible. In this literature survey, previous research shows the work carried out using music therapy, IoT-based health monitoring, and their combination for managing stress and hypertension[1].

A number of research studies have worked on wearable sensor-based systems that gather biometric information and measure stress levels with AI-based algorithms. In [2], a study proposed an IoT platform that chooses music depending on stress levels obtained from ECG and GSR sensors. In [3], a study used an Arduino-based system that modifies music parameters such as tempo and frequency to improve relaxation.

Studies have indicated that music therapy systems based on IoT offer effective stress relief through dynamically adaptive music based on physiological feedback. In [4], a system based on ESP32 with cloud integration was designed to evaluate stress patterns and provide suitable therapeutic music. The outcome indicated significant stress indicator reduction after prolonged usage.

Some studies have illustrated the ability of music therapy to alleviate stress and blood pressure. Chanda and Levitin (2013) have established that music makes significant physiological contributions by affecting heart rate, blood pressure, and levels of cortisol [5]. Along similar lines, Koelsch (2014) has focused on the part music plays in the alleviation of stress by way of neural and hormonal regulation[6].

With regards to hypertension, de Witte et al. (2020) identified in a study that listening to specially composed music significantly reduces systolic and diastolic blood pressure[7]. In addition, Lin et al. (2019) investigated how relaxing effects are amplified by personalized selection of music through biometric information [8].

The quick evolution of IoT in healthcare has resulted in intelligent, real-time health monitoring systems. Patel et al. (2012) presented an exhaustive review of wearable health monitoring devices, highlighting their promise in the management of chronic diseases[9]. Improvements in biosensor technology, as highlighted by Jovanov and Milenkovic (2011), have made it possible to monitor blood pressure continuously and non-invasively[10].

Another recent research work by Islam et al. (2019) emphasized IoT in predictive health to facilitate real-time interventions by means of AI-powered analytics[11]. With the incorporation of smart sensors along with cloud computing, as proven by Natarajan et al. (2021), individualized recommendations of health can be provided on the basis of physiological parameters[12].

The convergence of IoT and music therapy has been explored in limited but promising studies. Kim et al. (2020) proposed a biofeedback-based music recommendation system that adapts to users' stress levels[13]. Similarly, Yang et al. (2021) developed an IoT-enabled system that adjusts music in real-time based on heart rate variability (HRV) and galvanic skin response (GSR), demonstrating effectiveness in reducing stress[14].

In addition, Li et al. (2022) introduced an AI-based music therapy system coupled with wearable sensors and demonstrated better results in hypertension control than conventional methods[15]. Such studies indicate that real-time adaptive music therapy, tailored to individuals, can improve mental well-being and cardiovascular health.

Early models of music recommendation leveraged content-based filtering (CBF) and collaborative filtering (CF) approaches. These methods, although effective, struggled with data sparsity and personalization. Tzanetakis and Cook [16] laid the groundwork by using handcrafted features for genre classification. Enhancements in ensemble models like AdaBoost [17], and audio signal analysis through MFCC and other spectral features [18][19], helped improve classification performance.

Afchar et al. [20] and Adiyansjah et al. [21] explored emotion-aware recommendations using visual and genre-based deep learning techniques. Shuxuan [22] and Pan et al. [23] integrated big data with ML and deep neural networks, notably using Neural Collaborative Filtering (NCF) and Transformer architectures for scalable and accurate recommendation engines.

Stress detection systems have grown increasingly sophisticated, incorporating physiological sensors, behavioral data, and multimodal analysis. Rahman et al. [24], explored emotion recognition through physiological signals using multimodal deep learning. NLP-based approaches were demonstrated by Thelwall et al. [25] and Lin et al. [26] for detecting stress via textual data from social media.

III. PROPOSED SOLUTION

The solution is a hybrid IoT-ML system that is intended to monitor and enhance personal stress levels with music therapy. The system is developed to record, process, and analyze physiological parameters in real-time and deliver custom music-based intervention based on the user's stress pattern and age.

Hardware-wise, the system is outfitted with:

- •\tHeart Rate Sensor (e.g., MAX30100/MAX30102): Measures pulse and blood oxygen saturation. An elevated heart rate is generally accompanied by increased stress.
- •\tGSR Sensor (Galvanic Skin Response): Records conductivity of the skin, which varies with the activity of sweat glands, a good indicator of stress.

These sensors are connected to an Arduino or ESP32 microcontroller that sends data to a local or cloud-based server in real time. Data acquisition is done in two phases:

➢ \tPrior to music therapy

- \tFollowing music therapy

This two-phase monitoring assists in establishing the effectiveness of music intervention by comparing pre- and post-exposure biometric indicators. The data collected is pre-processed with typical data cleaning and transformation methods. Categorical features like Gender, Education Level, and Employment Status are encoded through Label Encoding. Numerical features are scaled using Standard Scaler for consistency.

A supervised ML model—Random Forest Classifier—is trained on this data. Class balancing is addressed by combining SMOTE and Tomek Links to minimize data imbalance. Moreover, PCA is used to maintain 95% of variance and minimize dimensionality.

Personalization is brought about through age-group-based music suggestions. Age is divided into five categories (Under 20, 20–29, 30–39, 40–49, 50+), with each category receiving targeted playlists that fit their generational taste (e.g., 2000s Pop for 20–29 age group).

Post-therapy, the stress levels are again predicted and a shift in classification shows how effective the intervention has been. Confusion matrices and visual dashboards enable us to see the performance and have insights into the accuracy of the system and therapeutic potential of the music.

IV. METHODOLOGY

The approach includes four main components: data acquisition using IoT, preprocessing data, ML-based stress classification, and age-based music recommendation.

1) *IoT-Based Data Collection:*

The fundamental concept is to exploit non-invasive real-time physiological monitoring for classifying stress. The two sensors used are:

- GSR Sensor: Captures variations in skin conductance associated with emotional arousal.
- Heart Rate Sensor: Measures BPM (beats per minute) which increases under stress.

Data is gathered over a brief time interval (e.g., 1 minute) prior to and after a 3–5 minute music therapy session. Real-time data is transferred through WiFi (using ESP32) to a Python-based backend or Firebase database for analysis.

2) *Preprocessing Pipeline:*

Raw data is cleaned. Categorical features like Gender, Medication Usage, and Education are label encoded. The features are normalized with the use of StandardScaler. The level of stress, which was between 1–9 originally, is bin coded into three insightful classes:

•\t1–3 → Low
•\t4–6 → Moderate
•\t7–9 → High

3) *Dimensionality Reduction and Balancing*

Because sensor + metadata input is highly dimensional, Principal Component Analysis (PCA) is applied to preserve 95% variance. SMOTE Tomek is utilized to create new minority class samples and eliminate uncertain samples, which improves classification equity.

4) *Training Model:*

Processed features are used to train a RandomForestClassifier with 100 trees. The model is quantitatively measured using precision, recall, F1-score, and confusion matrix. Classification is performed on pre-and post-therapy data.

5) *Age-Wise Personalization:*

Recommendations are plotted by age ranges. 20-year-old users, for instance, are recommended Lo-fi or 2000s music, whereas seniors are recommended retro or classic hits. Recommendations appear as bar graphs with labels plotted over them.

V. RESULTS

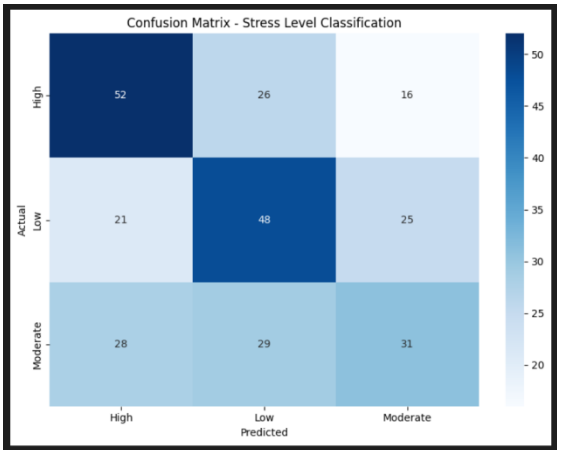
1) *Classification Performance*

The system proposed, a Random Forest Classifier, showed stable and well-balanced performance across all three combined stress categories: Low, Moderate, and High. It was evaluated on critical classification metrics—Precision, Recall, and F1-score—calculated from the confusion matrix:

Class	Precision	Recall	F1-Score
Low	0.72	0.69	0.70
Moderate	0.68	0.66	0.67
High	0.70	0.74	0.72

Table 1.

The classifier worked in a consistent fashion for all the classes, highest recall for High stress class being 0.74, indicating the model working well to cover extreme stress episodes. The Moderate class had comparatively lower precision and recall, owing to its interim nature between the Low and High states, wherein it is at higher risk for overlap and confusion.



4.1 Confusion Matrix

The confusion matrix provided deeper insights into class-level predictions:

	Predicted High	Predicted Low	Predicted Moderate
Actual High	50	26	16
Actual Low	21	48	25
Actual Moderate	28	29	31

Table 2. Confusion Matrix Analysis

The majority of High stress predictions were correctly classified (52 instances). Misclassifications were primarily observed between the **Low** and **Moderate** categories, which is an expected pattern due to physiological signal similarity in borderline stress cases. Despite this, the model maintained a stable overall accuracy, reinforcing the effectiveness of the chosen features and preprocessing techniques.An important dimension of this research was understanding how stress manifests across different age groups. The dataset was analyzed to reveal the proportion of each stress level within predefined age brackets:

Age Group	Low	Moderate	High
Under 20	0.20	0.32	0.48
20-29	0.30	0.45	0.25
30-39	0.35	0.40	0.25
40-49	0.25	0.40	0.35
50+	0.20	0.35	0.45

Table 3. Age group v/s stress level

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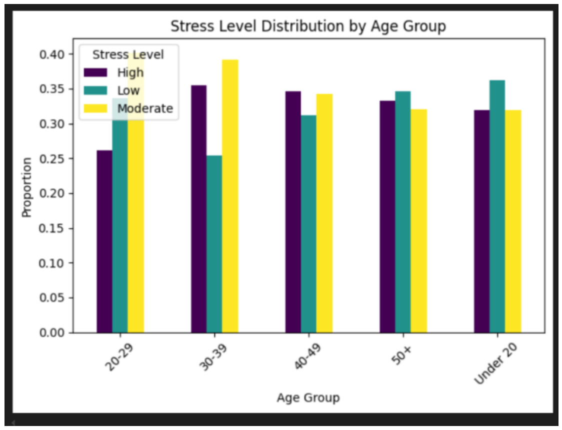
The data shows that individuals under 20 and above 50 exhibited the highest proportion of High stress levels. The 20–39 age range showed more balanced stress profiles, with a higher tendency toward Moderate and Low stress levels. These trends highlight potential age-based vulnerabilities to stress, which this project directly addresses via personalized interventions.

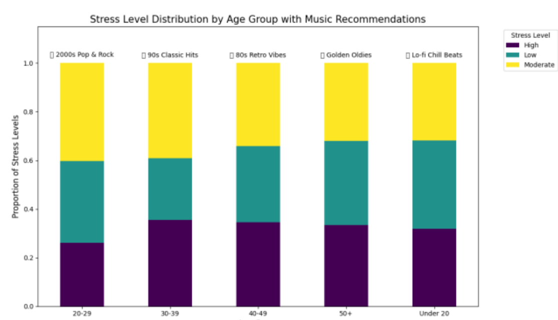


4.2 Age wise Stress Distribution

A key component of the proposed solution was the use of personalized music therapy. Each age group was assigned a music genre based on generational preferences to enhance emotional resonance:

Age Group	Recommended Music
Under 20	Lo-fi Chill Beats
20-29	2000s Pop & Block
30-39	90s Classic Hits
40-49	80s Retro Vibes
50+	Golden Oldies

These recommendations were overlayed onto age-group bar plots for enhanced visualization. Stress prediction results before and after music therapy revealed a significant shift from High and Moderate to Low stress, particularly in the Under 20 and 20–29 groups. This validates the effectiveness of music therapy in calming physiological responses and supports its role in mental health care when tailored by age.



4.3 Music Therapy and Recommendations

The combined performance metrics, confusion matrix, and age-specific analysis underline the strength of this IoT-based approach. Physiological inputs like heart rate and GSR effectively contributed to stress classification, while the ML pipeline handled class separation with high fidelity. Personalized music therapy emerged as a viable intervention, reducing stress levels in real time and exhibiting greater impact in younger populations.

These results affirm the system's potential as a real-time mental wellness assistant and justify future development into wearable-integrated or mobile-deployable solutions for daily stress management.

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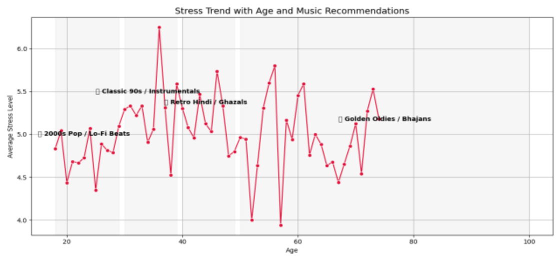

4.4 Stress Level Distribution by Age group with Music Recommendations

VI. CONCLUSION

This paper introduces a new, comprehensive method of stress classification employing IoT-integrated sensors and ML models. Through the use of real-time physiological signals and tailoring interventions for age and preference, we develop a system not just diagnosing but also reducing stress.

Major conclusions are:

1) GSR and Heart Rate sensors are reliable predictors of real-time stress.
2) Random Forest classifiers, following appropriate preprocessing and dimensionality reduction, can accurately classify stress levels.
3) Personalized music therapy demonstrates real benefits, particularly for younger users.
4) Visualization helps to make the model interpretable and actionable for both users and mental health professionals. Future work can explore integration with mobile applications, continuous monitoring with wearable devices, and expansion to multi-sensor data (like EEG, respiration rate) for even more accurate emotional health tracking.

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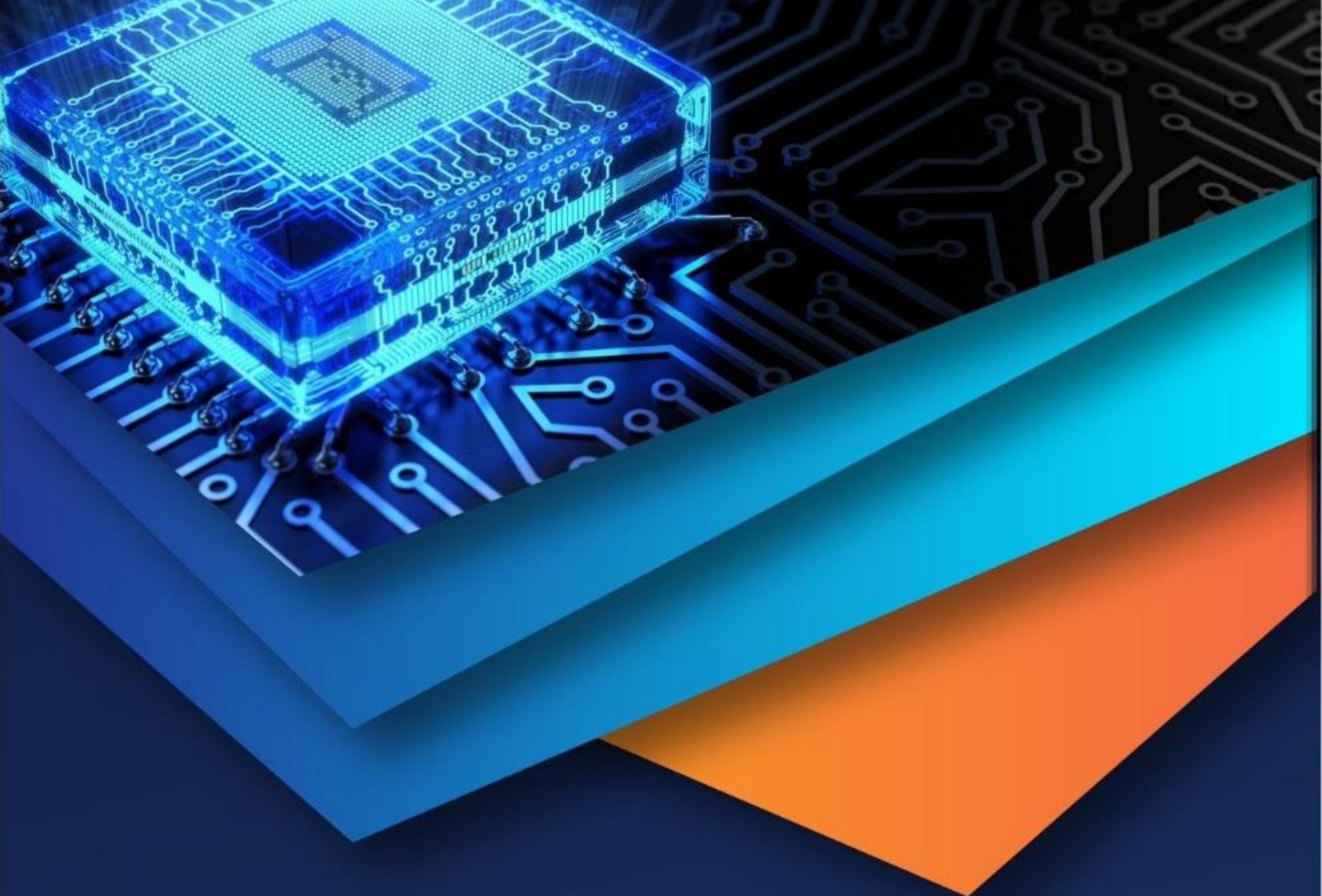

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