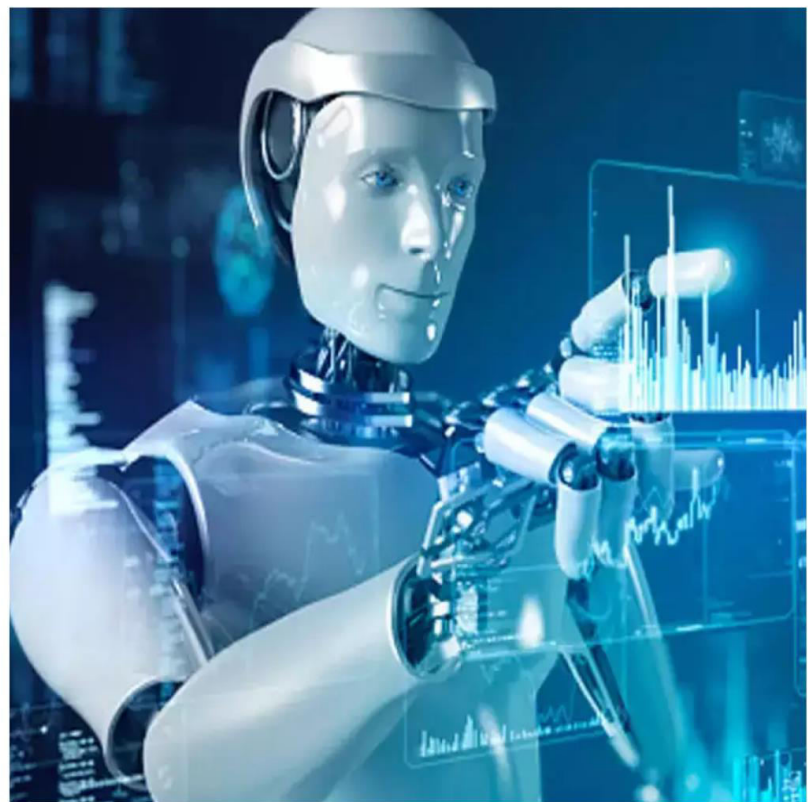




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An IOT-Based Machine Learning System for Real-Time Stress Level Prediction Using Wearable Sensors

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ABSTRACT: An evolution of the Internet of Things (IoT) and machine learning incorporation paves the crucial development in health care industry, especially for controlling physiological factors like stress level. A Stress-Track, an innovative technology is proposed in this research. In this model, stress is identified by examining the body temperature, sweat and motion data which is tracked from the wearable devices. In order to enhance the prediction accuracy, the machine learning classifiers, including Decision Tree, Gradient Boosting, Support Vector Machine (SVM), K-nearest neighbors (KNN), and Voting classifiers are combined and applied in this system. As a result of the model analysis, it is clearly shown that Gradient Boosting performs better than the other models by achieving overall accuracy of 91% where KNN also performs well with achieving accuracy of 90%. This model offers an immediate solution for stress control with budget constrained which leads to the development of smart healthcare industry by utilizing the preventive data about the individual stress levels. But data privacy and security issues still need to resolve to obtain the overall system optimization in health care.

I. INTRODUCTION

The Internet of Things (IoT) refers to a network of physical devices, vehicles, appliances, and other physical objects that are embedded with sensors, software, and network connectivity, allowing them to collect and share data.

IoT devices—also known as “smart objects”—can range from simple “smart home” devices like smart thermostats, to wearables like smartwatches and RFID-enabled clothing, to complex industrial machinery and transportation systems. Technologists are even envisioning entire “smart cities” predicated on IoT technologies.

IoT enables these smart devices to communicate with each other and with other internet-enabled devices. Like smartphones and gateways, creating a vast network of interconnected devices that can exchange data and perform various tasks autonomously. This can include:

- Monitoring environmental conditions in farms
- Managing traffic patterns with smart cars and other smart automotive devices
- Controlling machines and processes in factories
- Tracking inventory and shipments in warehouses

The potential applications of IoT are vast and varied, and its impact is already being felt across a wide range of industries, including manufacturing, transportation, healthcare, and agriculture. As the number of internet-connected devices continues to grow, IoT is likely to play an increasingly important role in shaping our world. Transforming the way that we live, work, and interact with each other.

In an enterprise context, IoT devices are used to monitor a wide range of parameters such as temperature, humidity, air quality, energy consumption, and machine performance.

This data can be analyzed in real time to identify patterns, trends, and anomalies that can help businesses optimize their operations and improve their bottom line.

II. RISKS AND CHALLENGES IN IOT

IoT offers many benefits, but it also poses several risks and challenges. Here are some of the most significant ones:

Security and privacy risks:

As IoT devices become more widespread, security and privacy become increasingly important. Many IoT devices are vulnerable to hackers and other cyber threats, which can compromise the security and privacy of sensitive data. IoT devices can also collect vast amounts of personal data, raising concerns about privacy and data protection.

Interoperability issues:

IoT devices from different manufacturers often use different standards and protocols, making it difficult for them to perform what's called "machine to machine" communication. This can lead to interoperability issues and create silos of data that are difficult to integrate and analyze.

Data overload:

IoT devices generate vast amounts of data, which can overwhelm businesses that are not prepared to handle it. Analyzing this data and extracting meaningful insights can be a significant challenge, especially for businesses that lack the necessary analytics tools and expertise.

Cost and complexity:

Implementing an IoT system can be costly and complex, requiring significant investments in hardware, software, and infrastructure. Managing and maintaining an IoT system can also be challenging, requiring specialized skills and expertise.

Regulatory and legal challenges:

As IoT devices become more widespread, regulatory, and legal challenges are emerging. Businesses need to comply with various data protection, privacy and cybersecurity regulations, which can vary from country to country.

Problem statement

Explain the growing concern over stress-related health conditions. Highlight the importance of early detection and continuous monitoring.

- Discuss how IoT can enable continuous, real-time health monitoring, offering a non-invasive way to track stress levels.

Stress Monitoring Parameters:

Physiological Indicators: Identify which parameters are important for stress detection:

- Heart Rate Variability (HRV)
- Galvanic Skin Response (GSR)
- Skin Temperature
- Blood Pressure
- Cortisol levels

- Wearable Sensors: List the types of sensors and devices (like smartwatches or fitness bands) that can capture these indicators.

Research Contribution and motivation

Highlight the significance of real-time health monitoring, especially for chronic diseases such as diabetes, hypertension, heart disease, etc.

IoT and Machine Learning? Discuss how IoT enables continuous monitoring and how machine learning can analyze this data to predict health conditions or detect abnormalities.

III. PROPOSED METHODOLOGY

Machine Learning Algorithms for Health Monitoring:

Supervised Learning:

- Classification Algorithms: Introduce the machine learning models suitable for health condition classification, such as:
 - Logistic Regression for binary classification (e.g., healthy vs. unhealthy).
 - Decision Trees or Random Forests for multi-class classification (e.g., different stages of heart disease).
 - Support Vector Machine (SVM) for separating health conditions with clear boundaries.

Unsupervised Learning:

- Clustering Algorithms: For anomaly detection or patient segmentation using K Means or DBSCAN, detecting outliers or unusual patterns in health data.

Deep Learning Models:

- Convolutional Neural Networks (CNNs): Particularly useful for medical image classification (e.g., detecting pneumonia in X-rays).
- Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM): To track time-series data like heart rate and detect irregularities over time.

Model Training and Evaluation:

Training Models: Discuss the process of training classification models on labeled datasets.

Evaluation Metrics:

- Accuracy, Precision, Recall, and F1 Score to evaluate classification models.
- ROC-AUC for binary classifiers.
- Confusion Matrix to visualize the performance of multi-class models.
- Cross-Validation: Techniques to validate model performance and avoid overfitting (e.g., k-fold cross-validation).

Data collection:

The system collects the live physiological data using three types of sensors with offering a comprehensive physical condition.

- **Temperature sensor:** This sensor continuously tracks the user's body temperature. Due to increased circulation or sweating, there will be slight modifications in body temperature result in stress. This temporal information is a major factor of stress and for tracking continuously.
- **Humidity Sensor:** Stress always simulates perspiration. Skin moisture levels are tracked by humidity sensors which has a direct connection to physical and emotional stress. A physiological impact of stress is related with skin moisture content level which is tracked by tis sensor.
- **Physical Activity Sensor:** This sensor is used to track motions and bodily instant restless or rapid motions especially during physical workout. This sensors movements. A stress can be indicated by any changes in physical activity such as evaluate the attributes like acceleration, movement frequency, and physical exertion.

The data from these three sensors are continuously recorded and saved in the dataset for further processing. This dataset specifies the individual's physical state in real time and it serves as the basic of the entire system.

Training and Testing:

Once the dataset is selected to the most related features, it is divided into training and testing set.

- **Training Set:** Training set consists of specific dataset which is used to train the machine learning classifiers. Each classifier acquire the knowledge of the data patterns. Based on these patterns, the predictive model is developed.
- **Testing Set:** Once the training is completed, the models are tested on various training set to analyze their generalization capacities. By using this process, it makes a promising nature of that the model can predict the stress on unknown data effectively without overfitting to the training data.

Proposed Ensemble Classifier:

An ensemble learning approach is the foundation of the system. Ensemble learning algorithm is that it combines the various ML algorithm's predictions to generate a more precise and robust prediction results. The following classifiers utilized in this system are:

Decision Tree: This model is tree like structure of having decisions and their possible outcomes which is beneficial for managing classified data and offering accessibility.

Gradient Boosting: A boosting method focuses mainly on difficult cases to improve the accuracy and compiles

various weak learners to develop an efficient predictive model.

Support Vector Machine (SVM): An efficient classifier is specially used for binary classification issues like stress identification (stress/no-stress) and determining the optimal hyperplane in high-dimensional area to distinguish the classes.

K-Nearest Neighbors (KNN): A simple and efficient method which classifies the new cases based on the majority label of their feature space's closest neighbors.

Voting Classifier: This method offers a more accurate and robust stress predictions by combining the predictions of all classifiers (Decision Tree, Gradient Boosting, SVM, and KNN) and accounting for a majority vote.

An ensemble classifier enhance the accuracy by utilizing the potentials of the every models. For instance, the gradient boosting and SVM can acquire more sophisticated data patterns while the decision tree may be more accessible.

Stress Level Prediction:

After the training and testing of ensemble model is completed, begin with deployment to predict the stress levels in real time basis. The model offers the prediction result that the whether the user is under stress and its levels based on the input data from the wearable devices. This prediction output is depend upon the physical attributes and strengthened through decision making method of ensemble classifier.

Results Validation:

In order to evaluate the system performance, the model's prediction results are finally validated on real time data. The validation comprises the following metrics are

- **Accuracy:** Evaluates the ratio of correct predictions (stress Vs. no stress).
- **Precision and Recall:** Calculate the potential of the model to detect the correct stress cases with mitigates the fake positives.
- **F1-Score:** It offers a balanced values of precision and recall, particularly used for unstable datasets.
- **Confusion Matrix:** It facilitates the performance of the model being visualized among various prediction classes (stress Vs no-stress)

From these validation process ensures that model is achieving more accurate of 99.5% and reliable in predicting stress levels in real time cases.

This framework establishes an efficiency of IoT and Machine learning incorporation for preventive stress management. This system offers a highly accurate and a real time stress level prediction by integrating the real time data collection, complex feature extraction, and a strong ensemble learning approach. This system is constructed with a beneficial tool for the medical professionals or individuals who can track and manage the stress and enhancing both physiological and mental health conditions.

IV. EXPERIMENTAL RESULTS

Accuracy: The accuracy is evaluated on the proportions of number of correct results with overall results. It usually starts with image extraction and then the extracted data is compared with total dataset by using the following expressions. The accuracy percentage is calculated based on two prime factors are data quality and errors.

$$\text{Accuracy} = \frac{(TN+TP)}{(TN+TP+FN+FP)} \quad (1)$$

Where TN-True Negative, TP-True Positive, FP-False positive, and FN-False Negative.

Sensitivity : The sensitivity is evaluated from the true positive values and the false negative values.

The true positive and false negativity is evaluated by measuring the count added to the true positive. The observation offers the amount of positive values and the outcome provides the sensitivity. The sensitivity is calculated in percentage (%) and is measured by the following mathematical expression.

$$\text{Sensitivity} = \frac{TP}{(TP+FN)} \quad (2)$$

Specificity : Specificity is declared as the outcome of proposed model implementation. Specificity is determined based on the prediction effects and the alterations from the original datasets.

They properly received the negative values which determine the specificity and measured in percentage(%).It is calculated based on the total amount of negative outcomes to the summation of true negative and false positive values.

It is expressed in mathematical format as follows

$$\text{Specificity} = \text{TN}/(\text{TN}+\text{FP}) \quad (3)$$

Table 1 Precision

Target	Decision Tree	Gradient Boosting	Support Vector Machine	k-nearest neighbors	Voting
0	0.88	0.86	0.85	0.93	0.83
1	0.92	0.94	0.97	0.87	0.94
2	0.86	0.93	0.87	0.89	0.89

In table 1, a comparative analysis of performance of five machine learning classifiers like Decision Tree, Gradient Boosting, Support Vector Machine (SVM), K-nearest neighbors (KNN), and Voting Classifier among three various target classes (0,1,2). KNN achieves the highest accuracy (0.93) for target 0 where the SVM performs better than other models with an accuracy of 0.97 for target 1. And for target 2, the gradient boosting achieves an highest accuracy of 0.93 which shows that one of the most robust model as whole. The Voting classifier reaches the more balanced consistent accuracy among all targets.

Table 2 Recall

Target	Decision Tree	Gradient Boosting	Support Vector Machine	k-nearest neighbors	Voting
0	0.91	0.92	0.92	0.91	0.91
1	0.90	0.87	0.86	0.87	0.84
2	0.86	0.95	0.90	0.92	0.90

Table 2, describes the comparison of performance of five ML classifiers which are Decision Tree, Gradient Boosting, Support Vector Machine (SVM), K-nearest neighbors (KNN), and Voting Classifier among three target categories (0,1 and 2).For target 0, Gradient Boosting and SVM achieves an recall value of 0.92.For target 1, Decision Tree performs

better with an recall of 0.90. For target 2, Gradient Boosting achieves highest recall of 0.95 which shows that the most efficient classifier in this category. The Voting Classifier remains consistent value but lower value compared to other models.

Table 3 F1 Score

Target	Decision Tree	Gradient Boosting	Support Vector Machine	k-nearest neighbors	Voting
0	0.89	0.89	0.88	0.92	0.86
1	0.91	0.91	0.91	0.87	0.89
2	0.86	0.94	0.89	0.91	0.90

In table 3, compares the F1 score value of five machine learning models like Decision Tree, Gradient Boosting, Support Vector Machine (SVM), K-nearest neighbors (KNN), and Voting Classifier across three target categories (0, 1, and 2). For target 0, KNN achieves a F1 score of 0.92. For target 1, Decision Tree, Gradient Boosting, and SVM all achieves a F1 score of 0.91. For target 2, Gradient Boosting acquires a F1 score of 0.94 making it the most efficient model in that classes. Voting Classifier remains stable but reaching lower performance among all other targets.

The overall accuracy of five machine learning classifiers is denoted in Table 4. Gradient Boosting outperforms than other models with an accuracy of 0.91 while K-nearest neighbors (KNN) reaches with 0.90. Both Decision Tree and Support Vector Machine (SVM) achieves an equal accuracy of 0.89. This outcomes shows that each model yield best result but Gradient Boosting is considered as the most reliable stress prediction method under these particular circumstances.

Table 4 Accuracy classifier

Classifier	Accuracy
Decision Tree	0.89
Gradient Boosting	0.91
Support Vector Machine	0.89
k-nearest neighbors	0.90
Voting	0.88

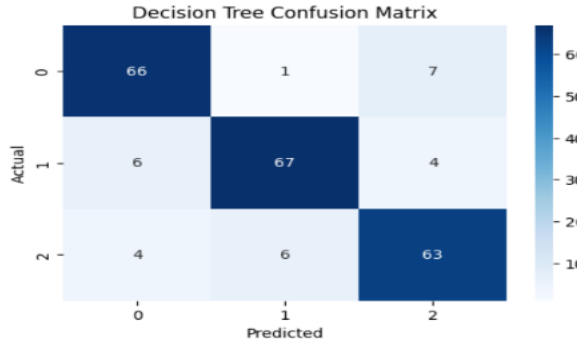


Figure 3 (a) Decision tree

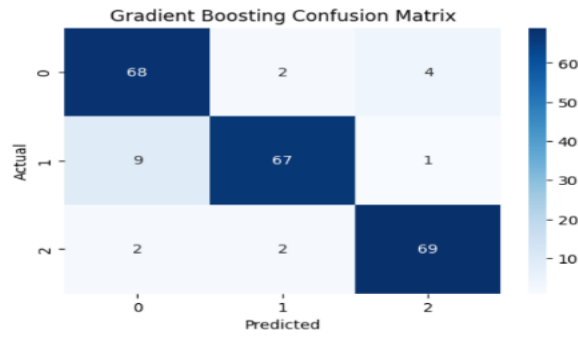


Figure 3 (b) Gradient boosting

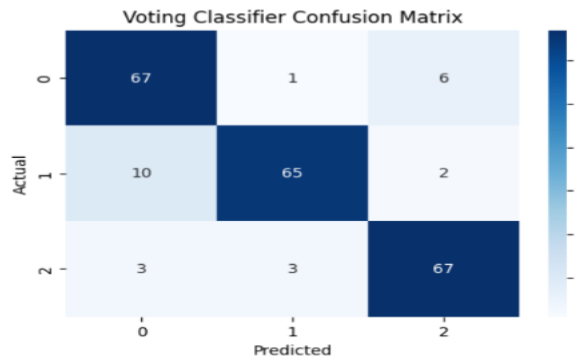


Figure 3 (c) Voting

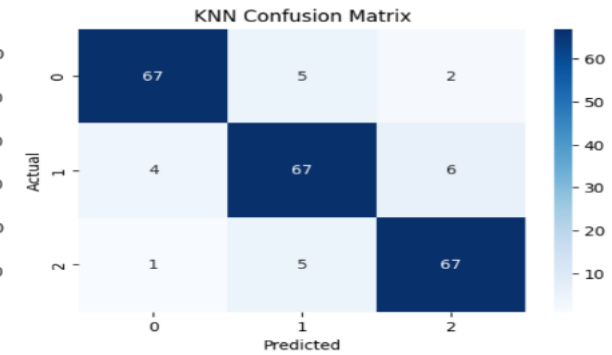


Figure 3 (d) KNN

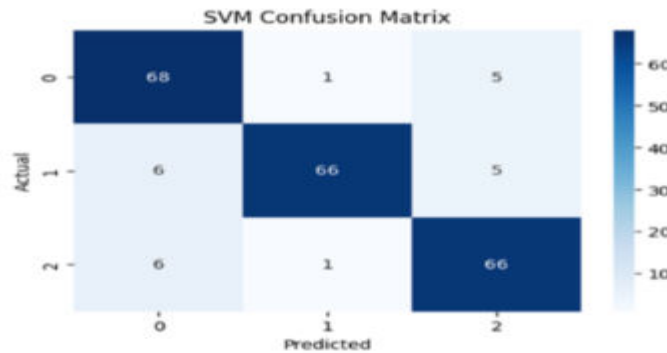


Figure 3 (e) SV

V. CONCLUSION

In this research, Stress-Track, a machine learning-based system is proposed which utilizes IoT and wearable devices to predict the stress levels through physical insights. A comparative study performed between various five classifiers like Decision Tree, Gradient Boosting, SVM, KNN, and Voting. This comparison results shows that gradient boosting is the most effective method with an accuracy of 91% where KNN reaches next to it. The ensemble approach is utilized in this system to predict accurate and reliable predictions which offers the real time stress monitoring in health care system. This system provides a most reliable stress prediction. However the further research is required to address the data anonymity and security, especially in vulnerable health conditions. This system's advancement has the ability to transform the stress management by offering accessible insights to the medical professionals and individuals for optimizing the overall health condition.

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