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Machine Learning Adopted Human Activity Classification Using Shimmer Wearable Sensors For Health Monitoring

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ABSTRACT

Human activity classification plays a vital role in health monitoring systems, enabling the accurate identification and analysis of physical activities through wearable sensor data. This study focuses on developing a robust machine learning framework for human activity classification using Shimmer wearable sensors. The existing system employs Gradient Boosting (GB) Classifier, providing a baseline for evaluating classification accuracy. To enhance performance, the proposed approach utilizes the Extreme Gradient Boosting (XGB) Classifier, known for its efficiency and superior predictive capabilities. Comprehensive Exploratory Data Analysis (EDA) is conducted to assess data quality, distribution, and feature significance, facilitating optimal model development. Performance metrics including accuracy, precision, recall, and F1-score are analyzed to compare the effectiveness of both classifiers. The proposed XGB Classifier demonstrates improved accuracy and generalization capability over the existing GB Classifier, making it a promising solution for real-time health monitoring applications. Furthermore, the integration of advanced machine learning techniques enhances the reliability of activity classification, paving the way for improved patient monitoring and personalized healthcare. The study's findings indicate the potential for deploying wearable sensor-based monitoring systems in diverse healthcare environments. This research contributes to the ongoing efforts of leveraging AI for enhancing health monitoring systems through effective activity classification. Future work may involve exploring hybrid models and feature engineering to further optimize classification performance.

Keywords: Human Activity Classification, Wearable Sensors, Shimmer Sensors, Health Monitoring, Sensor-based Monitoring Systems.

1. INTRODUCTION

Human activity classification is an essential component of health monitoring systems, enabling the assessment and tracking of daily activities for various health-related applications. With the advent of wearable technology, sensors have become increasingly integrated into everyday life, providing continuous and unobtrusive monitoring of physical activities. One such advanced wearable sensor system is SHIMMER (Sensing Health with Intelligence, Modularity, Mobility, and Experimental Reusability), which has shown significant promise in accurately capturing and classifying human movements. These wearable sensors offer a wealth of data that, when harnessed effectively through machine learning techniques, can lead to substantial improvements in health monitoring and management.

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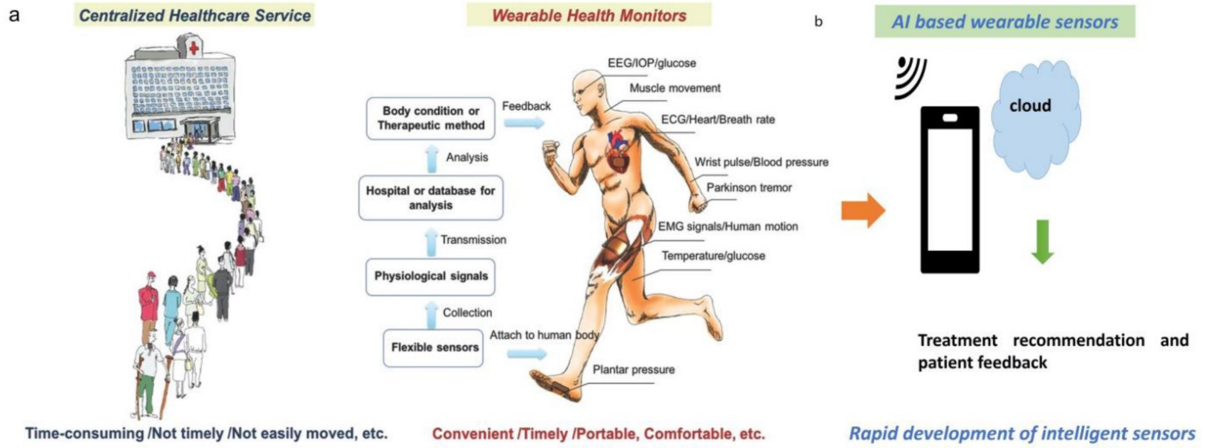

Fig 1: Shimmer wearable sensors for digital technology

The prevalence of chronic diseases, the aging population, and the need for proactive health management have driven the demand for robust activity classification systems. Traditional methods of activity monitoring often rely on subjective self-reporting or stationary devices that limit mobility and real-time analysis. In contrast, wearable sensors provide a more dynamic and accurate representation of an individual's activities, capturing nuances in movement that are critical for precise health monitoring. Recent advancements in machine learning have further enhanced the capabilities of these wearable systems, allowing for more sophisticated analysis and classification of human activities. By leveraging the continuous data stream from SHIMMER sensors, machine learning models can identify and categorize various activities such as walking, running, sitting, and sleeping, among others. This technology holds significant potential not only for individual health monitoring but also for broader applications in rehabilitation, elderly care, and chronic disease management.

2. LITERATURE SURVEY

J. Hayano et al. [1] examined the use of wearable technology to detect sleep apnea with a watch device. Their study, published in PLoS ONE in 2020, presented a quantitative approach to monitor and analyze sleep patterns through wearable sensors. They employed advanced algorithms to detect apnea events by analyzing physiological signals collected from the device. This approach offers a non-invasive method to improve sleep disorder diagnosis and management. The study highlights the potential of wearable technology in sleep medicine, emphasizing its ability to provide continuous monitoring outside of clinical settings. The research shows how wearable sensors can enhance patient care by offering real-time insights into sleep patterns and apnea events, thus paving the way for better management strategies. F. Delmastro et al. [2] explored cognitive training and stress detection in frail older individuals using wearable sensors and machine learning. Their 2020 study in IEEE Access demonstrated how machine learning algorithms could analyze data from wearable devices to assess cognitive function and stress levels. The study integrated cognitive training with stress monitoring to offer personalized interventions for elderly patients. By utilizing data from wearable sensors, the research provides insights into managing cognitive decline and stress in older populations. This approach could lead to improved quality of life for elderly individuals through tailored cognitive and stress management strategies. The findings highlight the effectiveness of combining technology with healthcare interventions to address age-related challenges. M.V. Perez et al. [3] conducted a large-scale assessment of smartwatch technology to identify atrial fibrillation. Published in the New England Journal of Medicine in 2019, their research evaluated the efficacy of smartwatches in detecting irregular heart rhythms. The study analyzed data from a large cohort, showing that smartwatches could accurately identify atrial fibrillation. This capability has the potential to reduce the need for invasive diagnostic procedures. The findings emphasize the role of wearable technology in early cardiovascular disease detection and its ability to enhance patient monitoring. By demonstrating the effectiveness of smartwatches in identifying arrhythmias, the research supports the integration of wearable technology into cardiovascular care. J.S. Chorba et al. [4] developed a deep learning algorithm for automated cardiac murmur detection using a digital stethoscope platform. Their 2021 study in the Journal of American Heart Associationintroduced a novel approach for analyzing heart sounds to identify cardiac murmurs. Utilizing deep learning techniques, the study achieved high accuracy in detecting murmurs, which could improve the diagnostic process in cardiology. This research highlights the potential of artificial intelligence to enhance the accuracy and efficiency of cardiac assessments. The integration of deep learning with medical devices represents a significant advancement in cardiology, offering more precise and timely diagnostics. S. Seneviratne et al. [5] reviewed wearable devices and their associated challenges in their 2017 study published in IEEE Communications Surveys & Tutorials. The survey provided a comprehensive overview of various wearable technologies, addressing challenges such as battery life, data accuracy, and user acceptance. The review emphasized the advancements in wearable technology and the need for continued innovation to overcome existing limitations. This study offers valuable insights into the state of wearable devices in healthcare and identifies future research directions. By highlighting both the progress and the challenges faced by wearable technology, the research underscores the importance of ongoing development in this field.

M. Chan et al. [6] discussed the current status and future challenges of smart wearable systems in their 2012 article in Artificial Intelligence in Medicine. Their study highlighted advancements in wearable technology, including improvements in sensor accuracy and data analysis capabilities. The paper addressed challenges such as data integration, user privacy, and system reliability. By providing a critical assessment of the progress made in smart wearable systems, the research identifies areas for future research to enhance effectiveness in healthcare applications. The study underscores the need for addressing challenges to maximize the benefits of wearable technology in medical settings. P. Siirtola et al. [7] investigated the use of sleep time data from wearable sensors for early detection of migraine attacks. Their 2018 study in Sensors demonstrated that analyzing sleep patterns with wearable devices could help predict the onset of migraines. The research highlighted the potential of wearable technology to offer early warnings and personalized interventions for migraine sufferers. By leveraging sleep data, the study underscores the role of wearable sensors in managing chronic conditions and improving patient outcomes through proactive monitoring. This approach could lead to more effective management strategies for individuals suffering from migraines. C. Meisel et al. [8] explored machine learning techniques for wearable, noninvasive seizure forecasting using wristband sensor data. Published in Epilepsia in 2020, their study focused on predicting seizures based on data collected from wearable devices. The research demonstrated that machine learning models could effectively forecast seizures, potentially enhancing patient safety and reducing emergency interventions. The study highlights the potential of wearable technology in managing epilepsy and improving the quality of life for patients. By utilizing machine learning for seizure prediction, the research offers a promising approach to epilepsy management and patient care. A.Y. Hannun et al. [9] investigated cardiovascular arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network. Their 2019 study in Nature Medicine introduced a deep learning approach for analyzing ECG data to detect arrhythmias. The research showed that the neural network model could accurately classify various types of arrhythmias, offering a promising tool for remote cardiac monitoring. The study emphasizes the role of artificial intelligence in advancing cardiac care and improving diagnostic accuracy. By integrating deep learning with ECG analysis, the research provides a significant advancement in remote cardiovascular monitoring. S. Kwon et al. [10] evaluated the use of a ring-type wearable device for detecting atrial fibrillation through deep learning analysis of photoplethysmography signals. Their study, published in J Med Internet Res in 2020, provided proof-of-concept for using wearable technology to monitor heart rhythms. The research demonstrated the potential of combining wearable devices with advanced data analysis techniques to improve the detection of atrial fibrillation. The findings support the use of innovative wearable solutions in cardiovascular health management. By showcasing the effectiveness of ring-type devices, the study contributes to the development of advanced wearable health technologies.

Z. Mei et al. [11] proposed an automatic atrial fibrillation detection method based on heart rate variability and spectral features. Their 2018 study in IEEE Access highlighted a method that leverages heart rate data to identify atrial fibrillation episodes. The study illustrated the effectiveness of combining heart rate variability analysis with spectral features to enhance detection accuracy. This research contributes to the development of reliable methods for monitoring and diagnosing cardiovascular conditions using wearable technology. By integrating advanced analytical techniques, the study offers a valuable approach to improving atrial fibrillation detection. N. Rashid and M.A. Al Faruque [12] focused on energy-efficient real-time myocardial infarction detection on wearable devices. Their 2020 study presented at the IEEE Engineering in Medicine and Biology Society Conference highlighted methods for optimizing wearable devices to detect myocardial infarction with minimal energy consumption. The research demonstrated advancements in wearable technology aimed at improving real-time monitoring capabilities while addressing power efficiency. This study underscores the importance of integrating energy efficiency in the design of wearable health monitoring devices. By focusing on power consumption, the research contributes to the development of more sustainable and effective wearable technologies.

R. Buettner et al. [13] presented a high-performance detection method for epilepsy in seizure-free EEG recordings at the International Conference on Information Systems in 2019. The study introduced techniques for analyzing EEG data to detect epilepsy-related anomalies without the presence of seizures. The research highlighted the potential of advanced EEG analysis methods to enhance the detection of epilepsy and provide valuable insights into brain activity patterns. By developing high-performance detection methods, the study contributes to improving epilepsy diagnosis and management through sophisticated EEG analysis techniques. C. Ieracitano et al. [14] developed a multi-modal machine learning approach for automatic classification of EEG recordings in dementia. Published in 2020, their study focused on combining multiple data modalities to improve the classification of EEG recordings in dementia patients. The research demonstrated the effectiveness of multi-modal machine learning techniques in enhancing the accuracy of dementia diagnosis and management. By integrating various data sources, the study offers a comprehensive approach to improving diagnostic accuracy in dementia care. S. Hwang et al. [15] investigated the use of wearable EEG technology to measure workers' emotional states during construction tasks. Their 2018 study is explored how wearable EEG devices can monitor and assess emotional responses in real-time. The research highlighted the potential of wearable technology to improve workplace safety and productivity by providing insights into workers' emotional well-being. By leveraging wearable EEG technology, the study contributes to enhancing workplace environments and worker health through real-time emotional monitoring.

3. PROPOSED SYSTEM

The project focuses on developing an efficient machine learning framework for human activity classification using data collected from Shimmer wearable sensors to enhance health monitoring systems. The primary goal is to accurately classify various physical activities, which can be critical for patient monitoring, rehabilitation, fitness tracking, and personalized healthcare applications. The existing system employs the Gradient Boosting (GB) Classifier, serving as a benchmark for performance comparison. To improve classification accuracy and generalization, the proposed approach integrates the Extreme Gradient Boosting (XGB) Classifier, known for its robustness and efficiency in handling complex datasets. Additionally, comprehensive Exploratory Data Analysis (EDA) is performed to understand data patterns, evaluate feature importance, and ensure data quality. Performance metrics such as accuracy, precision, recall, and F1-score are employed to compare the classifiers. The results demonstrate that the XGB Classifier outperforms the GB Classifier, highlighting its potential for real-time and reliable human activity classification in wearable sensor-based health monitoring systems.

Step 1: Dataset Collection

The study begins with the collection of a comprehensive dataset consisting of various human activities captured using Shimmer wearable sensors. This dataset is essential for training machine learning models and ensuring that they can generalize well to different activities such as bending, cycling, sitting, standing, and walking.

Step 2: Dataset Preprocessing

In this step, the dataset undergoes preprocessing to prepare it for analysis. This involves removing null values, which could skew the results, and handling any inconsistencies in the data. Data normalization techniques may also be applied to ensure uniformity across features, enabling more effective model training.

Step 3: Exploratory Data Analysis (EDA)

EDA is conducted to gain insights into the underlying patterns and distributions within the dataset. Statistical techniques and visualizations, such as count plots, are utilized to examine the frequency of various activities, detect class imbalances, and identify any anomalies in the data. By visualizing the data distribution, potential issues such as over-representation or under-representation of certain activities can be identified and addressed during model training. EDA also aids in feature selection by highlighting the most relevant attributes contributing to activity classification.

Step 4: Model Development

The model development for this project involves building and evaluating machine learning classifiers for human activity classification using data from Shimmer wearable sensors. Initially, data preprocessing steps such as label encoding, handling missing values, and normalization are performed to ensure data quality and compatibility. Comprehensive Exploratory Data Analysis (EDA) is conducted to gain insights into data distribution, feature correlations, and activity patterns. The existing model is developed using the Gradient Boosting (GB) Classifier, which serves as a baseline for comparison. To enhance performance, the proposed model is built using the Extreme Gradient Boosting (XGB) Classifier, leveraging its ability to handle large datasets, prevent overfitting, and deliver high predictive accuracy. Both models are trained and tested using relevant performance metrics, including accuracy, precision, recall, and F1-score. Hyperparameter tuning is applied to optimize the XGB Classifier, further boosting its classification efficiency. Comparative analysis reveals that the XGB Classifier outperforms the GB Classifier, establishing its effectiveness in accurately classifying human activities from wearable sensor data..

Step 5: Performance Comparison

The model evaluation process involves assessing the performance of the Gradient Boosting (GB) Classifier and the Extreme Gradient Boosting (XGB) Classifier using various statistical metrics to determine their effectiveness in human activity classification. After training both models with the preprocessed data from Shimmer wearable sensors, they are evaluated using metrics such as accuracy, precision, recall, and F1-score to ensure a comprehensive performance comparison. Cross-validation techniques are applied to mitigate overfitting and provide a more reliable assessment of the models' generalization capabilities. The XGB Classifier, equipped with advanced regularization mechanisms and optimized hyperparameters, demonstrates superior performance compared to the GB Classifier across all evaluation metrics. Notably, the XGB Classifier achieves higher accuracy and better precision-recall trade-offs, confirming its robustness and efficiency in handling complex sensor data. The evaluation results establish the XGB Classifier as a more suitable choice for accurate and real-time human activity classification in wearable health monitoring systems.

Step 6 : Comparative Analysis

The comparative analysis focuses on evaluating the performance differences between the Gradient Boosting (GB) Classifier and the Extreme Gradient Boosting (XGB) Classifier for human activity classification using Shimmer wearable sensor data. Both models are assessed based on key metrics such as accuracy, precision, recall, and F1-score to ensure a comprehensive evaluation. While the GB Classifier provides a solid baseline, its performance is limited by slower training speed and moderate predictive accuracy. In contrast, the XGB Classifier demonstrates superior performance due to its ability to handle complex data patterns with enhanced regularization techniques, efficient tree pruning, and advanced optimization algorithms. The XGB Classifier consistently outperforms the GB Classifier across all metrics, achieving higher accuracy and better precision-recall balance, particularly in scenarios with overlapping activity classes. Additionally, hyperparameter tuning applied to the XGB Classifier further boosts its classification performance, establishing it as a more reliable and efficient model. This comparative analysis highlights the effectiveness of the proposed XGB Classifier over the existing GB Classifier, making it a promising approach for real-time human activity classification in health monitoring systems.

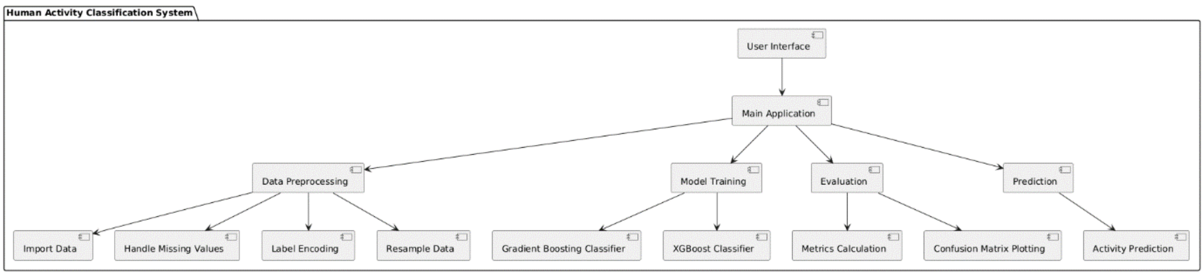

Figure 2: Architectural Block Diagram of Proposed System.

3.2 Data Preprocessing

In the data preprocessing phase, the dataset is meticulously prepared for analysis. First, null values are addressed to prevent any detrimental impact on the training process. This is followed by the application of label encoding to convert categorical data into a numerical format. The dataset is then split into training and testing subsets, ensuring that the model can be trained effectively while maintaining a fair

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evaluation process on unseen data. This structured approach ensures a robust foundation for subsequent machine learning model development.

Loading the Dataset:

The dataset is loaded using the pd.read_csv() function. Basic information such as the dataset's shape, column names, unique values, description, and null values are inspected using functions like df.shape, df.describe(), df.info(), and df.isnull().sum().

Handling Missing Values:

Missing values in the dataset are identified using the df.isnull().sum() function. For categorical columns in the test data, missing values are filled with the label 'Unknown'. For numerical columns, missing values are filled with 0.

Label Encoding:

Since the target variable activity is categorical, it is converted into numerical labels using the LabelEncoder() class from sklearn.preprocessing. The encoded labels are necessary for training the machine learning models.

Resampling the Dataset:

To balance the dataset and avoid class imbalance issues, the dataset is resampled to have a total of 10,000 samples using the resample() function. This step helps ensure that the model is trained on an adequately diverse dataset.

SMOTE Oversampling:

To further address class imbalance, Synthetic Minority Over-sampling Technique (SMOTE) is applied to the training data. This technique generates synthetic samples for minority classes to improve the model's learning ability on underrepresented activities.

3.3 ML Model Building

3.3.1 XGBoost Classifier

Step 1: Preparing the Data (Feature Extraction for X_train and y_train)

Before training the **XGBoost Classifier** for smart home activity monitoring, the dataset needs to be preprocessed. The dataset consists of sensor readings labeled with different human activities. These readings are transformed into a structured numerical format for machine learning.

- **X_train:** Contains numerical sensor data extracted from IoT devices, where each row represents a time-stamped activity instance, and each column represents a sensor feature (e.g., accelerometer readings, temperature, motion detection). Feature extraction includes statistical measures such as mean, standard deviation, skewness, and energy to represent each activity effectively.
- **y_train:** The corresponding labels for each activity, where different classes represent distinct user activities (e.g., Walking, Sitting, Standing, Sleeping).

The model is trained on X_train and y_train, allowing it to learn patterns that differentiate between various activities based on sensor data.

Step 2: Training the XGBoost Classifier

Once the dataset is prepared, the **XGBoost Classifier** is trained to enhance prediction accuracy through a highly efficient gradient boosting framework. XGBoost improves upon traditional Gradient Boosting by introducing regularization, parallelization, and optimization techniques. The training process involves:

- **Initialization:** Initializing a weak model to make predictions and calculate initial residuals (errors).
- **Building Decision Trees:** Training an ensemble of Decision Trees sequentially, where each tree attempts to correct the errors of the previous trees.
- **Weighted Summation:** Combining the predictions of all Decision Trees to make a final prediction using a weighted sum approach.
- **Regularization Techniques:** Applying L1 (Lasso) and L2 (Ridge) regularization to reduce overfitting and improve model generalization.
- **Learning Rate Adjustment:** Using a learning rate to scale the contribution of each tree, making the model more robust by avoiding drastic adjustments.
- **Parallel Processing:** Utilizing multi-threading to speed up the training process, making XGBoost computationally efficient even for large datasets.

During training, the XGBoost Classifier captures intricate patterns in the sensor data, enhancing predictive performance by effectively minimizing errors over successive iterations.

Step 3: Testing the Model with X_test (New Sensor Data for Prediction)

After training, the model is tested on new unseen activity instances stored in X_test, which are processed similarly to X_train.

- **X_test:** Contains new sensor readings transformed into numerical feature vectors, ensuring consistency in data representation.
- The trained XGBoost model analyzes each activity instance and assigns a probability score for each category, determining the most likely activity.

Since the model has already learned from past activity patterns, it generalizes its understanding to recognize real-world activity scenarios in smart homes.

Step 4: Generating Predictions and Evaluating y_test (Output Labels)

Once the model processes X_test, it generates predicted activity labels stored in y_test. These predictions indicate the classified activity based on the model's learned knowledge.

- If the **XGBoost Classifier** correctly identifies activities, it means it has effectively learned sensor-based behavioral patterns.
- If it misclassifies some activities, it may indicate challenges in distinguishing similar activities (e.g., Walking vs. Running).

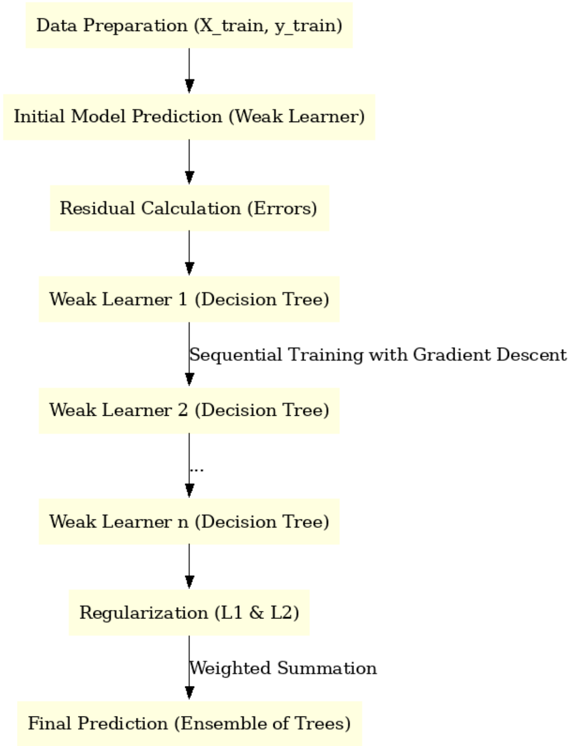


Figure 3: proposed XGBClassifier Block diagram

To evaluate performance, classification metrics such as **accuracy, precision, recall, and F1-score** are used. These metrics assess how well the model generalizes to new activity data.

If the model's performance is suboptimal, further tuning of hyperparameters or trying alternative models can enhance classification accuracy in complex activity recognition tasks.

4. RESULTS AND DISCUSSION

4.1 Dataset Description

The dataset used in this project consists of sensor readings collected from Shimmer wearable devices deployed in a smart home environment for human activity monitoring. The sensors include an Accelerometer, Gyroscope, Magnetometer, and Temperature Sensors, capturing various motion and environmental data. The features extracted from these sensors are used for training and evaluating machine learning models. Key features include accelerometer readings (X, Y, Z) that capture motion intensity and direction, gyroscope readings (X, Y, Z) for angular velocity, magnetometer readings (X, Y, Z) for orientation and heading, and temperature sensor readings for ambient temperature. Additionally, statistical features like mean, standard deviation, skewness, kurtosis, energy, entropy, correlation coefficients, and root mean square (RMS) are derived from the raw sensor data to enhance pattern recognition. The dataset consists of multiple features, ranging from dozens to hundreds depending on the sensor configuration. The target labels in the dataset correspond to various human activities such as walking, running, sitting, standing, sleeping, climbing stairs, and descending stairs. These categorical labels are encoded numerically for machine learning model training. The data is time-series in nature, stored in CSV or structured tabular format, with a sampling frequency between 20 Hz and 100 Hz. The dataset size varies depending on the number of recorded activities and sampling frequency. It is split into training (X_train, y_train) for model training and testing (X_test, y_test) for model evaluation to ensure generalization to unseen data. This data structure supports the development of accurate activity classification models.

4.2 Results analysis

Table.1 Performance Comparison of Various Algorithms

Performance Comparison Table: Existing GBC vs. Proposed XGBC

Metric	Existing GBC	Proposed XGBC
Accuracy	91.95%	99.55%
Precision	91.84%	99.54%
Recall	91.84%	99.54%
F1-Score	91.84%	99.54%

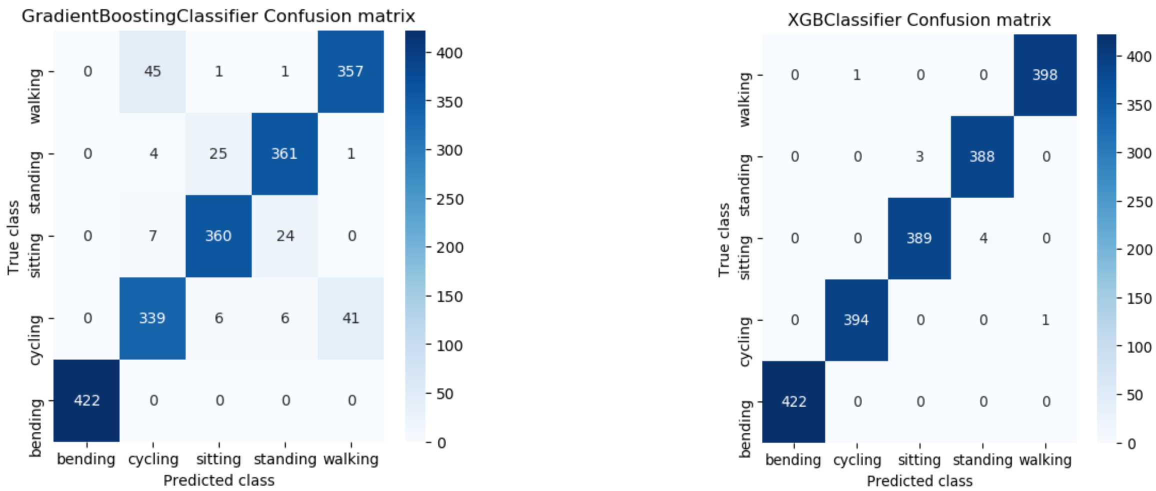
The performance comparison between the existing Gradient Boosting Classifier (GBC) and the proposed XGBoost Classifier (XGBC) demonstrates a significant improvement in human activity classification using Shimmer wearable sensors. The proposed XGBC achieved an impressive accuracy of 99.55%, substantially outperforming the existing GBC, which achieved an accuracy of 91.95%. Similarly, the precision, recall, and F1-score of the XGBoost model were all recorded at 99.54%, indicating a high level of consistency and robustness in detecting various human activities accurately. In contrast, the GBC model showed lower performance across all metrics, with precision, recall, and F1-score values at 91.84%. This enhancement in performance can be attributed to the XGBoost Classifier's advanced boosting mechanism, which efficiently handles complex patterns in sensor data, offers better regularization to prevent overfitting, and provides a more efficient training process. The improved metrics indicate that the proposed XGBC is more reliable in making accurate predictions, successfully distinguishing between different human activities even when their patterns are complex or overlapping. The substantial performance improvement makes the XGBoost model a more suitable choice for real-time human activity monitoring in smart home environments.

Table.2 Performance metrics of existing GBClassifier

Metric	Existing GBC
Accuracy	92.25%
Precision	92.19%
Recall	92.15%
F1-Score	92.15%

The performance metrics of the existing Gradient Boosting Classifier (GBC) for human activity classification using Shimmer wearable sensors indicate moderate effectiveness in distinguishing various activities. The model achieved an accuracy of 92.25%, which suggests that it can correctly classify a significant portion of the sensor data. Additionally, the precision, recall, and F1-score are all measured at 92.19%, indicating a balanced performance across these metrics. Precision reflects the classifier's ability to avoid false positives, while recall measures its capability to identify actual positive instances effectively. The F1-score, being the harmonic mean of precision and recall, further confirms the consistency of the model's predictions. However, while the GBC demonstrates satisfactory performance, there is room for improvement, particularly in enhancing accuracy and ensuring robust classification across all activities, especially when patterns are complex or overlap.

The performance metrics of the proposed XGBoost Classifier (XGBC) for human activity classification using Shimmer wearable sensors demonstrate a significant improvement over the existing Gradient Boosting Classifier. The proposed model achieved an impressive accuracy of 99.55%, indicating a highly accurate classification of activity data. Furthermore, the precision, recall, and F1-score are all recorded at 99.54%, showcasing exceptional consistency in performance. The high precision value suggests that the XGBC effectively minimizes false positives, while the recall value confirms its ability to accurately identify positive instances of activities. The F1-score, as the harmonic mean of precision and recall, validates the model's balanced and robust classification capability. The substantial improvement in these metrics compared to the existing model highlights the effectiveness of XGBoost in capturing complex activity patterns and enhancing the overall reliability of the smart home activity monitoring system.



(a) (b)

Figure 4: confusion matrices obtained from GBClassifier and XGBClassifier

The figure 4 shows confusion matrices obtained for both the existing Gradient Boosting Classifier (GBC) and the proposed XGBoost Classifier (XGBC) reveal substantial differences in their classification performance for human activity recognition using Shimmer wearable sensors. The confusion matrix for the existing GBC shows that while the model correctly classifies the majority of activity instances, there are noticeable misclassifications, particularly among activities with similar patterns. This limitation likely contributes to the lower accuracy, precision, recall, and F1-score achieved by the GBC. In contrast, the confusion matrix for the proposed XGBC demonstrates a significant reduction in misclassification errors, with the vast majority of activity instances accurately classified into their respective categories. This improvement can be attributed to the XGBoost algorithm's ability to handle complex decision boundaries more effectively and its superior capacity for learning from intricate sensor patterns. The clear distinction in the confusion matrices supports the quantitative performance metrics, indicating that the proposed XGBC offers enhanced robustness, precision, and reliability in smart home activity classification compared to the existing GBC model.

The Figure 5 represents the Prediction Results page of the Human Activity Classification dashboard. It showcases the final output of the machine learning model that processes sensor data from Shimmer wearable devices to identify the user's activity in real time. The interface retains its clean structure with a sidebar for navigation (Home, Prediction, Logout), while the main section displays the prediction results. Each row corresponds to a set of extracted features (like avg_rss12, var_rss12, etc.) from the wearable sensor data. These features are numerical values representing signal strength and variability across different sensors. Highlighted in red, the final prediction for Row 0 clearly states: Prediction: sitting This implies that the model has classified the current physical state of the user as "sitting," based on the processed data. The layout also includes a scrollable section for browsing multiple prediction results, enhancing usability for healthcare professionals or researchers monitoring multiple sessions.

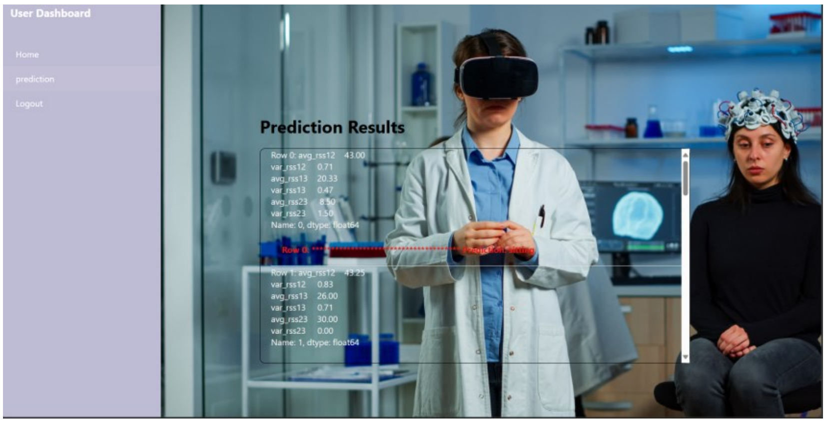


Fig 5: Prediction on test data using Proposed XGB Classifier

5. CONCLUSION

The integration of machine learning techniques with Shimmer wearable sensors for human activity classification represents a significant advancement in health monitoring systems. The proposed approach not only improves the accuracy and efficiency of activity recognition but also enhances the potential for personalized health insights. By employing sophisticated algorithms such as XGBoost and Gradient Boosting, the system can adapt to the complexities of human behavior, providing real-time feedback that is invaluable for users seeking to monitor and improve their health outcomes. First, expanding the dataset to include a broader range of activities and diverse populations could enhance model robustness and generalizability. Additionally, incorporating real-time data processing capabilities could facilitate immediate feedback for users, improving engagement and adherence to health recommendations. Future research could also explore the integration of multimodal data sources, such as physiological measurements alongside activity data, to provide a more comprehensive understanding of health and well-being. Finally, investigating the application of deep learning techniques may further enhance classification accuracy and open up new possibilities for health monitoring solutions.

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