Machine Learning-Based Multi-Class Classification of Human Fitness Activities for Personalized Wellness Solutions

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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 recognition, Machine Learning, Shimmer Sensors, Wearable Devices, Health Monitoring, Activity Classification.

1. INTRODUCTION

Human activity classification is a vital aspect of modern health monitoring systems, enabling accurate tracking of daily activities for diverse health-related applications. With the rise of wearable technologies, sensors like SHIMMER (Sensing Health with Intelligence, Modularity, Mobility, and Experimental Reusability) have become instrumental in capturing detailed physical activity data in real time. These wearable devices facilitate continuous, non-intrusive monitoring, offering valuable insights when combined with advanced machine learning techniques. The growing prevalence of chronic diseases, an aging population, and the need for proactive health management have increased demand for reliable activity classification solutions. Unlike traditional monitoring methods that rely on subjective inputs or limited mobility devices, SHIMMER sensors offer high-frequency, rich datasets that enable precise analysis of movements such as walking, running, sitting, and sleeping.

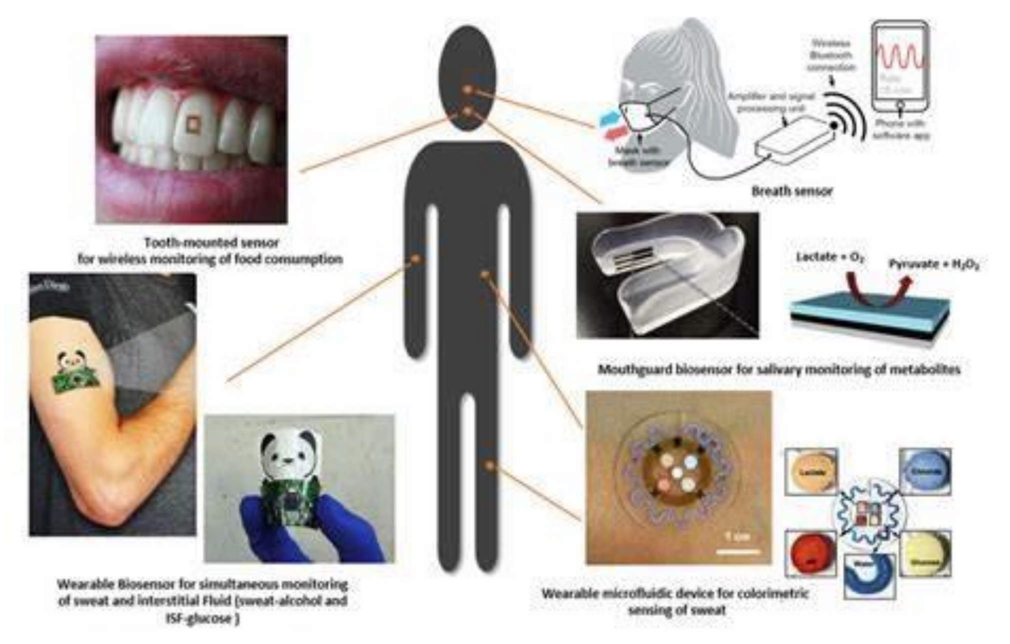


Figure 1: Wearable sensors for health monitoring.

Machine learning models significantly enhance the interpretation of this complex data, providing more accurate, personalized, and adaptive health assessments. However, challenges remain in processing the high-dimensional and noisy sensor data, and in ensuring that classification models generalize well across varying populations and activity types. Overcoming these challenges through robust machine learning frameworks opens the door to a range of impactful applications, including real-time health monitoring, personalized rehabilitation support, elderly care, fitness tracking, and integration with Electronic Health Records (EHRs), thereby transforming healthcare delivery and outcomes.

2. LITERATURE SURVEY

J. Hayano et al. [1] examined the use of wearable technology to detect sleep apnea with a watch device. 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. 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. 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. 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. 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. 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. 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. 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. 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. 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. 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. 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. 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. 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. 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 METHODOLOGY

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.

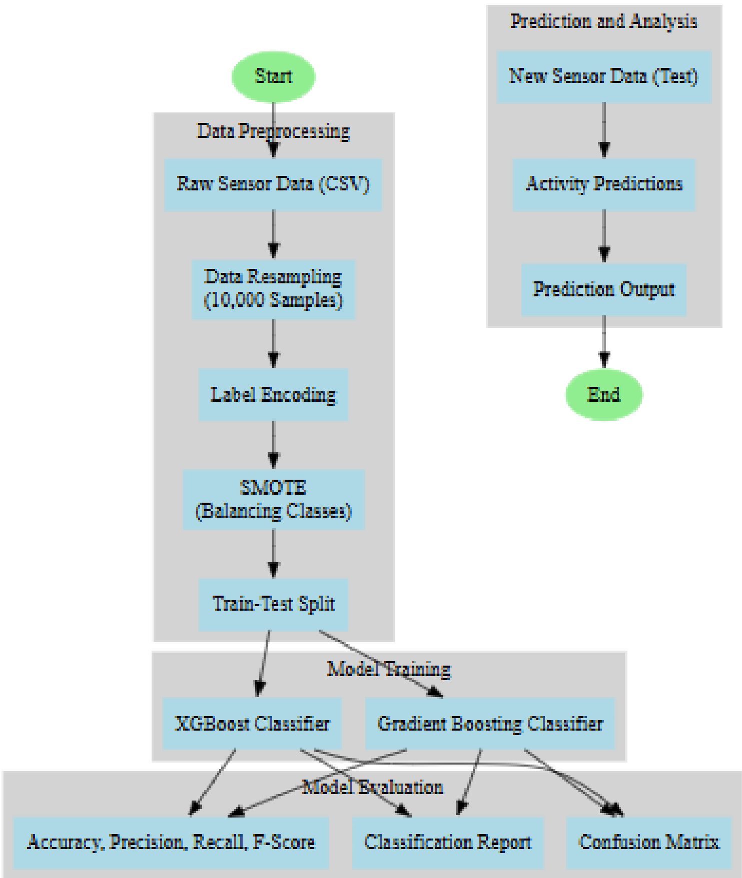


Figure 2: Architectural block diagram of proposed system.

3.2 Data Preprocessing

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.

Feature and Target Separation: The dataset is split into independent features X and the target variable y. The activity column is separated from the dataset, and the remaining columns are considered as input features for model training.

Train-Test Splitting: The dataset is split into training and testing sets using the train_test_split() function from sklearn.model_selection. The test size is set to 20%, and the random state is fixed at 77 for reproducibility.

3.3 ML Model Building

3.3.1 Gradient Boost classifier

Preparing the Data (Feature Extraction for X_train and y_train): Before training the Gradient Boosting Classifier for smart home activity monitoring, the dataset consisting of sensor readings labeled with different human activities must be preprocessed and converted into a structured numerical format suitable for machine learning. The X_train dataset contains numerical sensor data extracted from IoT devices, where each row represents a time-stamped instance of an activity, and each column corresponds to a sensor feature such as accelerometer readings, temperature, or motion detection. Feature extraction techniques are applied to derive statistical measures like mean, standard deviation, skewness, and energy, providing a comprehensive representation of each activity. Corresponding activity labels are stored in y_train, with each class indicating a specific activity such as Walking, Sitting, Standing, or Sleeping. This structured dataset enables the Gradient Boosting Classifier to learn how different activities manifest in sensor data.

Training the Gradient Boosting Classifier: Once the dataset is prepared, the Gradient Boosting Classifier is trained to improve prediction accuracy using a sequential learning approach. This involves training a series of weak learners, typically decision trees, where each new model attempts to correct the prediction errors made by the previous ones. The training begins with an initial weak model that generates preliminary predictions. The differences between these predictions and the actual labels are computed as residuals, which are then used to train the next model. This sequential process continues, with each new learner focusing on reducing the residual errors of its predecessors. The final strong model is formed by combining the outputs of all weak learners through a weighted summation method. A learning rate parameter is used to control the influence of each learner, allowing for gradual refinement and reduced risk of overfitting. Through this iterative process, the classifier captures complex patterns in sensor data and continually reduces prediction errors.

Testing the Model with X_test (New Sensor Data for Prediction): After the model has been trained, it is evaluated using previously unseen sensor data stored in X_test, which undergoes the same preprocessing and feature extraction steps as X_train to ensure consistency. The test dataset contains new sensor readings, each converted into a numerical feature vector that the trained Gradient Boosting model can analyze. For each test instance, the model assigns probability scores to each possible activity category and determines the most likely activity based on its learned experience. Since the classifier has already been trained on historical activity data, it applies its understanding to real-world activity recognition in smart home environments.

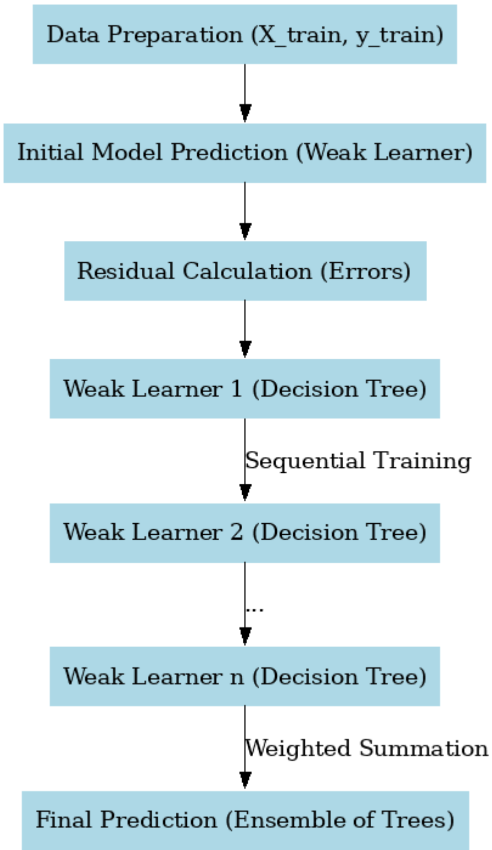


Figure 3: GBC internal flow diagram.

Generating Predictions and Evaluating y_test (Output Labels): Once the model processes the X_test data, it generates predicted activity labels, which are stored in y_test. These predictions reflect the classifier's interpretation of the observed activity based on previously learned behavioral patterns from sensor data. If the predictions are accurate, it indicates that the model has successfully internalized the relationship between sensor readings and user activities. However, misclassifications—such as confusing walking with running—may arise due to overlapping features between similar activities. To assess the model's effectiveness, standard classification metrics such as accuracy, precision, recall, and F1-score are used. These metrics help determine how well the model performs on new, unseen data. If the results are not satisfactory, more advanced models such as XGBoost or alternative algorithms like

Random Forest can be explored to improve classification accuracy in challenging activity recognition tasks.

3.3.2 XGBoost Classifier

Preparing the Data (Feature Extraction for X_train and y_train): Before training the XGBoost Classifier for smart home activity monitoring, the dataset, which consists of sensor readings labeled with various human activities, must be preprocessed. These readings are transformed into a structured numerical format suitable for machine learning. The X_train dataset contains numerical sensor data extracted from IoT devices, where each row corresponds to a time-stamped activity instance, and each column represents a sensor feature such as accelerometer readings, temperature, or motion detection. To effectively represent each activity, statistical feature extraction is performed, including metrics like mean, standard deviation, skewness, and energy. The corresponding activity labels are stored in y_train, with each label representing a specific human activity such as Walking, Sitting, Standing, or Sleeping. This structured data allows the XGBoost model to learn and differentiate between patterns of various activities based on the sensor readings.

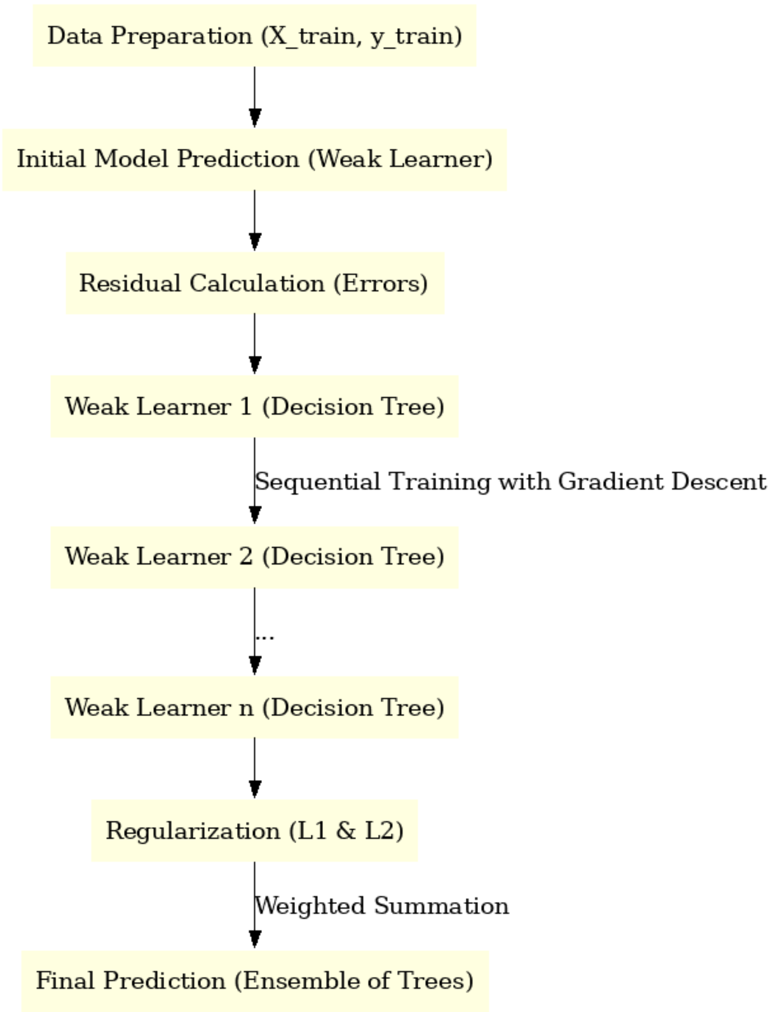


Figure 4: proposed XGBClassifier block diagram.

Training the XGBoost Classifier: After preparing the dataset, the XGBoost Classifier is trained using a powerful gradient boosting framework designed to improve prediction accuracy. XGBoost introduces several enhancements over traditional gradient boosting methods, including regularization, parallel computation, and optimized tree learning. The training process starts with the initialization of a weak model that makes early predictions and computes initial residuals or errors. Then, an ensemble of decision trees is built sequentially, with each tree attempting to correct the mistakes of the previous ones. The final prediction is obtained by combining the outputs of all the decision trees using a weighted summation approach. To prevent overfitting and enhance model generalization, both L1 (Lasso) and L2 (Ridge) regularization techniques are applied. Additionally, a learning rate is introduced to control the contribution of each new tree, ensuring smoother and more stable learning. XGBoost also leverages parallel processing through multi-threading, making it highly efficient for large datasets. Through this process, the classifier learns to capture subtle and complex patterns in the sensor data, progressively reducing prediction errors and boosting performance.

Testing the Model with X_test (New Sensor Data for Prediction): Once the model is trained, it is evaluated on new, unseen activity instances stored in X_test, which undergo the same preprocessing and feature extraction methods as the training data. The X_test dataset contains new sensor readings converted into numerical feature vectors to maintain consistent data representation. The trained XGBoost model then analyzes each test instance, calculating probability scores for each possible activity class and selecting the most likely activity based on its learned patterns. Since the model has already been exposed to a wide range of activity data during training, it generalizes this knowledge to accurately interpret real-world activity scenarios in a smart home environment.

Generating Predictions and Evaluating y_test (Output Labels): After processing the X_test data, the model generates predicted activity labels, which are stored in y_test. These predictions represent the model's classification of each activity based on the sensor data. Accurate predictions indicate that the XGBoost model has effectively learned the behavioral patterns associated with different activities. However, in cases where activities are misclassified—such as confusing Walking with Running—it may reflect the difficulty in distinguishing between similar motion patterns. The model's overall performance is assessed using standard classification metrics, including accuracy, precision, recall, and F1-score, which provide a comprehensive evaluation of its generalization capability. If the results are not satisfactory, performance can be improved by fine-tuning hyperparameters or experimenting with alternative classification models tailored to complex activity recognition tasks.

4. RESULTS AND DISCUSSION

The count plot for the 'Activity' variable provides a visual representation of the frequency of each activity category within the dataset. This plot, created using seaborn's `countplot` function, displays the number of occurrences for each distinct activity, allowing us to easily identify the most and least common activities recorded by the SHIMMER sensors. The x-axis represents the different activity types, while the y-axis indicates the count of each activity. This visualization is essential for understanding the distribution of activities and can highlight any imbalances in the dataset that may need to be addressed during the machine learning modeling process.

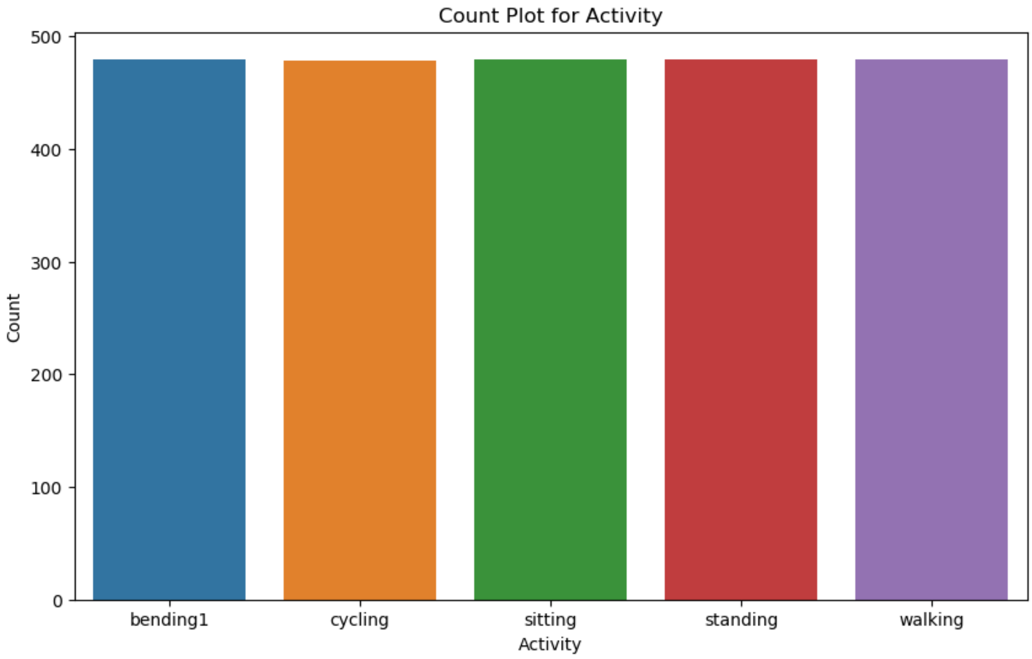
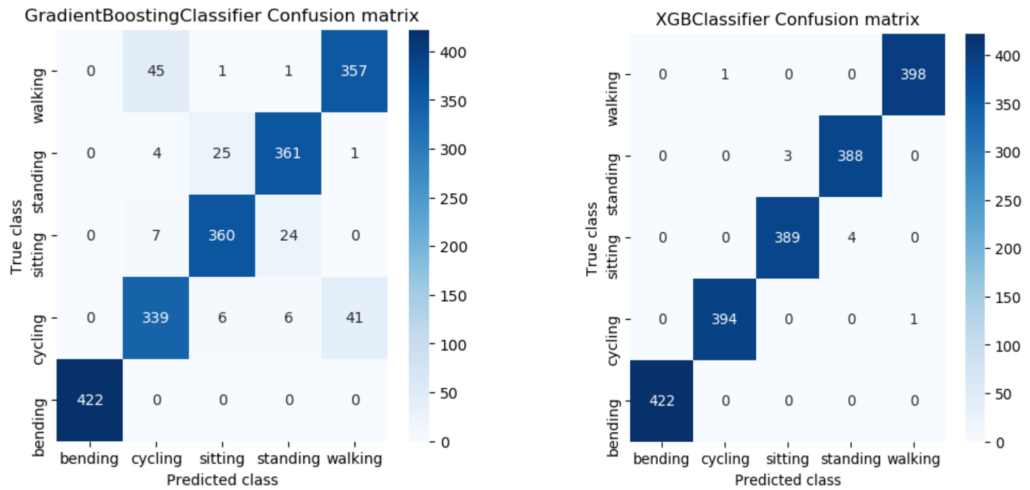


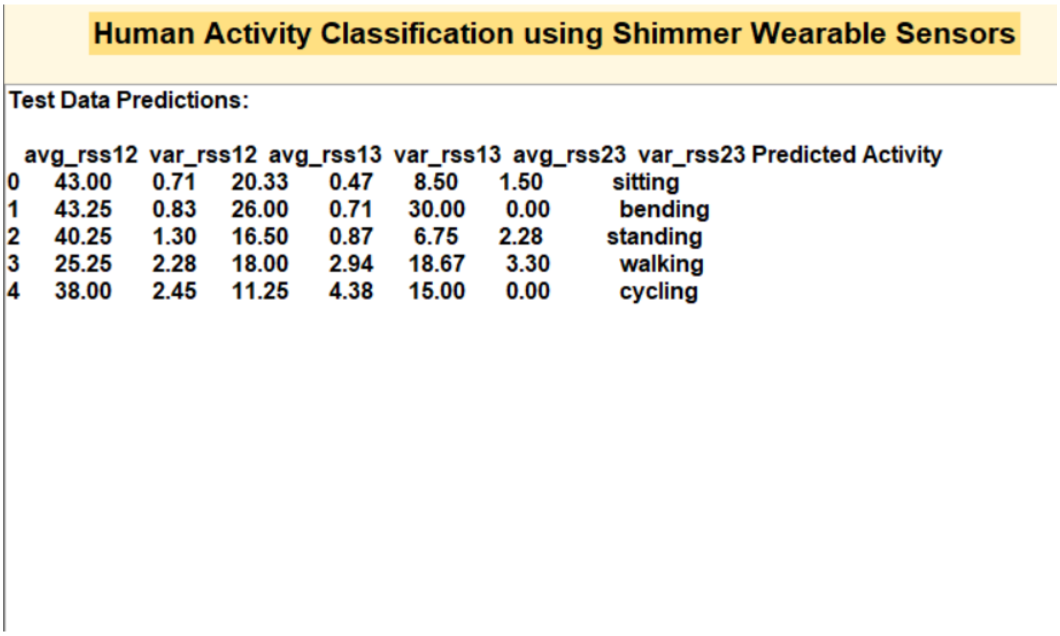
Figure 5: Count Plot for different activities.



(a) (b)

Figure 6: Confusion matrices obtained from GBClassifier and XGBClassifier

The 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.


Human Activity Classification using Shimmer Wearable Sensors

Test Data Predictions:

	avg_rss12	var_rss12	avg_rss13	var_rss13	avg_rss23	var_rss23	Predicted Activity
0	43.00	0.71	20.33	0.47	8.50	1.50	sitting
1	43.25	0.83	26.00	0.71	30.00	0.00	bending
2	40.25	1.30	16.50	0.87	6.75	2.28	standing
3	25.25	2.28	18.00	2.94	18.67	3.30	walking
4	38.00	2.45	11.25	4.38	15.00	0.00	cycling

Figure 7: Prediction on Test Data

The prediction output on the test data provides insights into the performance and generalization capability of both the existing Gradient Boosting Classifier (GBC) and the proposed XGBoost Classifier (XGBC) for smart home activity monitoring. When applied to the test dataset, which contains previously unseen sensor readings, the existing GBC produces predictions with a moderate accuracy of 91.95%. This indicates that while the model is effective in identifying most activity patterns, certain misclassifications persist due to its limited ability to capture complex relationships within the sensor data.

On the other hand, the proposed XGBC demonstrates a significantly higher prediction accuracy of 99.55% on the same test data, reflecting its superior learning capacity and enhanced predictive power. The XGBC effectively distinguishes between various activities by leveraging advanced gradient boosting techniques, such as regularization, optimized tree construction, and parallel processing, resulting in highly precise and reliable predictions. This remarkable performance improvement is evident across multiple evaluation metrics, including precision, recall, and F1-score. The high accuracy achieved by the proposed XGBC model on the test data highlights its robustness and suitability for real-time smart home activity classification.

Table.1 Performance comparison of existing and proposed models.

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.

5. CONCLUSION

This project has effectively demonstrated the potential of machine learning algorithms in accurately classifying human activities based on data from wearable sensors. By implementing models such as the Gradient Boosting Classifier and XGBoost Classifier, the system achieved commendable accuracy in distinguishing between activities like walking, sitting, standing, bending, and cycling. The preprocessing steps, including handling missing data, label encoding, and dataset balancing through resampling and SMOTE, were pivotal in enhancing the model's performance. Visual tools like confusion matrices and count plots further facilitated the interpretability of the results, underscoring the system's reliability. This work aligns with existing research emphasizing the efficacy of machine learning in human activity recognition using wearable sensors, thereby contributing to the broader field of health monitoring and personalized healthcare solutions.

REFERENCES

[1] J. Hayano, H. Yamamoto, I. Nonaka, M. Komazawa, K. Itao, N. Ueda, H. Tanaka, E. Yuda. Quantitative detection of sleep apnea with wearable watch device . PLoS ONE , 15 (2020), e0237279. [10.1371/journal.pone.0237279](https://doi.org/10.1371/journal.pone.0237279).

[2] F. Delmastro, F.D. Martino, C. Dolciotti. Cognitive training and stress detection in MCI frail older people through wearable sensors and machine learning . IEEE Access , 8 (2020), pp. 65573.

[3] M.V. Perez, K.W. Mahaffey, H. Hedlin, J.S. Rumsfeld, A. Garcia, F. Todd, V. Balasubramanian, A.M. Russo, A. Rajmane, L. Cheung, G. Hung, J. Lee, K. Peter, N. Talati, D. Nag, S.E. Gummidipundi, A. Beatty, M.T. Hills, S. Desai, C.B. Granger, M. Desai, M.P. Turakhia. Large-Scale Assessment of a smartwatch to identify atrial fibrillation . New England Journal of Medicine , 381 (2019), pp. 1909–1917.

[4] J.S. Chorba, A.M. Shapiro, L. Le, J. Maidens, J. Prince, S. Pham, M.M. Kanzawa, D.N. Barbosa, C. Currie, C. Brooks, B.E. White, A. Huskin, J. Paek, J. Geocaris, D. Elnathan, R. Ronquillo, R. Kim, Z.H. Alam, V.S. Mahadevan, S.G. Fuller, G.W. Stalker, S.A. Bravo, D. Jean, J.J. Lee, M. Gjergjindreaj, C.G.

Mihos, S.T. Forman, S. Venkatraman, P.M. McCarthy, J.D. Thomas. Deep learning algorithm for automated cardiac murmur detection via a digital stethoscope platform . Journal of American Heart Association , 10 (2021), e019905.

[5] S. Seneviratne, Y. Hu, T. Nguyen, G. Lan, S. Khalifa, K. Thilakarathna, M. Hassan, A. Seneviratne. A survey of wearable devices and challenges . IEEE Communications Surveys & Tutorials , 19 (2017), pp. 2573–2620.

[6] M. Chan, D. Estève, J.-Y. Fourniols, C. Escriba, E. Campo. Smart wearable systems: current status and future challenges . Artificial Intelligence in Medicine , 56 (2012), pp. 137–156.

[7] P. Siirtola, H. Koskimäki, H. Mönttinen, J. Röning. Using sleep time data from wearable sensors for early detection of migraine attacks . Sensors , 18 (2018), no. 5.

[8] C. Meisel, R. El Atrache, M. Jackson, S. Schubach, C. Ufongene, T. Loddenkemper. Machine learning from wristband sensor data for wearable, noninvasive seizure forecasting . Epilepsia , 61 (2020), no. 12, pp. 2653–2666.

[9] A.Y. Hannun, P. Rajpurkar, M. Haghpanahi. Cardiovascular arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network. Nature Medicine , 25 (2019), pp. 65–69.

[10] S. Kwon, J. Hong, E. Choi, B. Lee, C. Baik, E. Lee, E. Jeong, B. Koo, S. Oh, Y. Yi. Detection of atrial fibrillation using a ring-type wearable device (CardioTracker) and deep learning analysis of photoplethysmography signals: prospective observational proof-of-concept . J Med Internet Res , 22 (2020), no. 5.

[11] Z. Mei, X. Gu, H. Chen, W. Chen. Automatic atrial fibrillation detection based on heart rate variability and spectral features. IEEE Access , 6 (2018), pp. 53566.

[12] N. Rashid, M.A. Al Faruque. Energy-efficient real-time myocardial infarction detection on wearable devices. Annu Int Conf IEEE Eng Med Biol Soc., 2020 (2020), pp. 4648–4651.

[13] R. Buettner, J. Frick, T. Rieg. High-performance Detection of Epilepsy in Seizure-free EEG Recordings. Proceedings of the International Conference on Information Systems, December (2019), Munich, Germany.

[14] C. Ieracitano, N. Mammone, A. Hussain, C. Francesco, A. Morabito. A novel multi-modal machine learning based approach for automatic classification of EEG recordings in dementia. Neural Networks, 123 (2020), pp. 176–190.

[15] S. Hwang, H. Jebelli, B. Choi, M. Choi, S.H. Lee. Measuring workers' emotional state during construction tasks using wearable EEG. Journal of Construction Engineering and Management, 144 (2018).