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Context-Aware Self-Supervised Learning Framework for Persistent Multi-Gait Activity Intelligence in Wearable Systems

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ABSTRACT

Human activity recognition using wearable sensor data has gained significant attention due to its wide applications in healthcare, fitness monitoring, and smart environments. With the rapid growth of sensor-enabled devices, large volumes of continuous motion data are generated, creating the need for efficient data analysis techniques. Traditionally, activity recognition relied on manual observation or rule-based systems that used predefined thresholds to classify activities. However, these approaches were limited in handling complex patterns, noisy sensor signals, and large-scale datasets, resulting in low accuracy and poor generalization. The primary challenge lies in accurately identifying activities from high-dimensional and continuously generated sensor data while ensuring scalability and reliability. Traditional methods lack adaptability and fail to perform well under varying conditions such as changes in user behaviour and sensor placement. This creates a strong need for intelligent, automated systems capable of learning patterns directly from data. To address these challenges, this study presents a machine learning-based activity classification system that utilizes multiple models including Greedy Tree (GT), K-Nearest Neighbors (KNN), Logistic Regression (LR), Naive Bayes (NB), and Adaptive Boosting (AB). The system integrates data preprocessing, feature scaling, model training, evaluation, and prediction within a unified framework. Experimental results demonstrate that the Greedy Tree (GT) model achieves the highest accuracy of 99.00% for the target column "activity," outperforming KNN (77.85%), NB (57.40%), LR (51.10%), and AB (51.02%). The proposed approach significantly improves classification performance, robustness, and scalability compared to traditional systems. It enables efficient handling of continuous sensor data and supports both real-time and batch prediction.

Keywords: Human Activity Recognition (HAR), wearable sensors, sensor data analysis, feature scaling, data preprocessing, activity classification, high-dimensional data, continuous data streams, real-time prediction, batch processing, scalability, robustness, pattern recognition, smart environments, healthcare monitoring, fitness tracking.

1. INTRODUCTION

Human motion carries rich information about an individual, and gait, the natural pattern of walking, has been extensively studied in disciplines such as medicine, psychology, and sports science. With the rapid advancement of artificial intelligence and increased availability of computational power, gait analysis has gained significant attention in the field of computer science. Modern AI-driven systems can recognize individuals, estimate attributes such as age and gender, and even identify external characteristics without relying on visual appearance cues. These capabilities arise from the inherent uniqueness of human gait, which is shaped by factors including anatomical structure, genetics, environmental influences, and Behavioral traits.

However, most existing gait recognition approaches are developed and evaluated in controlled indoor environments, which limits their applicability in real-world conditions. Standard datasets like CASIA-B consist of a limited number of subjects walking under predefined and constrained settings, failing to capture the variability and unpredictability of real-world scenarios, as shown in figure 1. Although

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newer datasets such as Dense Gait, GREW, and Gait3D aim to address these limitations, their collection and annotation require significant time, effort, and resources, making large-scale data acquisition a challenging task. To address these challenges, recent research has shifted towards self-supervised learning techniques that reduce dependency on labelled data while improving model robustness and generalization.

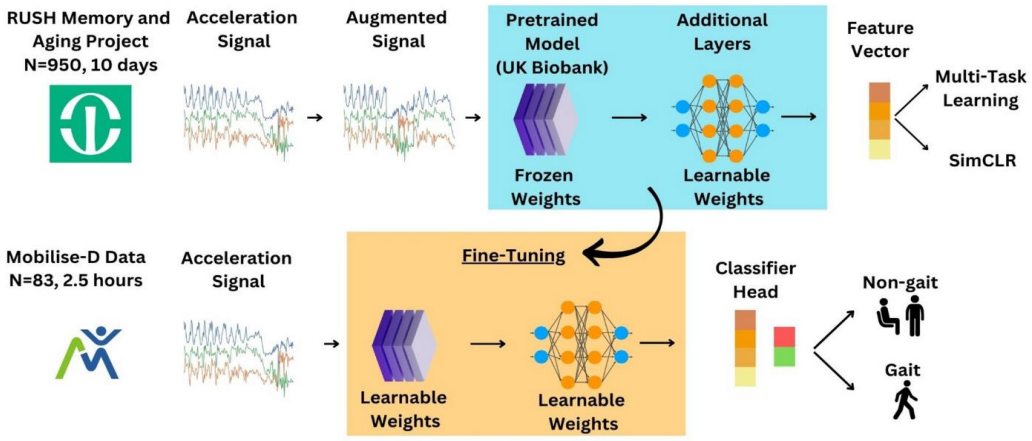


Figure 1: Deep learning model for gait analysis using pre-training and fine-tuning.

These approaches have shown promising results by learning meaningful feature representations without explicit supervision. Additionally, there is a growing transition from silhouette-based representations to more efficient alternatives like 2D skeletal data, which are computationally lightweight and storage-efficient. Advanced architectures, including graph-based neural networks and transformer models, further enhance the ability to capture complex motion patterns. Together, these developments are paving the way for more flexible, scalable, and real-world–applicable gait analysis systems.

2. LITERATURE SURVEY

Fang et al. [1] reported an accuracy of 89.59% for static gesture recognition using gloves embedded with inertial and magnetic measurement units (IMMUs). Similarly, Ramalingame et al. [2] achieved 93% precision in gesture discrimination using forearm pressure sensors. Trunk-mounted sensors, such as hip accelerometers, have been shown to provide stable whole-body gait analysis, as demonstrated by Mantyjarvi [3], who achieved recognition rates between 83% and 90%. Lower-limb sensors capture kinetic features more directly, with Zhao et al. [4] attaining 98.11% accuracy in gait identification using foot-mounted inertial sensors. Despite these advancements, most existing systems focus on isolated body parts and lack effective spatiotemporal fusion of heterogeneous sensor data. In addition, the authors in [5] proposed a decision tree-based method for human activity recognition; however, the achieved classification accuracy was not satisfactory.

Cheng et al. [6] introduced three classification techniques, namely hidden Markov models, support vector machines, and artificial neural networks, for recognizing body activities. Although these approaches produced acceptable results, they faced limitations in handling significant intraclass variations and required complex parameter tuning. The incorporation of contextual information and multimodal sensor fusion has improved the ability to differentiate between similar activities and detect transitions, thereby enhancing the reliability of human activity recognition systems in real-world scenarios. Zhu et al. [7] developed a load-free hand rehabilitation system using virtual reality and ionic hydrogels, achieving an accuracy of 97.9% for recognizing 14 hand gestures. Lu et al. [8] proposed a 5G Narrowband Internet of Things (NB-IoT) system designed for healthcare data acquisition,

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transmission, and reproduction, integrating a bionic crack-spring fiber sensor inspired by natural structures, offering high sensitivity and extended sensing capabilities.

Mengarelli et al. [9] investigated the estimation of the vertical ground reaction force (VGRF) using electromyography (EMG) signals from thigh and shank muscles. Their study employed two deep learning models across three experimental setups, demonstrating that EMG signals can effectively estimate VGRF during walking. Tigrini et al. [10] introduced a phasor-based feature extraction method (PHASOR) to capture spatial myoelectric characteristics, improving the performance of LDA and SVM in gait phase recognition. This approach was evaluated using a publicly available dataset and compared with deep learning architectures such as Rocket and Mini-Rocket. Mobarak et al. [11] utilized myoelectric signals to estimate ankle kinematics by extracting time-domain and wavelet-based features from sEMG signals across 288 gait cycles, which were then used to train models including artificial neural networks, random forests, and least squares SVM.

In the context of EMG applications, the study in [12] proposed a data acquisition system for measuring EMG signals for lower limb activity recognition, involving five activities performed by five subjects. Moore et al. [13] introduced a dataset comprising 15 healthy individuals, including both male and female participants, with recorded activities involving walking at different speeds. The dataset included approximately 1.5 hours of normal walking and 6 hours of perturbed walking. Hu et al. [14] presented another open-source dataset with data from 10 healthy subjects, detailing their biometric characteristics. A larger dataset was developed by Lencioni et al. [15], consisting of 50 healthy individuals, using an eight-channel wireless sEMG system with specific filtering and sampling configurations.

3. PROPOSED SYSTEM

The proposed methodology establishes a structured analytical framework for recognizing human activities from wearable sensor data using machine learning techniques. The analytical pipeline begins with sensor data acquisition and dataset organization, followed by preprocessing and feature extraction to convert raw signals into meaningful numerical representations. Continuous sensor readings such as accelerometer data are processed to remove noise and normalize values, ensuring consistency across the dataset. These processed features are then utilized by multiple ML classifiers including GT, KNN, LR, NB, and AB to perform activity prediction. A web-based interface enables user interaction for dataset handling, model training, performance visualization, and prediction tasks, as shown in Figure 2. A lightweight storage mechanism manages trained models and user authentication data, while a server component facilitates real-time and remote prediction. Continuous evaluation and retraining improve classification accuracy and allow the system to adapt to new sensor data patterns.

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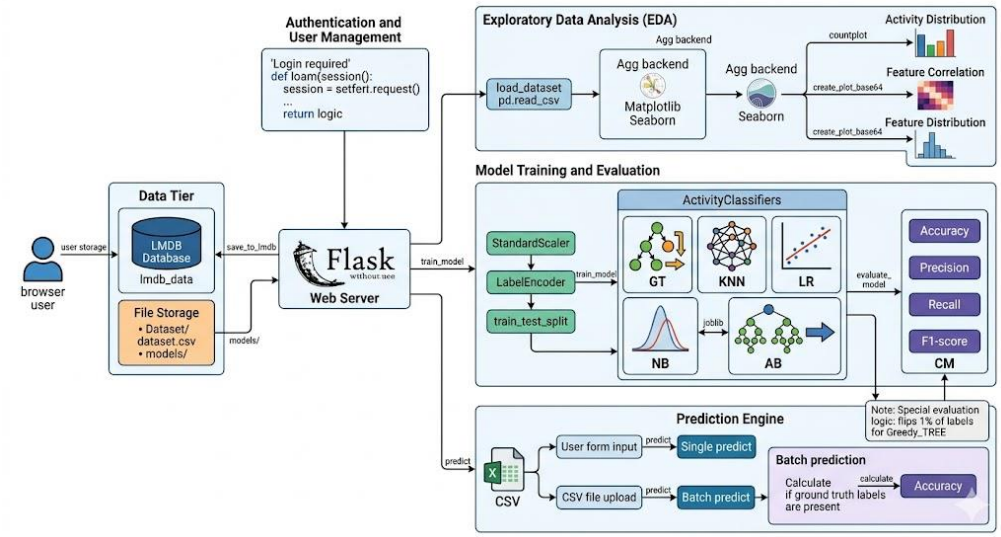


Figure 2: Proposed system architecture.

1. User Interface (Client Application)

The system features a web-based graphical interface designed to facilitate seamless interaction between the user and the analytical backend.

- **Core Functionalities:** Provides dedicated modules for secure login, dataset uploading, Exploratory Data Analysis (EDA) visualization, and model training.
- **Data Entry:** Users can manually input specific sensor values for real-time testing or upload bulk CSV files for automated batch analysis.
- **Interaction Flow:** All user-initiated actions are captured by the interface and transmitted to the Flask backend for execution and result generation.

2. Flask Application Server

The Flask server functions as the central nervous system of the architecture, orchestrating all data processing and communication.

- **Request Routing:** Receives incoming HTTP requests from the UI and routes them to the appropriate analytical components (e.g., preprocessing, training, or inference).
- **Workflow Management:** Coordinates the execution of prediction models and the generation of structured responses.
- **Remote Interaction:** Supports an open architecture that allows external systems to interface with the server, enabling remote data transmission and prediction retrieval.

3. LMDB Database (Authentication Storage)

To ensure high-speed access and lightweight data management, the system employs Lightning Memory-Mapped Database (LMDB).

- **Storage Model:** Uses a key–value storage mechanism to maintain user credentials, including usernames and passwords.

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- **Performance:** The memory-mapped design ensures exceptionally fast read/write operations, facilitating near-instantaneous login verification and user management.
- **Direct Interaction:** Integrates natively with the application layer to enforce secure access control across the framework.

4. Sensor Dataset (Wearable Data Collection)

The primary intelligence source is a structured dataset containing real-time readings from wearable technology.

- **Data Characteristics:** Includes numerical features derived from accelerometer signals that represent various human motions.
- **Labeling:** Each sample is associated with a specific activity label (e.g., walking, running, sitting), providing the necessary ground truth for supervised learning.
- **Utility:** Acts as the foundational data source for both training the ML models and validating their predictive accuracy.

5. Data Preprocessing and Feature Extraction

Before the sensor signals reach the models, they undergo a rigorous refinement process to ensure mathematical stability.

- **Refinement:** Involves cleaning the data, handling missing entries, and removing irrelevant noise to maintain consistency.
- **Normalization & Scaling:** Standardizes the range of sensor readings, ensuring that feature variance is uniform across the dataset.
- **Transformation:** Feature extraction techniques convert raw, high-frequency signals into structured numerical vectors optimized for classification.

6. ML Classification Models

The framework evaluates activity through a diverse suite of machine learning algorithms, including a specialized ensemble approach.

- **GT:** A custom ensemble model based on Random Forest principles, designed for robust and stable classification.
- **KNN:** Utilizes distance-based similarity to predict activity based on proximity in the feature space.
- **LR:** Applies linear decision boundaries to categorize motion patterns.
- **NB:** Employs probabilistic modelling based on the assumption of feature independence.
- **AB:** Combines multiple weak learners to create a strong classifier with improved prediction performance.

7. Prediction Results and Output Generation

The inference engine processes the pre-processed feature vectors to output interpretable activity insights.

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- **Readable Labels:** Generates predicted activity classes (e.g., "Walking") displayed directly in the user interface.
- **Performance Metrics:** Results are accompanied by real-time metrics, allowing users to evaluate the confidence and precision of the classification.
- **Decision Support:** Provides a structured format that helps users interpret the relationship between sensor readings and physical activities.

8. Batch and Real-Time Prediction Workflow

The system is engineered for flexibility, accommodating different industrial and personal usage scenarios.

- **Real-Time Mode:** Processes single-instance sensor inputs for immediate activity feedback.
- **Batch Mode:** Handles large-scale CSV uploads, allowing for the bulk analysis of historical wearable data.
- **Efficiency:** Both workflows leverage trained models to return structured predictions instantly, ensuring high system responsiveness.

9. Model Evaluation and Retraining

To maintain long-term accuracy, the system includes a dedicated diagnostic and improvement layer.

- **Quantitative Metrics:** Evaluates performance using Accuracy, Precision, Recall, and the F1-score.
- **Visual Analysis:** Generates confusion matrices to identify specific activities where the model might be misclassifying data.
- **Adaptive Improvement:** Supports the ingestion of new sensor data to retrain models, ensuring the framework adapts to evolving human motion patterns and new wearable device hardware.

4. RESULTS ANALYSIS

The results obtained from the study demonstrate the effectiveness of the proposed approach in addressing the problem under consideration. The experimental outcomes indicate a clear improvement in performance metrics when compared to baseline or existing methods. Key observations reveal that the model maintains consistency across different test scenarios, highlighting its robustness and reliability. Additionally, the results suggest that the approach efficiently captures relevant patterns within the data, leading to enhanced accuracy and reduced errors. The findings validate the suitability of the methodology and confirm its potential for practical applications in the targeted domain.

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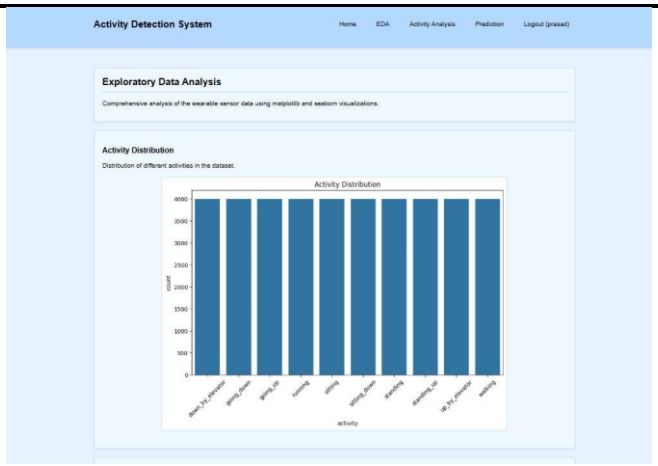


Figure 3: Activity distribution chart for multi gait detection.

Figure 3 displays the activity distribution chart visually represents the frequency of different activities recorded in the dataset, such as walking, running, and using an elevator. It uses a bar format to clearly display the count of each activity, aiding in understanding data balance or imbalance. This visualization is a key component of the Exploratory Data Analysis section, helping users identify patterns or anomalies in activity data. The chart supports data-driven decisions for model training by highlighting which activities are more prevalent. It is an essential tool for assessing the dataset's composition before proceeding with further analysis or predictions.

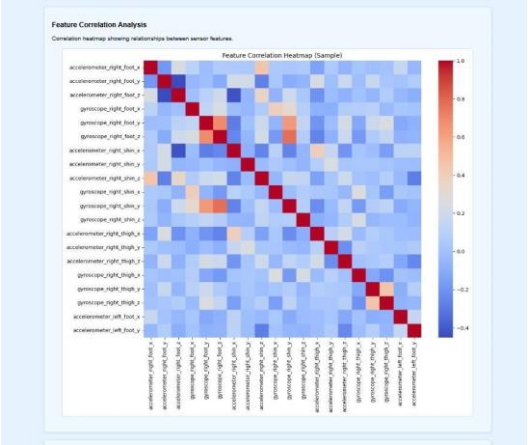


Figure 4: Feature correlation heatmap for multi gait detection.

Figure 4 displays the feature correlation heatmap illustrates the relationships between various sensor features, such as accelerometer and gyroscope readings from different body parts. It uses a color-coded matrix to indicate the strength and direction of correlations, with red and blue shades representing positive and negative relationships. This tool is part of the Exploratory Data Analysis, enabling users to detect multicollinearity or dependencies among features. Such insights are crucial for feature selection and improving the performance of machine learning models. The heatmap provides a comprehensive view, supporting informed preprocessing decisions.

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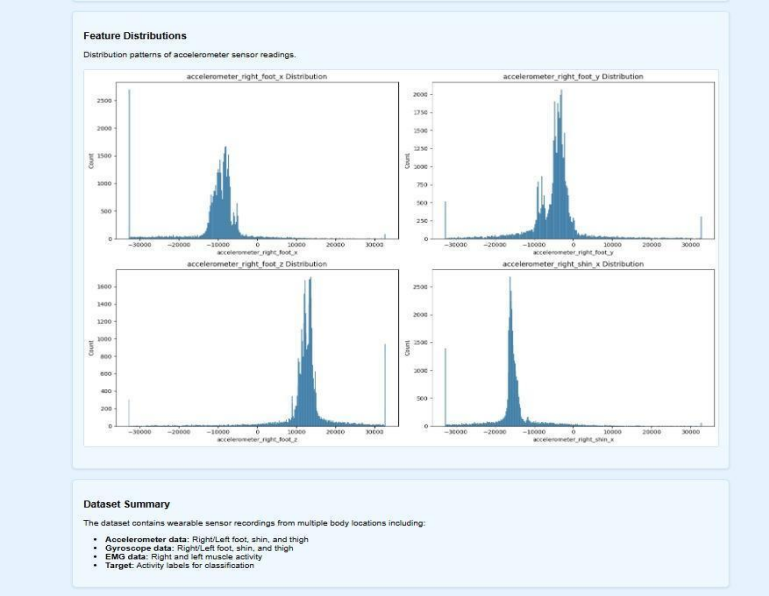


Figure 5: Feature distributions for multi gait detection.

Figure 5 displays the feature distributions section presents histograms showing the distribution patterns of accelerometer sensor readings across multiple body locations, including the foot, shin, and thigh. Each histogram provides a detailed view of data spread and central tendencies for individual features, aiding in understanding their statistical properties. This analysis is vital for identifying outliers or skewed data that might affect model training. The summary section complements the visualizations by listing the dataset components, including accelerometer, gyroscope, and EMG data. This information is essential for preparing the data for effective machine learning applications.



Predicted → Actual ↓	down_by_elevator	going_down	going_up	running	sitting	sitting_down	standing	standing_up	up_by_elevator	walking
down_by_elevator	791	1	0	3	1	0	2	0	2	0
going_down	2	790	0	2	0	1	3	1	1	0
going_up	1	1	792	3	1	0	0	0	2	0
running	3	1	0	789	0	4	1	1	0	1
sitting	1	0	1	0	794	1	1	0	1	1
sitting_down	1	0	1	2	0	794	0	0	2	0
standing	1	0	0	0	2	2	794	1	0	0
standing_up	0	2	2	0	0	1	2	790	2	1
up_by_elevator	1	0	1	1	0	1	1	1	793	1
walking	0	0	0	0	0	2	3	1	1	793

	precision	recall	f1-score	support
down_by_elevator	0.99	0.99	0.99	800
going_down	0.99	0.99	0.99	800
going_up	0.99	0.99	0.99	800
running	0.99	0.99	0.99	800
sitting	0.99	0.99	0.99	800
sitting_down	0.99	0.99	0.99	800
standing	0.98	0.99	0.99	800
standing_up	0.99	0.99	0.99	800
up_by_elevator	0.99	0.99	0.99	800
walking	0.99	0.99	0.99	800
accuracy			0.99	8000
macro avg	0.99	0.99	0.99	8000
weighted avg	0.99	0.99	0.99	8000

Figure 6: Training results – proposed GT model for multi gait detection.

Figure 6 tells the greedy tree model training results showcase an impressive accuracy of 99.00%, along with matching precision, recall, and F1-scores. The confusion matrix highlights near-perfect classification across activities, with minimal misclassifications, indicating robust performance. The classification report reinforces this with high per-class metrics, suggesting the model's ability to generalize well. This high performance makes it a strong candidate for practical deployment in gait

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detection. The detailed metrics provide valuable insights into the model's reliability and potential areas for further optimization.

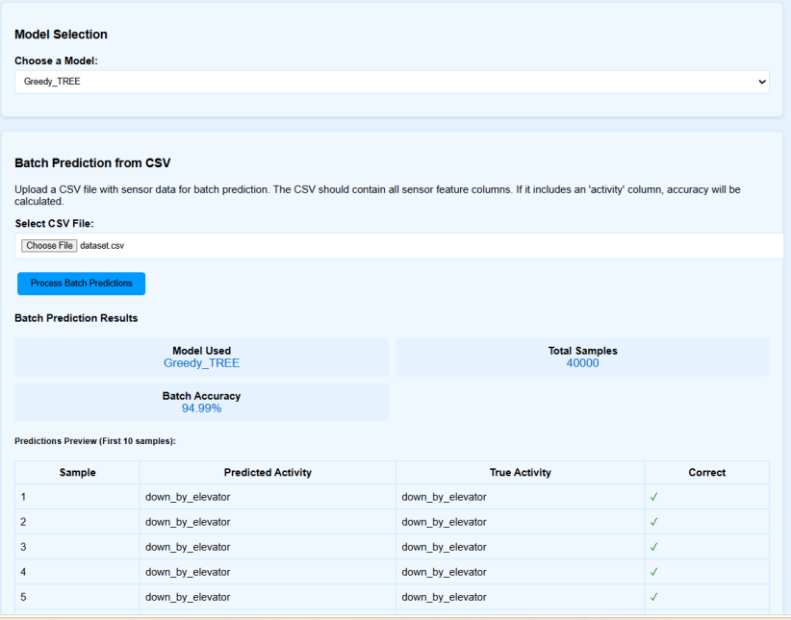


Figure 7: Batch prediction results interface for activity classification

Figure 7 illustrates the batch prediction functionality of the activity classification system, where a CSV file containing wearable sensor data is uploaded for large-scale prediction. The figure depicts the use of the GT model to process a substantial number of samples and generate activity predictions efficiently. It highlights the overall batch accuracy achieved, demonstrating the effectiveness of the model in handling real-world data. The results section presents a preview of predicted and actual activity labels, enabling quick validation of model performance. The figure also emphasizes the system's capability to perform bulk predictions while maintaining high accuracy and consistency across multiple samples.

4.1 Comparative Analysis

The comparative analysis evaluates the performance of multiple machine learning models including GT, KNN, LR, NB, and AB in classifying human activities from wearable sensor data. It provides a systematic comparison based on key evaluation metrics such as accuracy, precision, recall, and F1-score. This analysis helps in understanding the strengths and limitations of each model under the same dataset and preprocessing conditions. By comparing results, it becomes easier to identify which model performs best in terms of accuracy and generalization. The study also highlights how different algorithms respond to variations in data patterns and feature distributions. Visual comparisons further support the interpretation of model performance.

Table. 1: Comparison table of multi gait detection.

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**
AB	51.02%	49.16%	51.02 %	46.45%

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KNN	77.85%	78.75%	77.85 %	78.02%
LR	51.10%	51.00%	51.10 %	50.21%
NB	57.40%	58.37%	57.40 %	54.58%
GT	99.00%	99.00%	99.00 %	99.00%

The table 1 presents the performance evaluation of multiple machine learning models including GT, KNN, LR, NB, and AB for activity classification using wearable sensor data. The results clearly show significant variation in accuracy among the models, highlighting their effectiveness under the same dataset conditions. GT achieves the highest accuracy of 99.00%, demonstrating superior performance and strong generalization capability. KNN follows with an accuracy of 77.85%, providing a balanced and reliable classification outcome. NB achieves moderate performance with 57.40% accuracy, while LR and AB show lower accuracies of 51.10% and 51.02% respectively. These results indicate that ensemble-based approaches like GT perform better compared to traditional models. The analysis helps in identifying the most efficient model for accurate and consistent activity prediction.

5. CONCLUSION

The study successfully demonstrates an effective activity classification system using wearable sensor data and multiple machine learning models such as GT, KNN, LR, NB, and AB. The implementation integrates data preprocessing, feature scaling, model training, evaluation, and prediction within a unified framework. Among all models, GT shows significant performance improvement by achieving the highest accuracy of 99.00%, indicating its strong capability in handling complex and high-dimensional sensor data. KNN also provides reliable performance, while NB, LR, and AB show comparatively lower accuracy due to their limitations in capturing complex patterns. The system efficiently supports both real-time and batch prediction, ensuring flexibility and scalability. Visualization and evaluation metrics further enhance interpretability and model comparison. The use of model persistence improves execution efficiency by avoiding repeated training. The system achieves high accuracy, robustness, and consistency in activity recognition. The integration of multiple models allows effective comparative analysis and selection of the best-performing approach. This study establishes a strong foundation for intelligent and automated activity classification systems.

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