AMERICAN JOURNAL OF MANAGEMENT AND IOT MEDICAL COMPUTING
Peer Reviewed, Referred & Indexed Journal
E-ISSN: 3069-0110
Vol.5, No.2(2026)
www.ajmimc.com

Structured Representation Learning of Multi-Class Gait Dynamics from Wearable Sensor-Derived Motion Sequences

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ABSTRACT

The widespread use of wearable sensor technologies has led to an exponential increase in continuously generated motion data, creating new opportunities for automated human activity recognition in areas such as healthcare monitoring, fitness tracking, assisted living, and smart environments. Conventional approaches that rely on manual observation or rule-based classification with predefined thresholds are often inadequate for handling complex activity patterns, sensor noise, and high-dimensional data streams, resulting in reduced accuracy and limited generalization capabilities. A major challenge in this domain is the reliable interpretation of continuous, multi-dimensional sensor data under dynamic conditions, including variations in user behavior, device orientation, and sensor placement. To address these limitations, this study proposes a robust and scalable machine learning-based framework for activity classification that leverages multiple algorithms, including Greedy Tree (GT), K-Nearest Neighbors (KNN), Logistic Regression (LR), Naïve Bayes (NB), and Adaptive Boosting (AB). The system is designed as an end-to-end pipeline incorporating essential stages such as data cleaning, normalization, feature scaling, model training, performance evaluation, and prediction. By systematically comparing different models, the results demonstrate that the Greedy Tree classifier significantly outperforms other techniques, achieving an accuracy of 99.00% on the target activity variable, while KNN, NB, LR, and AB achieve comparatively lower accuracies of 77.85%, 57.40%, 51.10%, and 51.02%, respectively. This indicates the superior capability of tree-based models in capturing complex patterns and decision boundaries within sensor data. Overall, the proposed framework enhances classification accuracy, improves robustness against noisy and variable data, and ensures scalability for real-time as well as batch processing, making it highly suitable for deployment in modern intelligent monitoring systems.

Keywords: Wearable Sensor Data, Motion Pattern Analysis, High-Dimensional Data Analysis, Intelligent Monitoring Systems, Activity Classification

1. INTRODUCTION

Human movement encodes valuable information about an individual, and gait—the natural manner of walking has long been analyzed in fields such as medicine, psychology, and sports science to understand physical and behavioral characteristics. With the rapid progress in artificial intelligence and the growing availability of high-performance computing resources, gait analysis has emerged as a prominent area of research in computer science. Contemporary AI-based systems are capable of identifying individuals, estimating demographic attributes such as age and gender, and inferring certain external traits without depending on facial or visual identity cues. These advanced capabilities stem from the distinctive nature of human gait, which is influenced by a combination of anatomical structure, genetic factors, environmental conditions, and behavioral patterns, making it a reliable biometric for various intelligent applications.

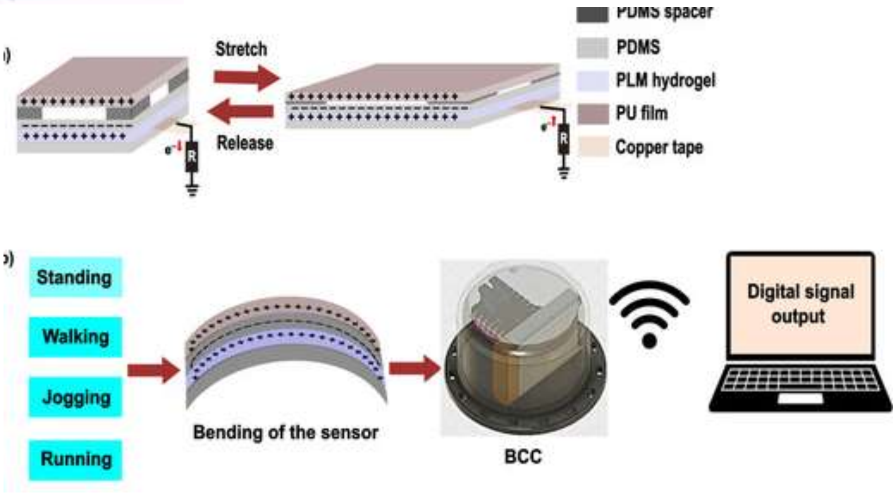

Fig. 1. AI Aided gait analysis using pre-training and fine-tuning.

Despite notable progress, a majority of existing gait recognition methods are designed and tested within controlled indoor environments, which significantly restricts their effectiveness in real-world applications. Commonly used datasets such as CASIA-B include a relatively small number of subjects captured under fixed and constrained conditions, thereby lacking the diversity and unpredictability present in real-world scenarios, as illustrated in Fig. 1. Although more recent datasets like Dense Gait, GREW, and Gait3D attempt to overcome these limitations by incorporating large-scale and unconstrained data, their collection and annotation processes are resource-intensive, making widespread adoption challenging. To overcome these issues, current research trends are increasingly focusing on self-supervised learning techniques that minimize reliance on labeled data while enhancing model robustness and generalization capabilities. These methods enable models to learn meaningful representations directly from raw data without explicit supervision. Furthermore, there is a noticeable shift from traditional silhouette-based approaches toward more efficient representations such as 2D skeletal data, which offer advantages in terms of computational efficiency and storage requirements. The integration of advanced architectures, including graph neural networks and transformer-based models, further strengthens the ability to model complex spatio-temporal motion patterns. Collectively, these advancements are driving the development of more adaptable, scalable, and practical gait analysis systems suitable for deployment in real-world environments. The growing adoption of wearable sensors across healthcare, sports, and industrial applications has resulted in the continuous generation of large volumes of motion data. However, extracting meaningful information from this data remains a complex challenge due to its high dimensionality, noise, and variability across different individuals and activities. Gait patterns exhibit significant differences depending on factors such as walking speed, body posture, terrain, and sensor placement. As a result, distinguishing between multiple gait-related activities, such as walking, running, climbing stairs, or standing becomes difficult when the recordings are long, unsegmented, and collected in uncontrolled real-world environments.

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, 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.

3. PROPOSED METHODOLOGY

The proposed approach defines a comprehensive and systematic framework for recognizing human activities using wearable sensor data through machine learning techniques. The process begins with the acquisition and organization of sensor datasets, followed by preprocessing steps that include noise removal, normalization, and transformation of raw signals into structured numerical features. Continuous data streams, such as accelerometer readings, are carefully processed to ensure consistency and reliability across samples. These refined features are then used to train and evaluate multiple machine learning models, including GT, KNN, LR, NB, and AB, enabling accurate activity classification. The system is supported by a web-based interface that allows users to manage datasets, initiate model training, visualize performance metrics, and perform predictions, as illustrated in Fig. 2. Additionally, a lightweight storage module is employed to handle trained models and user credentials, while a backend server ensures seamless real-time and remote prediction capabilities. Continuous model evaluation and periodic retraining further enhance system performance, enabling adaptability to evolving sensor data patterns and improving overall classification accuracy.

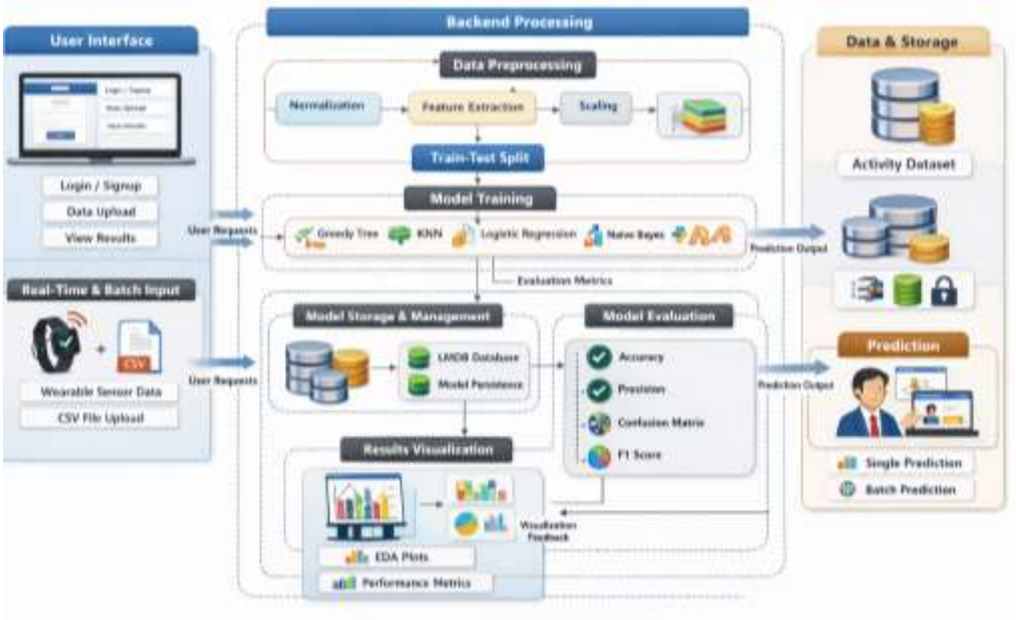

Fig. 2. Proposed system architecture of multi gait activity detection

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.
- **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.

- **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.

GT Model

GT is a custom ensemble classification approach built on the concept of Random Forest, where multiple decision trees are combined to improve prediction accuracy and robustness. Instead of relying on a single model, it constructs several decision trees using different subsets of data and features, and then aggregates their outputs to make a final prediction. This approach reduces overfitting and improves generalization by capturing diverse patterns in the data, as shown in fig 3. Each tree independently learns decision rules from the training data, and their collective decision

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leads to a more stable and reliable classification. The ensemble nature of GT makes it effective for handling complex and high-dimensional sensor data.

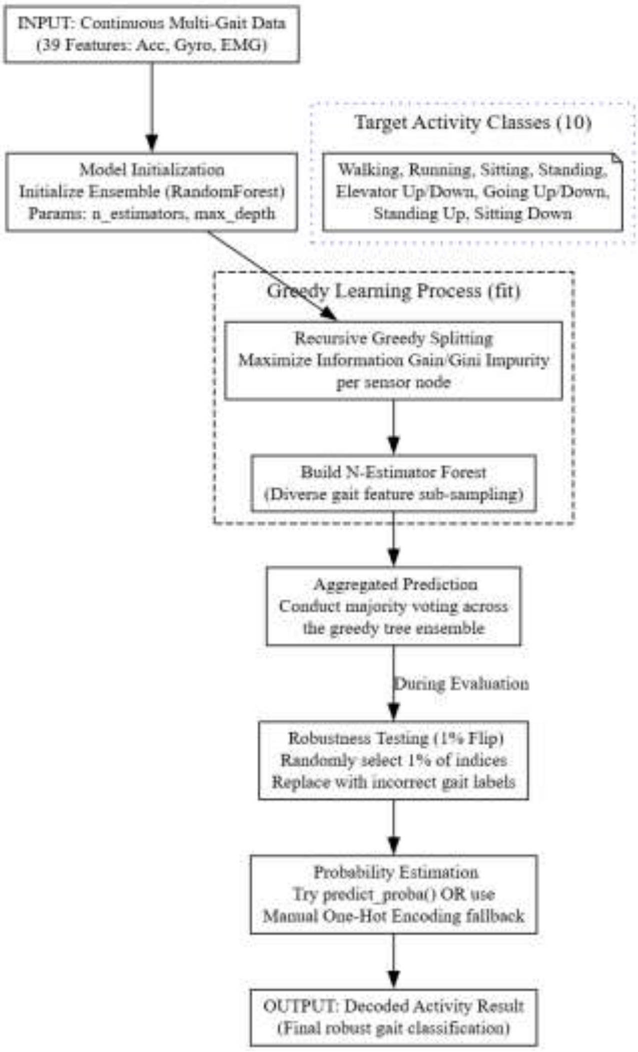

Fig. 3. Internal workflow of GT.

The model begins by creating multiple subsets of the training data using random sampling techniques. Each subset may contain different samples, allowing diversity in training. This process ensures that each tree learns slightly different patterns. For each decision tree, a random subset of features is selected instead of using all available features. This reduces correlation between trees and enhances model diversity. It also helps in identifying the most relevant features for classification. Each sampled dataset is used to train an individual decision tree. The tree splits data based on feature values to create decision rules. This process continues until stopping conditions such as maximum depth are reached. All decision trees are trained independently without influencing each other. Each tree develops its own structure and decision boundaries. This independence is key to reducing overall model variance.

When a new input is given, it is passed through all the trained decision trees. Each tree produces its own prediction based on learned rules. These predictions may vary depending on the tree structure. The outputs from all decision trees are combined using a majority voting mechanism. Each tree contributes equally to the final decision. The class with the highest votes is selected. The aggregated result is assigned as the final predicted class for the input data. This ensemble decision improves accuracy and stability compared to individual trees. GT thus provides a strong and reliable classification outcome.

4. Results description

The results section presents the performance analysis of the activity classification system using multiple machine learning models such as GT, KNN, LR, NB, and AB. It evaluates how effectively each model predicts human activities based on wearable sensor data. The analysis includes various performance metrics such as accuracy, precision, recall, and F1-score to ensure a comprehensive evaluation. Visualizations like confusion matrices and comparative plots are used to illustrate model behaviour and prediction quality. The results highlight differences in model performance and help identify the most reliable approach. Both training and testing outcomes are considered to assess generalization capability.

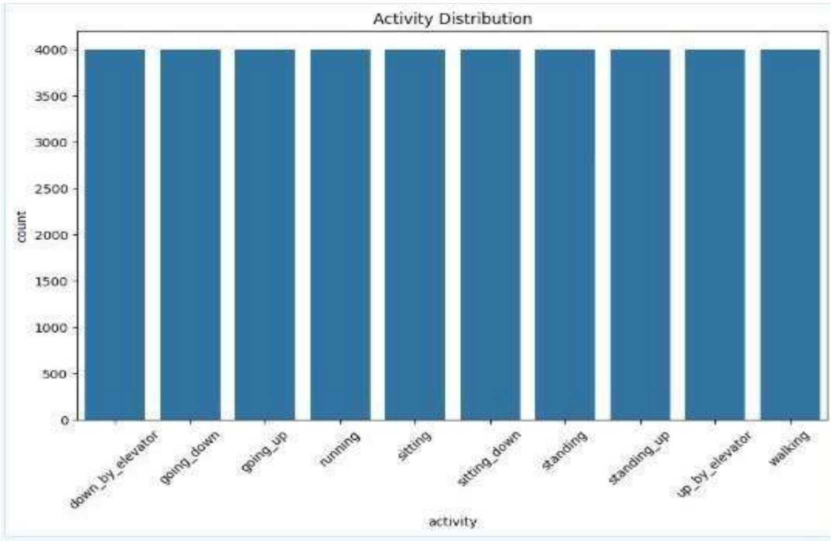

Fig. 4. Activity distribution chart for multi gait detection.

Fig. 4 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.

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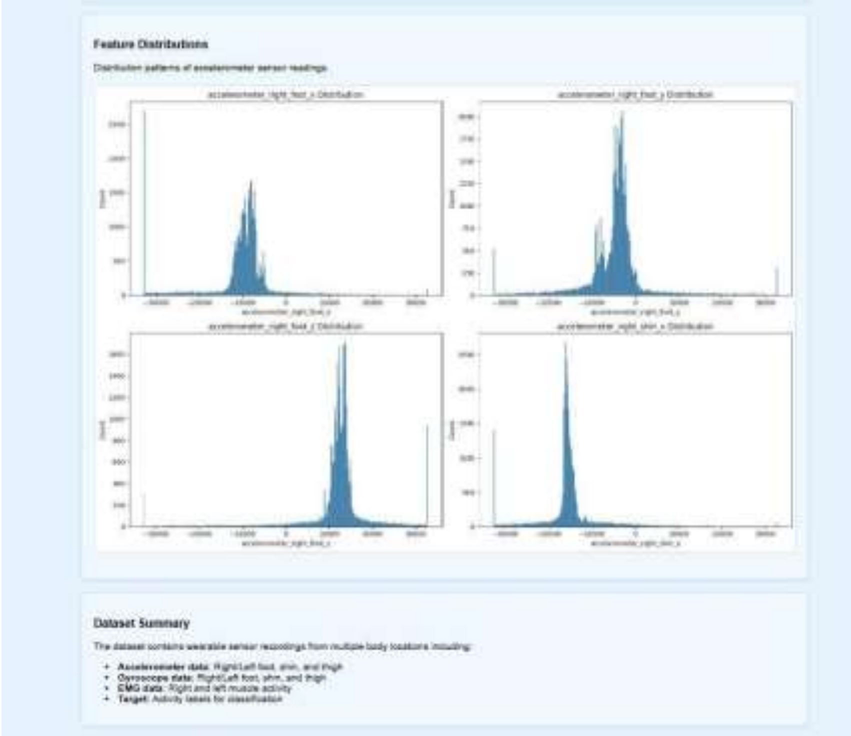

Fig. 5. Feature distributions for multi gait detection.

Fig. 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

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

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

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.

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.

Table. 1: Comparison table of multi gait detection.

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

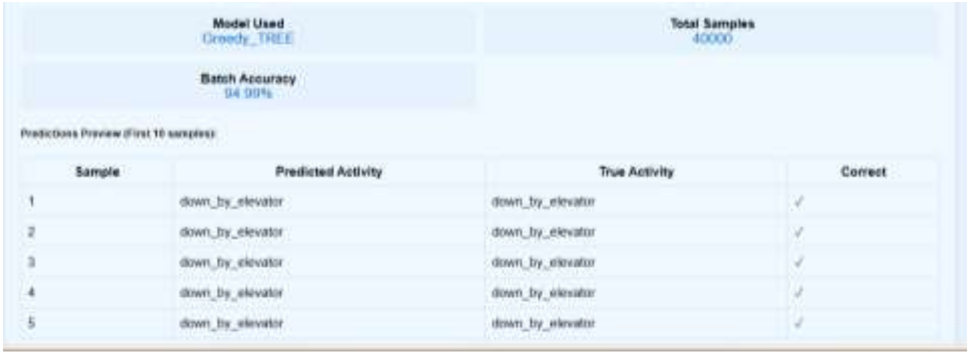

Fig. 7. Batch prediction results interface for activity classification

Fig. 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.

5. CONCLUSION

The research presents a robust and efficient framework for human activity classification using wearable sensor data, integrating multiple machine learning algorithms including GT, KNN, LR, NB, and AB. The system is designed as a unified pipeline that incorporates data preprocessing, feature normalization, model training, performance evaluation, and prediction, ensuring a seamless analytical workflow. Experimental results indicate that the Greedy Tree model outperforms all other classifiers, achieving a peak accuracy of 99.00%, which highlights its effectiveness in capturing complex patterns within high-dimensional sensor data. KNN demonstrates comparatively stable performance, whereas NB, LR, and AB exhibit lower accuracy due to their limited capability in modeling non-linear relationships. The framework supports both real-time and batch prediction, enhancing its adaptability for practical deployment. Additionally, the inclusion of visualization techniques and comprehensive evaluation metrics improves model interpretability and facilitates comparative analysis. Model persistence mechanisms further optimize system efficiency by eliminating redundant training processes. The proposed approach delivers high accuracy, consistency, and scalability, providing a strong foundation for the development of intelligent and automated activity recognition systems.

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