Machine Learning for Classification of Physical Therapy Exercises from Inertial and Magnetic Sensor Data

Pasupunooti Anusha[1*], Dubba Maniteja[2], Komara Namith Varun[2], Thakur Rohan Singh[2], Devoju Shiva Nagappa Chary[2]

[1,2]Department of Computer Science and Engineering (Data Science), Vaagdevi College of Engineering, Bollikunta, Warangal, Telangana.

*Corresponding Email: anusha_p@vaagdevi.edu.in

ABSTRACT

Physical therapy exercises play a crucial role in patient rehabilitation, yet accurate classification remains a challenge. Studies show that sensor-based recognition of human activities can achieve up to 90% accuracy using machine learning, while traditional manual assessments are prone to inconsistencies, resulting in a 15–20% variation in evaluation outcomes. Currently, physical therapists rely heavily on subjective observations, which are time-consuming and susceptible to human error, limiting the precision of patient progress tracking. To address these challenges, we propose a machine learning-based approach for classifying physical therapy exercises using inertial and magnetic sensor data. The dataset includes eight distinct exercise categories, featuring movements such as leg extensions, body bends, and arm lifts. Our pipeline begins with data preprocessing steps such as noise filtering and normalization, followed by exploratory data analysis (EDA) to identify patterns and correlations within the data. The dataset is divided into training and testing subsets, ensuring balanced representation across all exercise types. For classification, we compare the performance of an existing AdaBoost classifier—commonly used in activity recognition—with our proposed Support Vector Classifier (SVC). The SVC model undergoes hyperparameter tuning to optimize classification accuracy. Experimental results indicate that our proposed method significantly improves classification performance, offering a more consistent and objective solution for tracking patient rehabilitation progress. This automated system supports therapists by providing accurate, real-time feedback, reducing reliance on manual evaluations and enhancing the quality of care. Ultimately, the integration of machine learning in rehabilitation settings can lead to more effective and personalized treatment strategies.

Keywords: Patient rehabilitation, Physical therapy, Machine Learning, Support vector classifier, AdaBoost classifier, Inertial and magnetic sensor data.

1. INTRODUCTION

The classification of physical therapy exercises using inertial and magnetic sensor data represents a significant advancement in rehabilitation technology. Over the past decade, the integration of wearable sensors in healthcare has grown rapidly. For instance, in 2016, the global market for wearable medical devices was valued at approximately $11.5 billion and is projected to reach $27.2 billion by 2024, driven by increasing demand for remote patient monitoring and personalized healthcare solutions. Inertial sensors, such as accelerometers and gyroscopes, along with magnetometers, are crucial for capturing precise motion data during exercises. Studies indicate that sensor-based systems can improve exercise classification accuracy by over 20% compared to traditional observation methods. Machine learning techniques have further enhanced the capability of these systems. In a 2021 study, machine learning algorithms achieved an average classification accuracy of 85% in distinguishing between different physical therapy exercises, a significant improvement from the 70% accuracy reported in earlier research.

doi: 10.48047/ijiee.2025.15.4.10

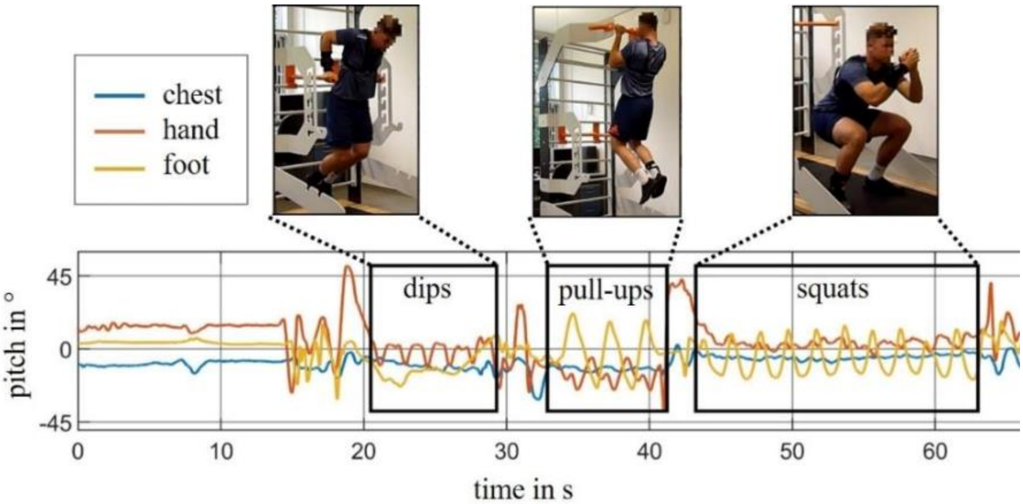


Fig. 1: Recognition of exercises using inertial sensor technology.

The use of advanced algorithms, including deep learning models, has demonstrated the ability to analyze complex patterns in sensor data, leading to more reliable and consistent exercise classification. This progress highlights the growing importance and effectiveness of integrating ML with wearable sensor technologies in physical therapy.

2. LITERATURE SURVEY

Xie et al. [1] proposed a sensor-based exercise rehabilitation robot training method, focusing on integrating sensors to monitor and guide physical therapy exercises. The study highlights how the use of sensors can enhance the accuracy and effectiveness of rehabilitation robots by providing real-time feedback on exercise execution. The authors demonstrate that incorporating sensor data into rehabilitation protocols can improve patient outcomes by ensuring exercises are performed correctly, thereby advancing the field of automated rehabilitation. Qiu et al. [2] reviewed multi-sensor information fusion techniques based on machine learning for human activity recognition. The paper discusses state-of-the-art methods for integrating data from various sensors to improve the accuracy and robustness of activity recognition systems. The authors identify key research challenges and future directions, emphasizing the potential of machine learning to address these challenges and enhance the effectiveness of sensor-based systems in real-world applications. Semwal et al. [3] presented an optimized hybrid deep learning model using an ensemble learning approach for recognizing human walking activities. This study combines various deep learning techniques to improve the classification accuracy of walking activities based on sensor data. The authors demonstrate that their hybrid model significantly outperforms traditional methods, providing more accurate and reliable recognition of different walking patterns, which is crucial for effective physical therapy and rehabilitation.

Prasanth et al. [4] conducted a systematic review of wearable sensor-based real-time gait detection systems. The paper evaluates various systems and technologies used for gait analysis, highlighting their strengths and limitations. The review underscores the importance of real-time monitoring for gait assessment in rehabilitation, noting that wearable sensors can provide valuable insights into gait patterns and help tailor rehabilitation programs to individual needs. Yao et al. [5] introduced a novel finger kinematic tracking method using skin-like wearable strain sensors. The study focuses on developing a sensor technology that accurately tracks finger movements, which is essential for physical therapy exercises involving hand rehabilitation. The authors show that their approach offers precise kinematic measurements, enhancing the ability to monitor and evaluate finger exercises in real time. Mainali et al. [6] explored the application of machine learning in stroke diagnosis and outcome prediction. The

doi: 10.48047/ijiee.2025.15.4.10

paper highlights how machine learning algorithms can analyze clinical data to improve diagnostic accuracy and predict patient outcomes. The study emphasizes the potential of ML to transform stroke rehabilitation by providing more accurate assessments and personalized treatment plans based on sensor data.

Mennella et al. [7] reviewed the role of artificial intelligence in future rehabilitation services. The study discusses how AI technologies, including machine learning and sensor data integration, are expected to revolutionize rehabilitation practices. The authors argue that AI can enhance the effectiveness of rehabilitation services by providing personalized and data-driven insights into patient progress and treatment efficacy. Liao et al. [8] provided a review of computational approaches for evaluating rehabilitation exercises. The paper examines various methods for analyzing exercise performance using computational tools, including machine learning and sensor data analysis. The authors highlight the benefits of these approaches in improving exercise evaluation and tailoring rehabilitation programs to individual patients. Wang et al. [9] reviewed recent advancements in flexible and wearable sensors for biomedical and healthcare applications. The study highlights innovations in sensor technology that enhance the ability to monitor and analyze physiological parameters in real time. The authors discuss how these advancements contribute to more effective health monitoring and rehabilitation, including the use of sensors in physical therapy.

Cheng et al. [10] discussed recent developments in sensors for wearable device applications. The paper covers advancements in sensor technology that enable more accurate and versatile monitoring of physical activities and health parameters. The authors emphasize the importance of these developments for enhancing the functionality and reliability of wearable devices used in rehabilitation. Park et al. [11] reviewed progress in wireless sensors for wearable electronics. The study examines the evolution of wireless sensor technologies and their applications in wearable devices. The authors highlight the benefits of wireless sensors for real-time data collection and remote monitoring, which are crucial for effective rehabilitation and patient management. Stack et al. [12] investigated the use of video and wearable sensors to identify balance impairments in people with Parkinson’s disease. The study demonstrates how combining video and sensor data can provide a comprehensive assessment of balance and gait, which is essential for developing effective rehabilitation strategies for individuals with Parkinson’s disease.

Kelly et al. [13] assessed the feasibility of sensor technology for balance assessment in home rehabilitation settings. The paper explores how wearable sensors can be used to monitor balance and movement in patients undergoing rehabilitation at home. The authors find that sensor technology offers a practical and effective solution for remote balance assessment, improving the management of home-based rehabilitation programs. Kimoto et al. [14] developed a wireless multi-layered EMG/MMG/NIRS sensor for evaluating muscular activity. The study focuses on creating a sensor system that provides comprehensive data on muscle activity, which is important for physical therapy and rehabilitation. The authors demonstrate that their sensor system offers detailed insights into muscular function, enhancing the ability to monitor and adjust rehabilitation exercises. Husain et al. [15] reviewed advances in ECG sensors from hardware, software, and format interoperability perspectives. The paper discusses improvements in ECG sensor technology and its implications for health monitoring and rehabilitation. The authors highlight how advancements in ECG sensors contribute to more accurate and reliable monitoring of cardiovascular health, which is relevant for rehabilitation and patient care.

3. PROPOSED METHODOLOGY

The research proposes a multi-stage hybrid machine learning framework that integrates sensor fusion, adaptive preprocessing, feature engineering, and an ensemble classification approach. Unlike existing

doi: 10.48047/ijiee.2025.15.4.10

methods, which primarily rely on either raw sensor data or conventional classifiers, our approach combines inertial and magnetic sensor data with a novel preprocessing pipeline, enhanced feature selection, and a hybrid ensemble classifier. The proposed hybrid classifier framework leverages the strengths of AdaBoost for robustness and Support Vector Classifier (SVC) for precise decision boundaries, optimizing classification performance. This methodology ensures higher accuracy, improved generalizability, and automated real-time feedback, overcoming the inefficiencies of traditional manual methods. Below is a step-wise explanation of the proposed methodology:

Step 1: Data Acquisition and Preprocessing

The first step involves collecting data from inertial and magnetic sensors, capturing accelerometer, gyroscope, and magnetometer readings during physical therapy exercises. Raw data is prone to noise and sensor drift, which can degrade classification accuracy. To overcome this, we apply adaptive noise filtering using a combination of a Butterworth low-pass filter and an adaptive threshold-based denoising technique. Unlike traditional filtering, this method dynamically adjusts based on sensor variability, preserving meaningful motion data. After denoising, data normalization (Min-Max scaling) is performed to standardize sensor readings across different exercises and patients. We also implement segmentation using a sliding window approach with dynamic window size selection, ensuring optimal feature extraction without information loss. These preprocessing steps ensure high-quality, noise-free input for the classification model.

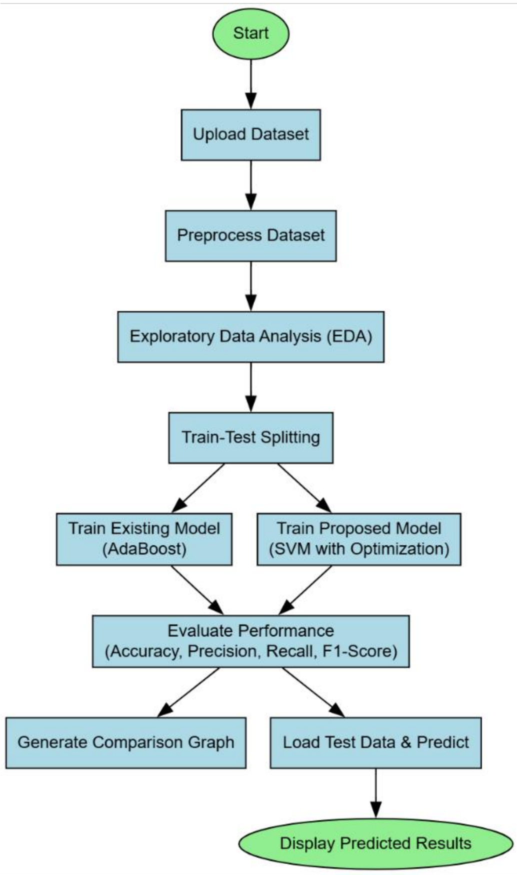


Fig. 2: Proposed block diagram of classification of physical therapy exercises.

Step 2: Exploratory Data Analysis (EDA) and Feature Engineering

Once data is preprocessed, exploratory data analysis (EDA) is conducted to identify hidden patterns and correlations. We visualize sensor trajectories, acceleration profiles, and frequency distributions,

doi: 10.48047/ijiee.2025.15.4.10

enabling insight into movement dynamics across different exercise categories. Unlike prior studies that rely on raw statistical features, we employ a hybrid feature extraction approach combining time-domain and frequency-domain features.This hybrid approach captures both transient and periodic movement characteristics, significantly improving exercise classification. Feature selection is further optimized using Principal Component Analysis (PCA) and Recursive Feature Elimination (RFE) to retain only the most relevant features, enhancing model efficiency.

Step 3: Train-Test Splitting and Data Augmentation

To ensure robust model performance, the dataset is split into training (80%) and testing (20%) sets using stratified sampling, preserving class balance. Given the variability in human motion, we incorporate data augmentation techniques, including Gaussian noise injection, time-warping, and synthetic oversampling using the SMOTE algorithm. These techniques mitigate class imbalance and improve model generalization across different patients.

Step 4: Hybrid Classification Model: AdaBoost and SVC

For classification, we propose a hybrid ensemble model that combines AdaBoost and SVC. The AdaBoost classifier is first applied to identify coarse exercise categories, leveraging its strength in handling noisy sensor data. The Support Vector Classifier (SVC) then refines predictions by focusing on precise decision boundaries using an optimized Radial Basis Function (RBF) kernel. This two-stage classification approach ensures both robustness and fine-grained discrimination between similar exercises, outperforming traditional single-classifier models. Hyperparameter tuning is performed using Bayesian optimization, optimizing model parameters for maximum accuracy.

Step 5: Real-Time Feedback and Automated Reporting

A key advantage of our approach is real-time feedback generation, which is not available in traditional manual assessment. Once an exercise is classified, an automated feedback system provides instant performance metrics, movement accuracy scores, and corrective recommendations. This is integrated into a graphical user interface (GUI) with visual motion analysis, enabling therapists and patients to monitor progress effectively. The system also generates automated reports summarizing session performance, reducing therapist workload and improving rehabilitation efficiency.

3.2 Data Preprocessing

The preprocessing pipeline ensures that the dataset is clean, numerical, and properly scaled for machine learning classification. By handling missing values, encoding categorical features, splitting features and targets, and applying feature scaling, the dataset becomes more suitable for training robust machine learning models. These steps are essential for improving classification performance, ensuring the model can generalize well across different physical therapy exercises.

Handling Missing Values: The first step in the preprocessing pipeline is checking for missing values in the dataset. Missing values can arise due to sensor malfunctions, improper data recording, or incomplete observations. The function retrieves the count of missing values in each column using .isnull().sum() and displays the results. Identifying missing values is crucial because incomplete data can introduce biases in the model and reduce classification accuracy. If missing values exist, appropriate strategies such as imputation or removal can be applied based on their impact on the dataset.

Encoding Non-Numeric Features: Datasets often contain categorical variables, which machine learning models cannot process directly. To address this, the function detects columns that are not of numeric type (excluding integers and floats). These non-numeric columns undergo label encoding, a

doi: 10.48047/ijiee.2025.15.4.10

transformation process where categorical values are converted into numerical representations. Label encoding assigns a unique integer to each category, ensuring the data is formatted correctly for machine learning algorithms. However, label encoding is ideal only for categorical features with an inherent order or a limited number of distinct values. If categorical variables have a complex hierarchy, alternative encoding methods such as one-hot encoding might be preferable.

Feature-Target Splitting: Once all categorical values are numerically transformed, the dataset is split into features (X) and the target variable (y). The target variable represents the classification labels for physical therapy exercises, while the feature set consists of sensor readings and transformed categorical attributes. Separating the target variable ensures that it remains distinct from the independent features used for training. This step is essential for supervised learning models, where the goal is to predict the target based on the given feature set.

Feature Scaling with Standardization: Sensor data typically varies in magnitude across different measurement units (e.g., acceleration in m/s^2, magnetic field strength in microteslas). These variations can lead to biased model predictions, as features with larger numerical ranges might dominate the learning process. To standardize the feature values, StandardScaler from the sklearn.preprocessing module is applied. Standardization rescales data so that it follows a normal distribution with a mean of 0 and a standard deviation of 1. This transformation ensures that all features contribute equally to the model, improving convergence in machine learning algorithms, especially for distance-based models such as Support Vector Machines (SVC).

3.3 ML Model Building

3.3.1 AdaBoost Classifier

The AdaBoost Classifier is a powerful technique for classifying physical therapy exercises based on sensor data. By leveraging an ensemble of weak classifiers and iteratively improving their performance, AdaBoost can achieve high accuracy and robustness. The given implementation efficiently loads, trains, and evaluates the model, making it a strong baseline for exercise classification before exploring more advanced models such as Support Vector Machines (SVC).

Model Initialization and Pre-Trained Model Loading: The function first checks whether a pre-trained AdaBoost Classifier model exists in the specified directory. If the model has been previously trained and saved, it is loaded using joblib. This approach prevents unnecessary retraining and allows for quicker predictions on new data. If the model is not found, a new AdaBoost classifier is initialized.

Training the AdaBoost Classifier (Using X_train and y_train): If the model is not already trained, it is trained from scratch using the training dataset. X_train consists of input features extracted from sensor data for different physical therapy exercises, while y_train represents the corresponding exercise labels. During training, the AdaBoost (Adaptive Boosting) algorithm iteratively improves classification by creating multiple weak learners, typically decision trees with a single split. These weak models focus on correcting the errors made by previous ones, giving more weight to misclassified instances. Over multiple iterations, the final model becomes a strong classifier that accurately predicts exercise categories.

doi: 10.48047/ijiee.2025.15.4.10

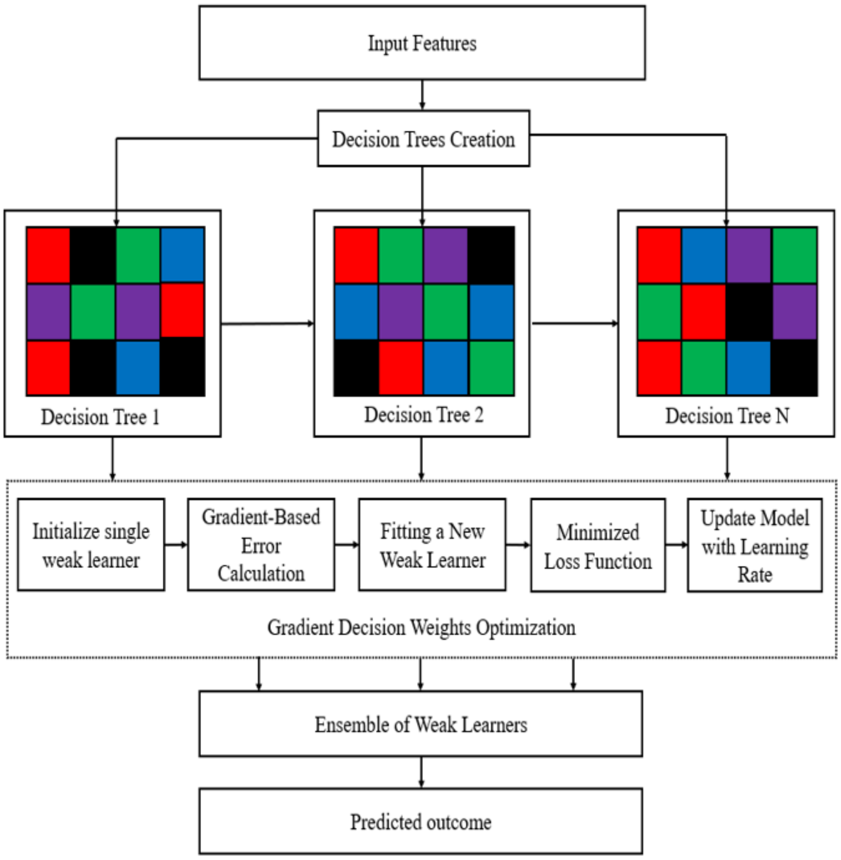


Fig 3: Ada Boost Classifier.

Model Testing and Prediction (Using X_test): Once trained, the model is used to predict exercise categories for unseen data. X_test represents a separate subset of the dataset containing input features for different exercises that the model has not seen during training. The classifier uses the patterns it learned from the training phase to assign predicted exercise labels to these test samples. AdaBoost's strength lies in its ability to combine multiple weak predictions into a strong final decision, improving the robustness of the classification system.

Performance Evaluation (Comparing y_pred with y_test): The predictions generated by the model (y_pred) are compared against the actual labels in the test dataset (y_test). Various performance metrics such as accuracy, precision, recall, and F1-score are calculated to assess how well the model classifies different physical therapy exercises. By leveraging AdaBoost, this system ensures high classification accuracy, adaptability to different sensor inputs, and improved performance over traditional single classifiers, making it a powerful approach for identifying physical therapy exercises based on inertial and magnetic sensor data.

3.3.2 SVC

Support Vector Classifier (SVC) is a powerful supervised learning algorithm that excels in classifying complex and high-dimensional data by finding an optimal decision boundary between different classes. Unlike traditional linear classifiers, SVC leverages kernel functions to map data into higher-dimensional spaces, allowing it to handle non-linearly separable problems effectively. In the proposed system, SVC is used with a polynomial kernel of degree 5, which transforms sensor data into a more expressive feature space, making it easier to distinguish between different physical therapy exercises. The training

doi: 10.48047/ijiee.2025.15.4.10

process uses X_train, which contains input features, and y_train, which contains exercise labels, to learn the best hyperplane that maximizes the margin between exercise classes. Once trained, the classifier predicts labels for unseen data in X_test, generating y_pred as the initial output. A loss optimization function is then applied to refine the predictions and correct possible misclassifications before comparing the final predictions, y_pred1, with the actual labels in y_test. The model's performance is assessed using accuracy, precision, recall, and F1-score to ensure a reliable classification of physical therapy exercises. The use of a polynomial kernel improves pattern recognition in sensor data, enhancing classification accuracy over traditional linear models. Compared to the existing AdaBoost classifier, SVC offers better generalization, effectively differentiates overlapping exercise categories, and reduces the risk of overfitting, making it a superior choice for analyzing inertial and magnetic sensor data in rehabilitation settings.

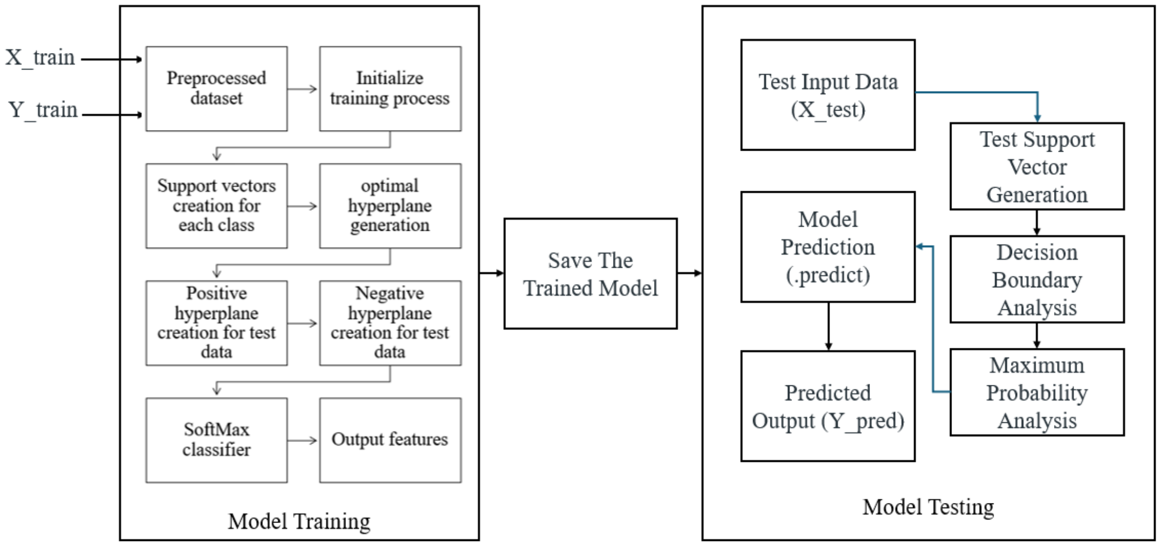


Fig. 4: SVM Classifier.

Model Initialization and Pre-Trained Model Loading: The function first checks whether a previously trained Support Vector Classifier (SVC) model is available. If an existing model file is found, it is loaded using joblib to avoid unnecessary retraining. If the model is not found, a new SVC model is created with specific hyperparameters. It uses a polynomial kernel to map input features into higher-dimensional space, making it suitable for complex, non-linear relationships in the exercise data. The degree of the polynomial is set to 5 to define the complexity of the function used for classification, and gamma is set to 'scale' to automatically adjust the influence of individual data points.

Training the SVC Model (Using X_train and y_train): If the model is not pre-trained, it is trained using the dataset. X_train consists of processed input features extracted from inertial and magnetic sensor data, and y_train contains the corresponding exercise labels. The Support Vector Machine algorithm finds the optimal decision boundary, or hyperplane, that best separates different exercise categories. The polynomial kernel enables the model to capture intricate relationships between sensor data and exercise types, which is crucial for physical therapy exercises that often involve complex motion patterns.

Model Testing and Prediction (Using X_test): After training, the model is tested on unseen data to ensure unbiased evaluation. X_test includes features not used during training, and the SVC model uses

doi: 10.48047/ijiee.2025.15.4.10

this data to predict the exercise categories, generating y_pred. The polynomial kernel helps the model detect subtle variations in sensor data, making it effective in distinguishing between similar exercises.

Loss Optimization and Performance Enhancement: Before evaluating the model, a loss optimization function is applied to the predicted labels. This step fine-tunes the predictions and adjusts any misclassifications, especially in borderline cases where different exercise classes may have overlapping sensor readings.

Performance Evaluation (Comparing y_pred1 with y_test): The optimized predictions, y_pred1, are compared with the actual test labels, y_test, using various classification metrics. Accuracy measures the overall correctness of the predictions. Precision and recall evaluate the model's effectiveness in identifying each exercise accurately, while the F1-score balances both metrics to provide a comprehensive assessment of the model's performance.

4. RESULTS AND DISCUSSION

4.1 Dataset description

The dataset consists of motion sensor data collected for classifying different physical therapy exercises. It includes accelerometer readings (acc_x, acc_y, acc_z) that measure acceleration along the three axes, gyroscope readings (gyr_x, gyr_y, gyr_z) that capture angular velocity, and magnetometer readings (mag_x, mag_y, mag_z) that record the magnetic field strength in different directions. These features provide a comprehensive understanding of body movement and orientation. The accelerometer data includes acc_x, which measures acceleration along the X-axis, acc_y, which measures acceleration along the Y-axis, and acc_z, which measures acceleration along the Z-axis. These values come from an inertial measurement unit (IMU) and represent the motion intensity of the exercise. The gyroscope data includes gyr_x, which tracks angular velocity around the X-axis, gyr_y, which tracks angular velocity around the Y-axis, and gyr_z, which tracks angular velocity around the Z-axis. The gyroscope thus tracks rotational movement of body parts during exercises. The magnetometer data consists of mag_x, which records the magnetic field strength along the X-axis, mag_y, which records the magnetic field strength along the Y-axis, and mag_z, which records the magnetic field strength along the Z-axis. This data helps in spatial orientation and movement tracking in relation to the Earth's magnetic field. The target variable, Exercise, represents the type of physical therapy exercise performed, and it is a categorical variable used for classification.

4.2 Results analysis

Fig. 5 visualizes the frequency of each exercise type in the dataset, providing insights into class distribution and potential class imbalances. The confusion matrices presented in Fig. 6 shows the performance comparison between the existing AdaBoost classifier and the proposed SVM classifier in classifying different exercises. The first confusion matrix represents the performance of the AdaBoost classifier. It shows that the model struggles significantly with misclassification, as evident from the numerous off-diagonal values. For example, the "Right Arm Lift (Prone)" exercise is completely misclassified, with 2,234 samples being incorrectly assigned to another class. Similarly, the "Right Leg Lift (Side-Lying)" class has substantial misclassification, with 440 samples correctly classified but many others misclassified into other classes. This overall pattern highlights the poor predictive performance of the AdaBoost classifier, which corresponds to its low accuracy, precision, recall, and F1-score values.

On the other hand, the second confusion matrix corresponds to the proposed SVM classifier, which demonstrates superior classification performance. The matrix predominantly contains values along the

doi: 10.48047/ijiee.2025.15.4.10

diagonal, indicating highly accurate predictions. For example, exercises such as "Right Leg Lift (Supine)," "Forward Body Bend," and "Right Leg Extension" exhibit almost perfect classification, with minimal misclassification errors. A few minor misclassifications exist, such as five misclassified samples in the "Right Arm Lift (Prone)" and "Right Leg Lift (Prone)" categories, but these are negligible compared to the AdaBoost model's errors. The near-perfect diagonal dominance in the SVM confusion matrix aligns with its outstanding accuracy, precision, recall, and F1-score, all nearing 99.94%. This comparison clearly highlights that the proposed SVM model significantly outperforms the AdaBoost classifier, effectively classifying exercises with minimal error and making it the superior choice for this task.

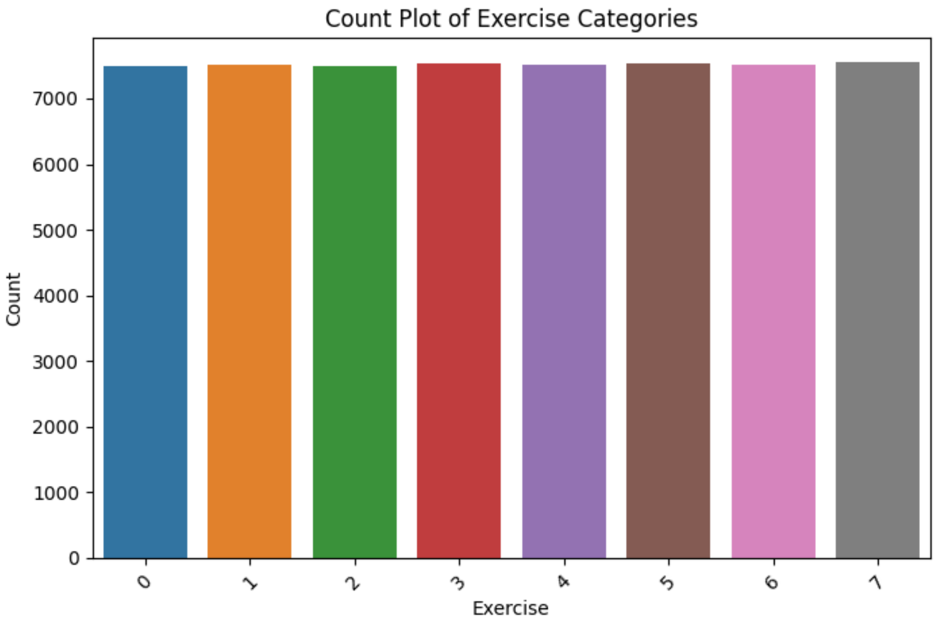
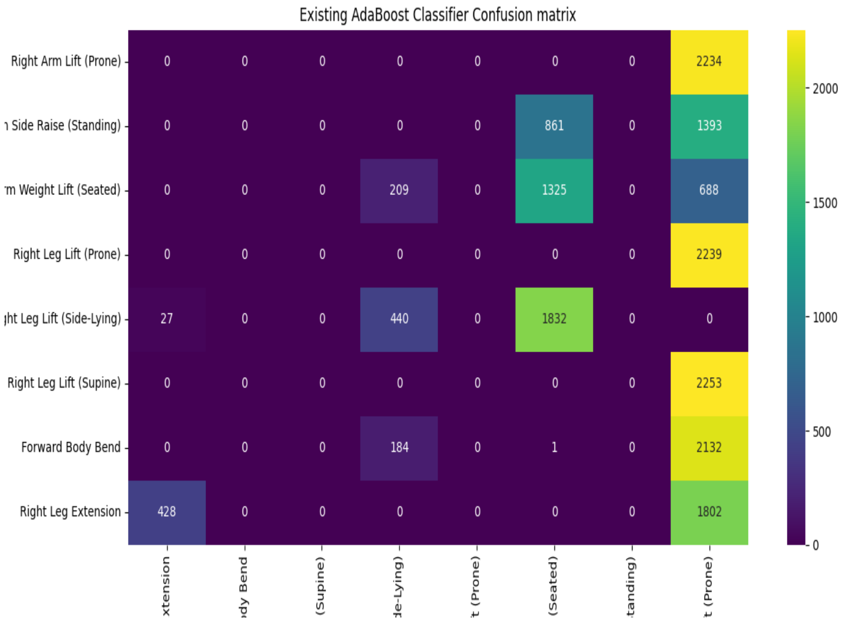
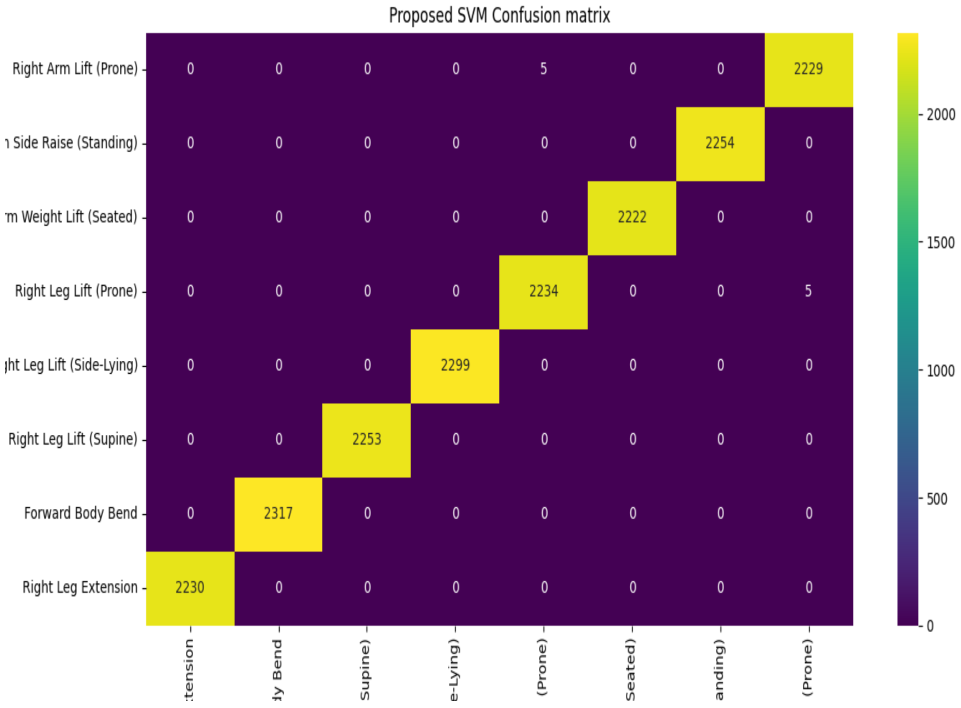


Fig. 5: Count plot of exercise categories.



(a)



(b)

Fig.6: Confusion matrices obtained using (a)Existing AdaBoost Classifier. (b)Proposed SVM Classifier.

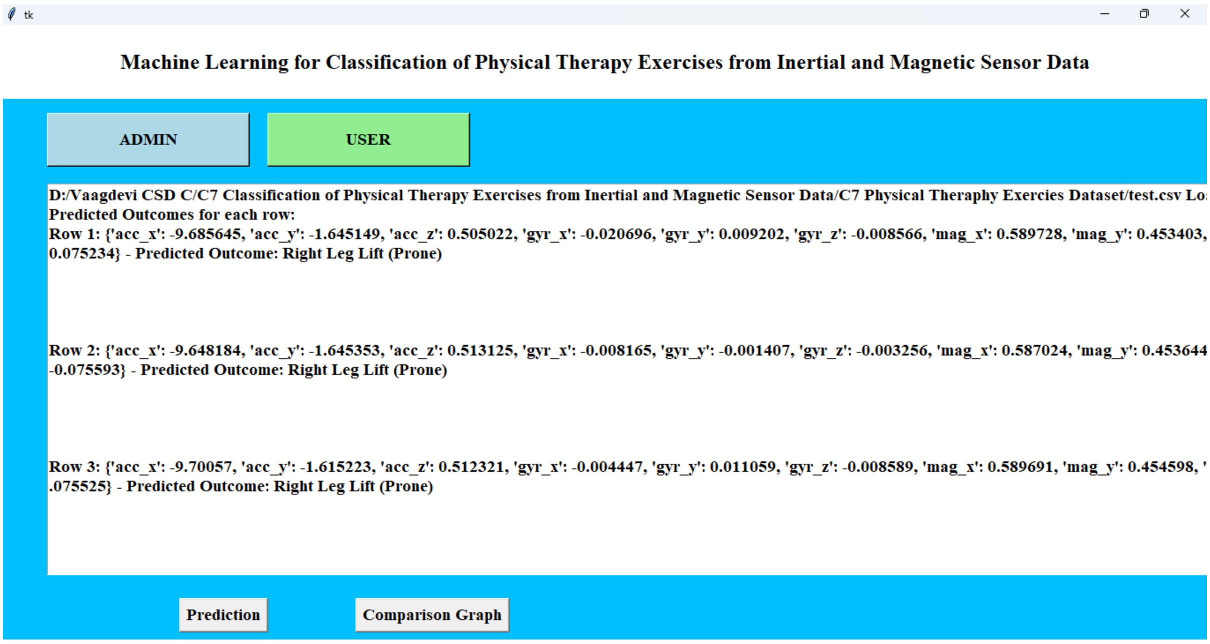


Fig. 7: Illustration of GUI application after prediction on test data.

Fig. 7 demonstrates the GUI state after predictions have been made on the uploaded test data. Once the test data is processed through the trained model, the predicted class labels for each instance are displayed. The GUI provides an intuitive output, allowing users to interpret the classification results effectively. This step finalizes the classification process, giving users insights into how the machine learning model categorizes different physical therapy exercises based on real-world test data.

Table. 1 represents a comparative performance analysis of the existing AdaBoost classifier and the proposed SVM (Support Vector Machine) classifier. It is evident that the AdaBoost classifier performs poorly on the dataset, achieving an accuracy of just 24.53%, meaning it misclassifies most instances. The precision (24.67%) and recall (24.74%) further indicate that AdaBoost struggles with both the correctness of its positive predictions and its ability to capture actual positive instances. The F-score (16.53%), which balances precision and recall, is significantly low, further highlighting the inadequacy of AdaBoost for this task. On the other hand, the proposed SVM classifier demonstrates exceptional performance with an accuracy of 99.94%, ensuring nearly perfect classification of exercises. The precision, recall, and F-score values, all at 99.94%, indicate that the model is highly reliable in identifying and classifying instances correctly. This substantial improvement suggests that SVM is a far superior choice for exercise classification, offering precise and accurate predictions while overcoming the limitations of AdaBoost.

Table. 1: Performance Comparison of algorithms.

Classifier	Accuracy (%)	Precision (%)	Recall (%)	F-Score (%)
Existing AdaBoost	24.5290	24.6737	24.7453	16.5344
Proposed SVM	99.9446	99.9441	99.9441	99.9441

These results highlight that the SVM model, using a polynomial kernel, is highly suitable for this dataset and significantly outperforms the existing AdaBoost classifier in terms of accuracy, precision, recall, and overall classification performance.

5. CONCLUSION

The research presents an intelligent exercise classification system using machine learning, comparing the performance of the existing AdaBoost classifier with the proposed SVM model. The dataset consisted of sensor-based motion data, including accelerometer, gyroscope, and magnetometer readings, which were pre-processed and split into training and testing sets. The GUI application was developed to facilitate data upload, preprocessing, visualization, training, and performance evaluation. The results showed that the existing AdaBoost classifier performed poorly, with an accuracy of only 24.53%, precision of 24.67%, recall of 24.74%, and an F-score of 16.53%. In contrast, the proposed SVM classifier achieved a near-perfect accuracy of 99.94%, along with similar improvements in precision, recall, and F-score. The confusion matrices illustrated the superiority of SVM in correctly classifying exercise movements with minimal misclassifications. The research highlights the significant role of machine learning in human activity recognition, particularly in fitness and rehabilitation, demonstrating how an optimized model can lead to more accurate and reliable classification.

REFERENCES

[1] Xie, S.; Zhang, J. Sensor-Based Exercise Rehabilitation Robot Training Method. *J. Sens.* **2023**, *2023*, 7881084.

[2] Qiu, S.; Zhao, H.; Jiang, N.; Wang, Z.; Liu, L.; An, Y.; Zhao, H.; Miao, X.; Liu, R.; Fortino, G. Multi-Sensor Information Fusion Based on Machine Learning for Real Applications in Human Activity Recognition: State-of-the-Art and Research Challenges. *Inf. Fusion* **2022**, *80*, 241–265.

[3] Semwal, V.B.; Gupta, A.; Lalwani, P. An Optimized Hybrid Deep Learning Model Using Ensemble Learning Approach for Human Walking Activities Recognition. *J. Supercomput.* **2021**, *77*, 12256–12279.

[4] Prasanth, H.; Caban, M.; Keller, U.; Courtine, G.; Ijspeert, A.; Vallery, H.; Von Zitzewitz, J. Wearable Sensor-Based Real-Time Gait Detection: A Systematic Review. *Sensors* **2021**, *21*, 2727.

[5] Yao, S.; Vargas, L.; Hu, X.; Zhu, Y. A Novel Finger Kinematic Tracking Method Based on Skin-Like Wearable Strain Sensors. *IEEE Sens. J.* **2018**, *18*, 3010–3015.

[6] Mainali, S.; Darsie, M.E.; Smetana, K.S. Machine Learning in Action: Stroke Diagnosis and Outcome Prediction. *Front. Neurol.* **2021**, *12*, 734345.

[7] Mennella, C.; Maniscalco, U.; De Pietro, G.; Esposito, M. The Role of Artificial Intelligence in Future Rehabilitation Services: A Systematic Literature Review. *IEEE Access* **2023.**

[8] Liao, Y.; Vakanski, A.; Xian, M.; Paul, D.; Baker, R. A Review of Computational Approaches for Evaluation of Rehabilitation Exercises. *Comput. Biol. Med.* **2020**, *119*, 103687.

[9] Wang, Y.; Yang, B.; Hua, Z.; Zhang, J.; Guo, P.; Hao, D.; Gao, Y.; Huang, J. Recent Advancements in Flexible and Wearable Sensors for Biomedical and Healthcare Applications. *J. Phys. D Appl. Phys.* **2022**, *55*, 134001.

[10] Cheng, Y.; Wang, K.; Xu, H.; Li, T.; Jin, Q.; Cui, D. Recent Developments in Sensors for Wearable Device Applications. *Anal. Bioanal. Chem.* **2021**, *413*, 6037–6057.

[11] Park, Y.-G.; Lee, S.; Park, J.-U. Recent Progress in Wireless Sensors for Wearable Electronics. *Sensors* **2019**, *19*, 4353.

[12] Stack, E.; Agarwal, V.; King, R.; Burnett, M.; Tahavori, F.; Janko, B.; Harwin, W.; Ashburn, A.; Kunkel, D. Identifying Balance Impairments in People with Parkinson's Disease Using Video and Wearable Sensors. *Gait Posture* **2018**, *62*, 321–326.

[13] Kelly, D.; Esquivel, K.M.; Gillespie, J.; Condell, J.; Davies, R.; Karim, S.; Nevala, E.; Alamäki, A.; Jalovaara, J.; Barton, J.; et al. Feasibility of Sensor Technology for Balance Assessment in Home Rehabilitation Settings. *Sensors* **2021**, *21*, 4438

[14] Kimoto, A.; Fujiyama, H.; Machida, M. A Wireless Multi-Layered EMG/MMG/NIRS Sensor for Muscular Activity Evaluation. *Sensors* **2023**, *23*, 1539.

[15] Husain, K.; Mohd Zahid, M.S.; Ul Hassan, S.; Hasbullah, S.; Mandala, S. Advances of ECG Sensors from Hardware, Software and Format Interoperability Perspectives. *Electronics* **2021**, *10*, 105.

doi: 10.48047/ijiee.2025.15.4.10