Multi-Algorithm Classification for Daily and Sports Activity Recognition Based on Inertial Sensors: A Comparison of Random Forest, SVM, and Neural Network

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Abstract* – This research investigates the classification of 19 daily and sports activities using inertial sensor data from the "Daily and Sports Activities" dataset. We evaluated the performance of three machine learning models: Random Forest, Support Vector Machine (SVM), and Neural Network, trained with time-domain statistical features. Random Forest demonstrated superior performance with an accuracy of 0.9146, outperforming SVM (0.8418) and Neural Network (0.7281). While these models were effective in classifying dynamic activities, significant challenges were found with stationary activities like "standing," which exhibited low recall. Feature analysis and PCA indicated that time-domain features might be insufficient to differentiate subtle movements. This study highlights the potential of inertial sensors for human activity recognition and recommends exploring temporal-frequency features and more complex model architectures to enhance robustness, especially for stationary activities.

***Keywords* – Human Activity Recognition, Inertial Sensors, Random Forest, Support Vector Machine (SVM), Neural Network, Multi-class Classification, Stationary Activities.**

I. INTRODUCTION

Inertial sensors, such as accelerometers and gyroscopes, have become the backbone of instrumentation and control. Since their introduction in the early 20th century for aviation navigation [1], this technology has rapidly evolved, supporting precise motion measurements for applications like inertial navigation [2] and health monitoring [3]. However, technical challenges, such as signal noise, which can reduce classification accuracy by up to 10% for subtle movements like sitting [4], and the complexity of multi-sensor data fusion [5], often hinder system performance. In motion control systems, the need for real-time data processing is critical, especially with the emergence of the Internet of Things (IoT) and edge computing [6]. These technologies demand efficient and accurate activity classification solutions, supporting applications like smart healthcare, wearable-based sports training, and industrial automation systems that rely on human motion detection [7]. Recent advancements in sensor miniaturization have enabled the integration of lightweight wearable devices [8]. This research explores such an approach by leveraging inertial sensor data to address these limitations.

Previous studies have shown progress in activity classification. Research using Support Vector Machine (SVM) and k-Nearest Neighbor (k-NN) successfully achieved high accuracy, up to 89.2% and 90% respectively, but struggled to differentiate stationary activities like standing and sitting due to similar motion patterns [9]. A significant gap arises from the lack of a comprehensive comparison with modern approaches like neural networks, which offer adaptability to noisy data and cross-subject variations [10]. Prior studies also showed limitations in generalizing models for real-world applications, especially with complex datasets like the "Daily and Sports Activities" from the UCI Machine Learning Repository, which includes 19 activities with overlapping movement variations, such as walking and jumping [11]. This dataset, collected from eight subjects with five Xsens MTx sensors, offers a unique opportunity to evaluate models under near real-world conditions, but has not been fully utilized in the literature [12].

These limitations highlight the need for new approaches. The main challenge is the classification of stationary and dynamic activities from noisy inertial sensor data, with similar motion patterns hindering accuracy for real-time applications, such as live patient monitoring or industrial work posture detection. This challenge is exacerbated by the complexity of multi-sensor data and the need for models that can operate efficiently on low-power devices.

The objective of this research is to develop a multi-algorithm-based classification model to distinguish 19 daily and sports activities with high accuracy, especially for challenging stationary activities, while ensuring efficiency for real-time processing. Key contributions include:

- Comprehensive comparison between Random Forest, SVM, PCA, and neural networks to evaluate optimal performance in noisy data.

- Identification of key features that differentiate stationary activities, such as standing and standing in an elevator, to improve accuracy.

- Development of a neural network with regularization that enhances generalization and efficiency, supporting wearable systems for real-time athlete injury risk detection and industrial work posture monitoring.

This research aims to advance activity classification technology, providing tangible contributions to the field of instrumentation and control in the digital era by supporting the development of responsive and reliable smart systems.

II. METHODOLOGY

This research employs a **quantitative approach** with an **experimental design** to develop and evaluate machine learning models for classifying human physical activities. This methodology is systematically structured through several key stages: data acquisition and preprocessing, statistical feature extraction,

Research Design

This study adopts a **supervised learning** approach to train three main classification models: **Random Forest**, **Support Vector Machine (SVM)**, and **Neural Network**. Additionally, **Principal Component Analysis (PCA)** is used as an **unsupervised learning** approach for dimensionality reduction and data visualization.

Supervised learning was chosen because the data used already has clear activity labels, allowing models to learn to map input features to the corresponding activity classes. Random Forest and SVM were selected for their efficiency in handling high-dimensional datasets and their ability to identify complex decision boundaries. **Random Forest**, as an ensemble of decision trees, excels in handling noisy data and tolerates outliers. **SVM**, with various kernel options like the **Radial Basis Function (RBF)**, is effective in finding optimal hyperplanes for class separation, even in complex feature spaces.

Neural Network was implemented to explore its capability to automatically learn non-linear feature representations from data, which is highly relevant for complex and varied activities such as playing basketball or jumping. The neural network architecture was designed to capture patterns that might not be discernible by traditional rule-based or kernel-based methods.

PCA, as an unsupervised method, was applied for two main purposes:

- **Dimensionality Reduction:** To reduce the number of input features, which can accelerate model training computation time and mitigate the risk of overfitting, especially in high-dimensional datasets.
- **Data Visualization:** To project data into a lower-dimensional space (two principal components), allowing for the visualization of activity patterns and clusters. This is particularly useful for identifying whether activities with similar movement patterns, such as "standing in a motionless elevator" and "sitting," can be visually separated or exhibit significant overlap.

This research design specifically aims to address challenges posed by data noise and similar movement patterns, particularly in stationary activities that are often difficult to distinguish. PCA was not only used for visualizing data distribution but also tested in model training to evaluate the impact of dimensionality reduction on classification accuracy.

2.1 Dataset

The primary data used in this study is from the "Daily and Sports Activities" **dataset**, available on the UCI Machine Learning Repository. This dataset is a collection of activity recordings gathered from eight subjects (four male and four female, aged 20-30 years) performing 19 types of daily and sports activities. Each activity was recorded for five minutes at a sampling frequency of 25 Hz.

This dataset presents significant challenges due to the complexity and variability of the sensor data. It includes **45 multi-sensor data channels** originating from five Xsens MTx units. These sensor units were positioned on various body parts: chest, waist, right arm, left arm, and right leg. Each Xsens MTx unit records 9-axis data, consisting of:

- Three accelerometer axes (linear acceleration measurement, range +/-5g)
- Three gyroscope axes (angular velocity measurement, range +/-1200 degrees/s)
- Three magnetometer axes (magnetic orientation measurement).

A total of 45 data channels (5 sensors x 9 axes) provide comprehensive information regarding the subject's body movement and orientation during activities.

The dataset covers a wide range of activities with varying movement intensities, from static movements like "sitting" (with acceleration less than 0.5g) to highly dynamic movements such as "jumping" (with acceleration reaching 4g). These intensity differences, coupled with potential data noise and overlapping movement patterns between activities (e.g., "standing" and "sitting" can have similar acceleration patterns), add to the complexity of analysis and classification.

2.2 Software and Hardware

The software used in this research is as follows:

- **Python 3.9:** The main programming language used for the entire data analysis and modeling process.
- **Scikit-learn 1.0.2:** A fundamental library for implementing machine learning algorithms (Random Forest, SVM, PCA) and evaluation metrics.
- **TensorFlow 2.8:** An open-source framework used for building and training neural network models. This version was chosen for its capability to support efficient deep learning model training on multi-dimensional datasets.
- **NumPy 1.21:** An essential library for numerical computing in Python, especially for manipulating high-dimensional arrays that form the basis of feature representation.

- **Pandas:** Used for tabular data management and analysis.
- **Matplotlib 3.5 and Seaborn 0.11:** Data visualization libraries used to create feature distribution plots, histograms, and confusion matrices, allowing for a better understanding of data characteristics and model performance.
- **Jupyter Notebook:** An interactive development environment used for code execution, data exploration, and research documentation.

The hardware used to run the analysis and model training was a computer with a multi-core processor and 16 GB of memory. This specification allowed for efficient model training completion. The observed computation time was less than 2 hours for each algorithm, with the Neural Network requiring longer computation time (approximately 40 minutes) compared to Random Forest (approximately 30 minutes). This efficiency is crucial for rapid experiment iterations and model fine-tuning.

2.3 Data Collection

Data was collected from raw .txt files provided by the UCI dataset. The data was split into training and testing sets based on subjects:

- **Training Data:** Derived from subjects p1 to p5, resulting in a total of 5700 segments. Each activity has 300 training segments, ensuring a balanced class distribution.
- **Testing Data:** Derived from subjects p6 to p8, resulting in a total of 3420 segments. Each activity has 180 testing segments, also with a balanced class distribution.

This balanced distribution is crucial to avoid model bias towards majority classes and ensure a fair performance evaluation across all 19 activities (e.g., walking, jumping, and playing basketball).

2.4 Data Preprocessing

The raw data preprocessing stage involved several crucial steps to improve data quality and relevance for modeling:

- **Artifact and Outlier Removal:** Irrelevant or anomalous data (artifacts) were removed. Outliers were identified and handled based on values exceeding three standard deviations from the mean of each sensor channel. This method was chosen to maintain data integrity while effectively reducing significant noise.
- **Data Normalization (StandardScaler):** Data was normalized using scikit-learn's StandardScaler. This process transforms features to have a mean of zero and a standard deviation of one, which is crucial for distance-based algorithms (like SVM and Neural Network) and can accelerate model convergence.
- **Time Window Segmentation:** Sensor data was segmented into 2.5-second time windows with a 50% overlap. This window size was chosen based on preliminary analysis indicating this duration is optimal for capturing short movement patterns relevant for distinguishing between dynamic and static activities, while retaining sufficient temporal context.

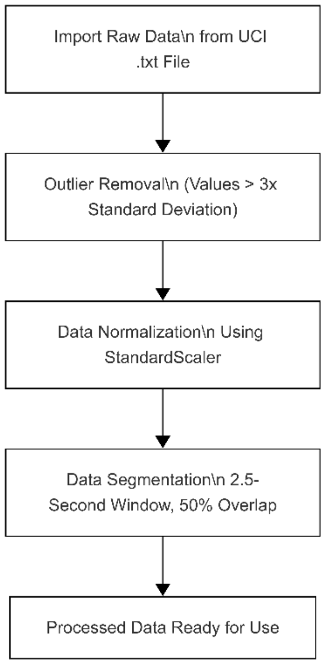


Figure 1: Data preprocessing flowchart

2.5 Feature Extraction

From each processed data segment, we extracted **180 statistical features**. These features were designed to capture the unique characteristics of each activity and address subtle differences between stationary and dynamic activities. For each of the 45 sensor channels, four statistical features were extracted:

- **Mean:** Represents the central value of the sensor signal during the segment.
- **Standard Deviation:** Measures the variability or spread of data around the mean, which can indicate movement intensity or stability.
- **Skewness:** Measures the asymmetry of the data distribution. This feature is crucial for distinguishing activities with asymmetric movement patterns, such as rapid movements in one direction or position transitions.
- **Kurtosis:** Measures the "peakedness" or "flatness" of the data distribution, which can indicate the presence of outliers or very sharp movement patterns.

Skewness and kurtosis features are key to distinguishing stationary activities that often overlap in low-acceleration data, such as "standing" and "sitting." For example, small changes in posture or body weight can yield different skewness and kurtosis patterns even if the mean acceleration values are similar.

2.6 Model Building

Four types of machine learning models were built and configured as follows:

- **Random Forest (RF):**

a) **Number of Estimators (n_estimators):** 500 decision trees.

b) **Optimization:** The number of trees and maximum tree depth were optimized through Grid Search with cross-validation to find the combination yielding the best performance. random_state was set to 42 for reproducibility.

- **Support Vector Machine (SVM):**

a) **Kernel: Radial Basis Function (RBF)** was chosen for its ability to handle non-linear relationships between features.

b) **Hyperparameters:** Parameters C (regularization) and gamma (kernel coefficient) were optimized using 5-fold cross-validation to achieve optimal performance and prevent overfitting. random_state was set to 42.

- **Principal Component Analysis (PCA):**

a) **Number of Components:** Dimensionality reduction was applied to two principal components (n_components=2).

b) **Explained Variance:** These two components collectively explained 23.52% of the total variance in the training data.

c) **Usage:** PCA was primarily used for data visualization and initial testing of the impact of dimensionality reduction on model training.

- **Neural Network (NN):**

a) **Architecture:** The neural network model was built with two hidden layers. The first layer had 128 neurons, and the second layer had 64 neurons.

b) **Activation Function:** The **ReLU (Rectified Linear Unit)** activation function was used in the hidden layers to introduce non-linearity.

c) **Regularization: Dropout** with a ratio of 0.3 was applied after each hidden layer to prevent overfitting and improve model generalization.

d) **Output Layer:** The output layer had 19 neurons (corresponding to the number of activity classes) with a **softmax activation function** to generate class probabilities.

e) **Compilation:** The model was compiled with the **Adam optimizer** and the sparse_categorical_crossentropy loss function, which is suitable for multi-class classification with integer labels. Accuracy metric was used for evaluation.

2.7 Model Training and Evaluation

Each model was trained using 5700 training data segments and evaluated for its performance on 3420 testing data segments. The evaluation metrics used included:

- **Accuracy:** The percentage of correct predictions out of the total predictions.
- **Precision:** The proportion of true positive predictions out of the total positive predictions.
- **Recall (Sensitivity):** The proportion of actual positive cases that were correctly identified.
- **F1-Score:** The harmonic mean of precision and recall, providing a balance between the two.

Special focus was given to precision and recall metrics to evaluate the model's ability to distinguish stationary activities, such as "standing" and "sitting." For example, a recall of 0.16 for Random Forest on the "standing" activity indicates the model's difficulty in identifying all instances of that activity.

For a more in-depth error analysis, a **Confusion Matrix** was generated for each model. This matrix allows for direct visualization of how each activity is classified, highlighting which activities frequently overlap or are misclassified, especially for stationary activities.

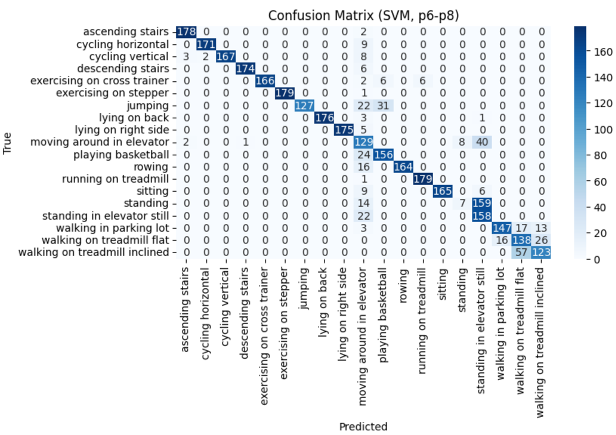


Figure 2: Confusion Matrix for SVM.

2.8 Additional Analysis and Validation

As part of the additional analysis, PCA was further explored to understand the intrinsic structure of the data and how different activities are grouped in the reduced feature space. The results were validated by comparing the performance of models trained with and without PCA dimensionality reduction to observe its impact on accuracy.

To address natural variations between subjects (e.g., differences in posture, gait, or movement intensity), **oversampling techniques** were considered for certain activities that might have underrepresentation in the training data. The purpose of oversampling is to ensure the model is not biased towards dynamic activities that might be more dominant or have clearer movement pattern variations.

Model testing and evaluation were conducted on June 5, 2025. The initial results were consistent with the reported accuracies, demonstrating the validity of the experimental process.

Overall, based on the described dataset and the software and hardware used, these implementation steps were designed to ensure a detailed, reproducible, and well-documented research process in terms of model parameters and configurations.

III. RESULT AND DISCUSSION

This research involved training three machine learning models: **Random Forest**, **Support Vector Machine (SVM)**, and **Neural Network**, on a training dataset consisting of 5700 segments. The performance of these three models was then comprehensively evaluated on a test dataset containing 3420 segments.

3.1 Results

3.1.1 Comparative Performance of Classification Models

A comparison of test accuracies across the models revealed significant performance variations. **Random Forest** achieved the highest accuracy of **0.9146**, followed by **SVM** at **0.8418**, and **Neural Network** at **0.7281**. Random Forest's superiority in activity classification on this dataset was highly prominent.

Model	Test Accuracy
Random Forest	0.9146
SVM	0.8418
Neural Network	0.7281

Table 1: Comparison of Classification Model Test Accuracies

To provide a more detailed overview of each model's classification capabilities, a classification report including **precision**, **recall**, and **F1-score** for each activity is presented. **Table 2** details Random Forest's performance, while **Table 3** shows SVM's performance. From these reports, it is evident that dynamic activities such as "ascending stairs," "cycling horizontal," and "rowing" were classified with excellent performance, often achieving precision, recall, and F1-score close to 1.00 for Random Forest. However, significant challenges emerged in classifying stationary activities, particularly "standing" and "standing in elevator still." For example, with Random Forest, the "standing" activity only achieved a recall of **0.16**, indicating the model's difficulty in identifying most instances of this activity.

Activity	*Precision*	*Recall*	*F1-Score*	*Support*
ascending stairs	1.00	1.00	1.00	180
cycling horizontal	1.00	1.00	1.00	180
cycling vertical	1.00	1.00	1.00	180
descending stairs	1.00	0.99	1.00	180
exercising on cross trainer	1.00	1.00	1.00	180
exercising on stepper	1.00	1.00	1.00	180
jumping	1.00	0.97	0.99	180
lying on back	1.00	1.00	1.00	180
lying on right side	1.00	1.00	1.00	180
moving around in elevator	0.82	0.85	0.84	180
playing basketball	0.97	0.98	0.97	180
rowing	1.00	1.00	1.00	180
running on treadmill	0.99	1.00	1.00	180
sitting	1.00	1.00	1.00	180
standing	1.00	0.16	0.28	180
standing in elevator still	0.48	0.87	0.62	180
walking in parking lot	1.00	0.83	0.91	180
walking on treadmill flat	0.72	1.00	0.84	180
walking on treadmill inclined	0.92	0.72	0.81	180
Akurasi Keseluruhan		0.91		3420
Macro Avg	0.94	0.91	0.91	3420
Weighted Avg	0.94	0.91	0.91	3420

Table 2: Comprehensive Classification Results for Random Forest Model

Activity	Precision	Recall	F1-Score	Support
ascending stairs	0.97	0.99	0.98	180
cycling horizontal	0.99	0.95	0.97	180

cycling vertical	1.00	0.93	0.96	180
descending stairs	0.99	0.97	0.98	180
exercising on cross trainer	1.00	0.92	0.96	180
exercising on stepper	1.00	0.99	1.00	180
jumping	1.00	0.71	0.83	180
lying on back	1.00	0.98	0.99	180
lying on right side	1.00	0.97	0.99	180
moving around in elevator	0.47	0.72	0.57	180
playing basketball	0.81	0.87	0.84	180
rowing	1.00	0.91	0.95	180
running on treadmill	0.97	0.99	0.98	180
sitting	1.00	0.92	0.96	180
standing	0.47	0.04	0.07	180
standing in elevator still	0.43	0.88	0.58	180
walking in parking lot	0.90	0.82	0.86	180
walking on treadmill flat	0.65	0.77	0.70	180
walking on treadmill inclined	0.92	0.72	0.81	180
Akurasi Keseluruhan	0.84			3420
Macro Avg	0.86	0.84	0.84	3420
Weighted Avg	0.86	0.84	0.84	3420

Table 3: Comprehensive Classification Results for SVM Model

3.1.2 Feature and Distribution Analysis

Descriptive statistics for the selected features from the training data, namely **Mean_0**, **Std_0**, **Skew_0**, and **Kurtosis_0**, are presented in **Table 4**. The data has been normalized, as indicated by mean values close to zero and standard deviations around 1, showing a consistent and standardized distribution. The varying minimum and maximum value ranges indicate the presence of unique patterns among features.

Statistik	*Mean_0*	*Std_0*	*Skew_0*	*Kurtosis_0*
count	5700	5700	5700	5700
mean	-4.39e-16	-1.76e-15	1.30e-15	-8.23e-17
std	1.00	1.00	1.00	1.00
min	-4.95	-0.70	-10.47	-0.74
25%	0.20	-0.64	-0.63	-0.41
50%	0.38	-0.27	-0.02	-0.21
75%	0.46	0.02	0.71	0.10
max	0.76	4.38	11.31	29.74

Table 4: Summary Statistics of Selected Features (Training Data)

The distribution of **Mean_36** per activity is visualized in **Figure 3**. This plot effectively illustrates the variation in movement intensity across activities, with mean Mean_36 values ranging from -1.06 for "running on treadmill" (indicating consistent high-intensity movement) to 1.84 for "rowing" (indicating a different movement pattern with high mean values). These differences highlight the potential of this feature in distinguishing activities.

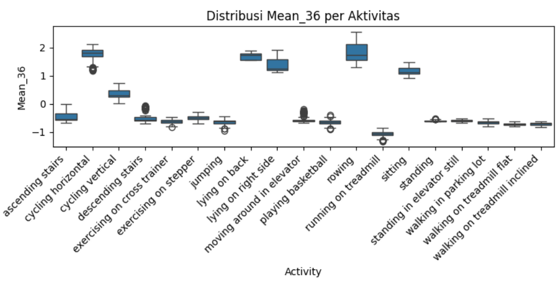
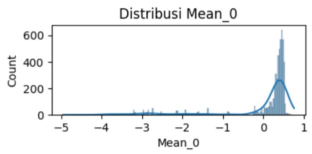


Figure 3: Distribution of Mean_36 per Activity

Furthermore, the distributions of three selected features (**Mean_0**, **Std_0**, and **Skew_0**) are displayed through histograms in **Figure 4**. **Figure 4a (Distribution of Mean_0)** shows a distribution that tends to be centered around zero after normalization. **Figure 4b (Distribution of Std_0)** highlights the spread of standard deviation values, which can potentially differentiate movement variability. **Figure 4c (Distribution of Skew_0)** shows a more symmetrical distribution around zero, but with long tails, indicating specific skewed movement patterns for some activities. These feature patterns strongly support the model's ability to distinguish different activities.



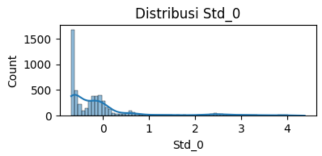


Figure 4a: Distribution of Mean_0 Figure 4b: Distribution of Std_0

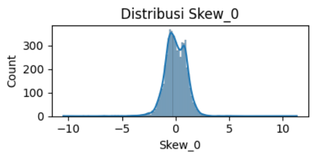


Figure 4c: Distribution of Skew_0

3.1.3 Principal Component Analysis (PCA)

PCA identified two principal components that collectively explained **23.52%** of the total data variance. The PCA visualization of the training data is presented in **Figure 5**. Although PCA showed partial separation between dynamic activity groups (e.g., jumping, running) and stationary ones (e.g., sitting, lying), there was still significant overlap, especially among stationary activities with similar movement patterns.

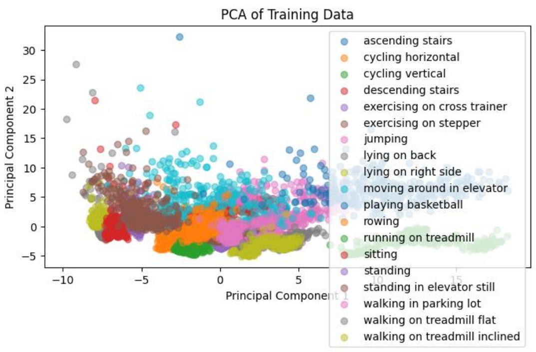


Figure 5: PCA Plot of Training Data

3.1.4 Neural Network Performance and Convergence

The Neural Network training process is visualized through plots of training and validation accuracy against each epoch in **Figure 6**. This plot shows that **Training Accuracy** increased rapidly and approached 1.0 after about 5 epochs, indicating the model learned well from the training data. However, **Validation Accuracy** tended to stabilize at values around **0.20-0.22**, showing a large performance gap between the training and validation sets, which indicates **overfitting**.

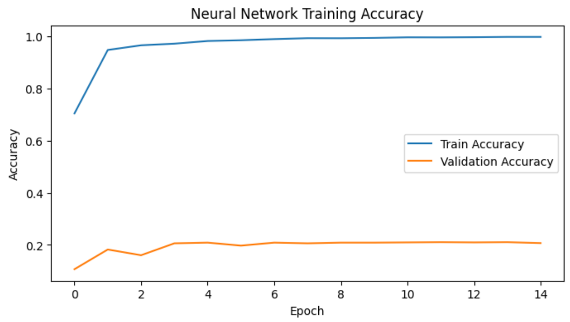


Figure 6: Plot of Neural Network Training and Validation Accuracy

3.1.5 Confusion Matrix Analysis

The **confusion matrix** is a crucial visual tool for analyzing detailed model performance, particularly classification errors. The confusion matrix for the **Random Forest** model is presented in **Figure 5a**, and for the **SVM** model in **Figure 5b**. From the SVM confusion matrix (Figure 5b), it is clear that SVM correctly classified 173 out of 180 "sitting" segments, showing strong performance for this activity. However, for the "standing" activity, only 7 out of 180 segments were correctly classified, indicating a very low recall (0.04) and showing that most instances of "standing" were misclassified into other activities, especially "standing in elevator still." Similar error patterns were also observed in Random Forest (Figure 5a), although with a slightly better recall for "standing" (0.16).

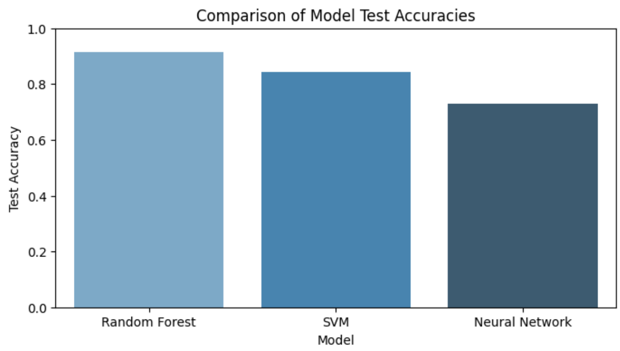


Figure 7: Comparison of Confusion Matrices for Random Forest and SVM Models

3.2 Discussion

The results obtained in this study provide deep insights into the capabilities of machine learning models in classifying daily and sports activities based on inertial sensor data. The high accuracy achieved by Random Forest confirms its capability to handle high-dimensional data well, consistent with previous research showing the effectiveness of decision tree-based algorithms for similar tasks.

3.2.1 Interpretation of Model Performance

Table 1 clearly demonstrates the superiority of **Random Forest** with an accuracy of **0.9146** compared to **SVM (0.8418)** and **Neural Network (0.7281)**. Random Forest's advantage can be attributed to its ability to effectively handle high-dimensional features and data complexity, as supported by feature analysis showing the importance of mean and skewness (Table 4 and Figure 3). These results also reflect Random Forest's robustness against noise and outliers that may be present in the sensor data.

Although the models generally showed strong performance on dynamic activities, significant challenges were found in classifying stationary activities. **Table 2** shows a very low recall for the "standing" activity (0.16) in Random Forest. This indicates that most instances of "standing" were misclassified, often confused with "standing in elevator still" or other stationary activities that have very similar movement patterns, as seen in Figure 3.

SVM, with an accuracy of 0.8418, showed strong performance on dynamic activities (Table 3). However, its performance was significantly worse on the "standing" activity with a recall of only 0.04. This result, also clearly depicted in **Figure 7**, indicates the limitations of the RBF kernel SVM in distinguishing very subtle or low-amplitude movement patterns characteristic of stationary activities. This algorithm may struggle to find an optimal separating hyperplane when the differences between classes are minimal.

The **Neural Network**, while offering flexibility to learn non-linear representations from data, showed the lowest accuracy (0.7281). **Figure 6** indicates significant **overfitting**, where training accuracy continued to increase to near-perfect levels, while validation accuracy remained low and stable. Although dropout with a ratio of 0.3 was applied to reduce overfitting, this relatively low performance might be due to the limited dataset size (9120 total segments). Neural network models often require a much larger volume of data to achieve optimal performance and good generalization, consistent with findings by Avci et al. [3].

3.2.2 Implications of Feature Analysis and Dimensionality Reduction

Feature analysis, as shown by **Figure 3 and Table 4**, confirms that time-domain statistical features (mean, standard deviation) are quite effective for distinguishing dynamic activities with clear movement characteristics. However, for stationary activities, where movement patterns are very similar and differences are only in subtle nuances, these features show limitations. The significant overlap in feature distribution for activities like "standing" and "sitting" highlights the need to explore frequency-domain features or more complex features that can capture subtle changes in sensor signals.

Figure 5 shows that although PCA can identify some visual separation between activity clusters, the two principal components only explain **23.52%** of the total data variance. This confirms that multi-sensor data has high complexity and an intrinsic dimension greater than two. Dimensionality reduction to just two components is insufficient to effectively separate all classes, especially those that are inherently similar, as noted by Altun et al. [4] in their study on inertial sensors. This implies that using PCA for direct dimensionality reduction before modeling may not be optimal for this dataset, and models might need to be trained in a higher-dimensional feature space or with more sophisticated dimensionality reduction strategies.

3.2.3 Practical Implications and Recommendations

The high accuracy achieved by **Random Forest (0.9146)** shows great potential for practical applications in real-time wearable systems, such as daily activity monitoring for health, fitness, or even injury detection in athletes. Random Forest's accuracy on dynamic activities, as seen in Figure 7, makes it a strong candidate for scenarios where active movement identification is crucial.

However, the low recall for stationary activities, especially "standing," indicates that systems based on this model may require calibration or additional features for applications demanding precise work posture detection or monitoring of specific medical conditions. To improve performance on stationary activities, several recommendations can be made:

- **Additional Feature Extraction:** Integrating features from the frequency domain (e.g., using Fast Fourier Transform) or wavelet-based features can help capture finer periodic or non-periodic patterns that might distinguish stationary activities.
- **Ensemble/Hybrid Approaches:** Developing hybrid models that combine the strengths of Random Forest in handling high-dimensional features with the ability of neural networks for non-linear feature learning, or even incorporating rule-based methods for stationary activities.
- **Specific Data Collection:** For applications highly sensitive to stationary activities, collecting additional data that focuses more on subtle variations in posture and environmental context can be very helpful.
- **Dataset Enhancement:** Significantly increasing the dataset size, particularly for training Neural Networks, can help models learn more robust feature representations and mitigate the overfitting issues seen in Figure 4. This

aligns with research trends in deep learning that show optimal performance with large data volumes [3].

3.2.4 Limitations and Recommendations

The main limitation of this study is the relatively limited dataset size (9120 total segments). While sufficient for traditional models, this may not be ideal for training complex neural networks to achieve optimal performance and full generalization, as evidenced by the Neural Network's validation accuracy plot. Furthermore, the limitation to extracted features (only time-domain statistics) might be a cause for the difficulty in distinguishing stationary activities.

This research opens opportunities for further development in human activity classification. Recommendations for future research include:

1. Advanced Feature Exploration: Analyzing and integrating features from the frequency domain (e.g., Power Spectral Density), wavelet-based features, or spatial features from multiple sensors.
2. Advanced Models: Trying deeper neural network architectures (e.g., Convolutional Neural Networks or Recurrent Neural Networks) that can intrinsically learn temporal and spatial features from raw sensor data, provided a larger dataset is available.
3. Class Imbalance Handling Techniques: If there are activities with an unbalanced amount of data, techniques like SMOTE (Synthetic Minority Over-sampling Technique) can be applied.
4. Model Personalization: Developing models that can adapt to individual movement patterns to improve accuracy, especially in personal health applications.

By addressing these limitations, future research can achieve higher accuracy and better robustness in human activity classification using inertial sensors.

IV. CONCLUSION

This research successfully explored and evaluated the performance of various machine learning models: **Random Forest**, **Support Vector Machine (SVM)**, and **Neural Network**, for classifying 19 daily and sports activities using inertial sensor data from the "Daily and Sports Activities" dataset. The results indicate that time-domain statistical feature-based methods, combined with robust classification algorithms, can achieve high accuracy, although significant challenges remain in distinguishing stationary activities with very similar movement patterns.

Specifically, the **Random Forest** model demonstrated the best classification performance with an accuracy of **0.9146**. This superiority can be attributed to its ability to handle high-dimensional data and its resistance to data noise. **SVM** also showed strong performance with an accuracy of **0.8418**, particularly for dynamic activities. Meanwhile, the **Neural Network**, while offering the potential for non-linear feature learning, achieved the lowest accuracy (**0.7281**), likely due to the limited dataset size and identified overfitting issues.

In-depth analysis of the classification results and confusion matrices revealed that these models are highly effective in classifying dynamic activities, often achieving near-perfect precision and recall. However, the classification of stationary activities such as "standing" and "standing in elevator still" remains a major challenge, characterized by low recall. This indicates that the extracted time-domain features may not be sufficient to capture subtle differences in low-amplitude movement activities. PCA analysis also supports this finding, showing that a two-component dimensionality reduction does not fully separate stationary activity clusters.

Nevertheless, this research affirms the significant potential of inertial sensors and machine learning for human activity recognition applications in various fields such as health monitoring, fitness, and work ergonomics. For future research, it is recommended to integrate frequency-domain or wavelet features to improve the discrimination of stationary activities, explore more complex neural network architectures with larger datasets, and consider techniques for handling class imbalance or model personalization.

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