

Performance Evaluation of Hybrid Intelligent Models for Human Activity Recognition

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Abstract

Information on human activities is critical for the general wellbeing of people and health management. In recent times, machine learning has gained popularity in human activity recognition modelling. However, the machine learning algorithms suffer from the curse of dimensionality due to the several recorded features in the data collected and utilized in the human activity recognition. To overcome the drawback, dimensionality reduction is utilized to reduce the dimensionality of the data and extract the most relevant features. However, in machine learning modeling, the type of dimensionality reduction method utilized is a critical factor that affects the machine learning performance. This study evaluates and compares the impact of four dimensionality reduction methods namely, principal component analysis (PCA), Kernel PCA (KPCA), Nonlinear PCA (NLPCA), and Independent Component Analysis (ICA) in human activity recognition using machine learning. First, the discrete wavelet transform (DWT) was applied as a preprocessing step to decompose the time series data into different frequency bands. Then, the PCA, KPCA, NLPCA and ICA were applied to each frequency band. Finally, Support Vector Machine (SVM) as the classification technique was selected and used to classify the activities. The performance of each method was evaluated using a benchmark dataset: UCI-HAR Postural Transitions dataset. The dataset consists of 561 features extracted from smartphone accelerometers and gyroscope signals from smartphones worn by human subjects. The results show that the DWT-ICA-SVM method achieved the highest classification accuracy, precision, recall, and F1-score results on both datasets, followed by DWT-NLPCA-SVM, DWT-KPCA-SVM, and DWT-PCA-SVM. The performance of the foregoing hybrid models with the traditional PCA-SVM method was compared, and the results show the hybrid models superior performance. The paper also investigated the effect of different decomposition levels of the DWT on the classification performance and found that the decomposition level of 4 or 5 provided the best performance for both datasets. Overall, the results suggest that the hybrid dimensionality reduction methods, particularly DWT-ICA-SVM, can effectively reduce the dimensionality of the data and improve the classification accuracy for human activity recognition tasks. The findings of this study are useful for researchers and practitioners working on activity recognition systems using wearable sensors.

Categories: Smart health and connected health, Machine Learning (ML), Mobile Health

Keywords: human activity recognition, dimensionality reduction, discrete wavelet transform, machine learning, sensors

Introduction

Human Activity Recognition (HAR) can be defined as the process of identifying and keeping tabs on the daily physical activity patterns of individuals based on a series of observations in a specified environment [1]. HAR, which among other things, involves taking readings from sensors such as GPS, gyroscopes, etc., as input and predicting users' activities, has

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become an active research area [2]. This paradigm shift is inspired by the ever-evolving advancements in smartphone technologies in terms of improved computing, networking, and sensing capabilities, which unveil new opportunities for the development and deployment of novel application platforms [3,4]. The human activity mentioned supra can broadly be categorized into two, viz., movement-related and non-movement-related activities. The movement-related activities refer to an embodiment of all kinds of moderate to vigorous physical activities (MVPA) associated with some form of locomotion, such as walking, running, exercising, etc. Non-movement-related activities, on the other hand, refer to activities that do not incorporate locomotor skills involving movement from one place to another, such as sleeping, sitting, standing, etc.

HAR has evolved into a task that has attracted immense research interest in a myriad of domains such as medical [5], sport and fitness [6], entertainment, ambient assisted elderly living, surveillance-based security, and commerce applications [7-9]. In the medical domain, for instance, patients living with conditions such as diabetes, obesity, or heart disease, sometimes referred to as silent killers, may be required to perform a specific routine of moderate to vigorous physical activities (physical exercises), under constant supervision, as part of their treatment. The ability to automatically recognize and continuously monitor such physical activities as walking, running, or resting becomes indispensable in encouraging the patients and providing feedback on their behavior to the caregivers, in such instances [1]. To accurately recognize human activities, scholars have resorted to the use of machine learning techniques [10-13]. However, in the application of machine learning, a persistent challenge of the curse of dimensionality leading to model complexity must be surmounted [14-17]. This identified challenge is due to the large number of recorded features from sensor data, making dimensionality reduction (DR) essential.

Most studies [18] in literature have employed Principal Component Analysis (PCA) as the primary preprocessing technique in intelligent HAR modelling due to its simplicity and effectiveness in reducing feature dimensions while retaining variance. This reduces the ML model complexities and improves convergence rate. This assertion is confirmed in a recent study by Minhas et al. [19]. The study proposes a human action recognition framework using hybrid features derived from 3D Dual-Tree Complex Wavelet Transform (3D DT-CWT) and affine SIFT descriptors. The method improves efficiency by processing video data volumetrically while enhancing feature representation through directional and shift-invariant complex filter banks. Bidirectional 2D-PCA is applied for DR to preserve spatial structure and correlations in video frames.

Aljarrah and Ali [20] investigated the use of PCA for DR in HAR using mobile sensor data. The study employed the University of California Irvine (UCI) Machine Learning Repository HAR dataset, which comprises 561 features derived from accelerometer and gyroscope signals. By applying PCA, the feature set was reduced to 70 principal components, thereby eliminating redundancy and noise. The reduced features were then used to train an Artificial Neural Network (ANN), specifically a Multi-Layer Perceptron. Experimental evaluation showed that the PCA-ANN hybrid model achieved a high classification accuracy of 96.17%, while also offering a substantial reduction in training time compared to models trained on the full feature set. This demonstrated the effectiveness of PCA in improving both the efficiency and accuracy of sensor-based HAR systems. In another study by Zhu et al. [21], the authors introduced a hybrid approach that leverages PCA for DR followed by a Bidirectional Long Short-Term Memory (BiLSTM) network for classification. Using the mHealth dataset, which records 12 different human activities performed by 10 subjects via wearable sensors, they applied PCA to reduce the original feature set by 34.7%, resulting in 15 principal components that captured at least 85% of the dataset's variance. Training a BiLSTM classifier on this reduced dataset achieved a high recognition accuracy of 97.64%, outperforming traditional machine learning models like support vector machine (SVM), which scored as low as 64.67%. Another study by Thakur et al. [22] applied PCA to raw smartwatch accelerometer and gyroscope data collected from multiple users performing seven daily activities. This study proposes an ensemble learning framework using TSFEL for automatic feature extraction and PCA for DR. The approach improves activity recognition performance and achieves 96% accuracy in classifying six human activities. The Principal Component-based Wavelet Convolutional Neural Network (PCWCNN) model proposed by Showmik et al. [23] introduces a hybrid preprocessing and classification pipeline for HAR using Wi-Fi CSI data. The method integrates PCA for feature reduction and Discrete Wavelet Transform (DWT) for time-frequency representation, followed by segmentation of activity segments. These processed features are classified

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using a Wavelet-based CNN, designed to capture multi-resolution information akin to ResNet and DenseNet architectures. Empirical evaluations on a real-world dataset indicate that PCWCNN outperforms existing Wi-Fi CSI-based HAR approaches, demonstrating robustness and efficiency suitable for real-time applications.

The insights from previous HAR studies indicate that PCA is the most dominant DR technique. However, PCA is fundamentally a linear transformation method, which limits its capability to capture complex, nonlinear relationships present in sensor-based HAR data [24]. Given the nonlinearity exhibited in human activities, more sophisticated DR methods such as kernel PCA (KPCA), nonlinear PCA (NLPCA) [25], and independent component analysis (ICA) [26] could be explored. Moreover, studies [27] have established that the choice of DR method directly impacts the performance of ML models. Additionally, there is limited comparative evaluation of linear and nonlinear DR methods performance in a hybrid ML model for HAR. This research gap motivates the need to systematically evaluate and compare multiple DR techniques to ascertain their efficiency levels in HAR. The choice of utilizing KPCA, NLPCA, and ICA as preprocessing techniques in this study is motivated by their ability to uncover more informative feature representations for HAR. For instance, KPCA extends the traditional PCA by integrating kernel functions, enabling the capture of nonlinear relationships within the data [28]. This property has been shown to improve classification accuracy in applications such as image recognition [29], speech processing [30], and bioinformatics [31], making it promising for complex and nonlinear sensor signals. NLPCA advances this idea further by leveraging neural networks with auto associative structure to effectively uncover latent nonlinear dependencies, thereby providing richer and more expressive feature spaces. Furthermore, its ability to compress and reconstruct nonlinear patterns supports both DR and interpretability [32]. In contrast, ICA focuses on decomposing multivariate signals into statistically independent components, which is particularly beneficial for separating overlapping sources, a feature extensively exploited in electroencephalography and magnetoencephalography analysis for isolating neural activity [33,34]. Beyond neuroscience, ICA has been successfully applied in finance, telecommunications, and image processing for discovering hidden factors [35].

Collectively, these advanced DR methods (KPCA, NLPCA, and ICA) go beyond the limitations of linear PCA, offering complementary advantages in capturing nonlinearity, latent structures, and independent sources. Their proven success across multiple disciplines provides a strong rationale for their adoption in HAR. Additionally, there is a lack of HAR research on integrating signal decomposition with KPCA, NLPCA, and ICA to enhance feature extraction and improve ML model classification accuracy. This study adopted DWT, which is a popular signal decomposition technique to provide multi-resolution representation of the sensor data by capturing both time and frequency information [35,36]. The study therefore systematically evaluates the combination of DWT with PCA, KPCA, NLPCA, and ICA in conjunction with SVM to assess their influence on HAR classification performance. It is noteworthy that several ML classifiers have been used in HAR, including K-nearest neighbour (k-NN), random forest (RF), and ANNs. However, these classifiers have notable limitations that influenced the choice of SVM for this study. k-NN, for instance, requires a large memory to store training data and can become computationally expensive as the dataset size increases [36]. RF, while efficient, may struggle with interpretability and require extensive parameter tuning to achieve optimal results [37]. ANNs, though powerful, are computationally intensive and prone to overfitting, especially when dealing with small training datasets [38].

In contrast, SVM's ability to efficiently handle relatively small datasets while maintaining high classification accuracy makes it a suitable choice for HAR applications. This is supported by Ashraf et al. [39], who conducted a comparative study of machine learning algorithms for HAR using IMU sensor data and reported that SVM demonstrated superior generalization performance relative to K-NN, decision tree (DT), and ANN classifiers. Given the structured nature of human-activity signals and the need for a classifier that balances accuracy with computational efficiency, SVM [40] emerges as an optimal choice for this study. By evaluating the performance of applying a three-stage hybrid approach, this study aims to advance the HAR system and provide valuable insights into the effectiveness of combining DWT with DR methods (PCA, KPCA, and NLPCA) and SVM. To this end, the main contributions of this work compared with existing literature are listed as follows:

- i. First, we introduced an alternative approach to activity recognition that leverages DWT to extract meaningful features from sensor data, improving the efficiency of feature representation.

- ii. Second, we compared for the first time the performance of different feature extraction methods including PCA, KPCA, NLPCA, and ICA when combined with SVM for HAR.
- iii. Finally, we highlighted the potential of continuous smartphone sensor data for HAR, demonstrating its practicality, scalability, and cost-effectiveness compared with specialized sensing infrastructures and complex multi-sensor configurations.

Materials And Methods

Dataset description

The study utilised the UCI machine learning repository HAR Postural Transitions dataset (<https://archive.ics.uci.edu/ml/datasets/human+activity+recognition+using+smartphones>). This data is widely used for evaluating human activity monitoring models using smartphone-based sensor data. The dataset was collected from 30 volunteers aged between 19 and 48 years while performing a protocol of different activities composed of six basic activities: three static postures (standing, sitting, lying) and three dynamic activities (walking, walking downstairs, walking upstairs). The experiment also included postural transitions that occurred between the static postures: stand-to-sit, sit-to-stand, sit-to-lie, lie-to-sit, stand-to-lie, and lie-to-stand [1]. Each participant wore a Samsung Galaxy S II smartphone on the waist, which recorded tri-axial accelerometer and gyroscope signals at a sampling rate of 50 Hz. The use of a single smartphone model ensured consistent sensor characteristics and minimized device-related variability, allowing the study to focus on evaluating the proposed DWT-based feature extraction and classification framework. The dataset exhibits moderate class imbalance, with dynamic activities generally contributing more samples than some transitional activities. To provide a balanced evaluation, model performance was assessed using class-wise precision, recall, and F1-score in addition to overall accuracy. Furthermore, since human movement patterns vary across individuals, subject-independent training and testing partitions were employed to reduce subject bias and improve the generalizability of the developed models.

The raw signals obtained from the accelerometer and gyroscope were pre-processed using noise filters and then segmented into fixed-width sliding windows of 5 seconds (128 readings per window) with a 50% overlap between consecutive windows. From these windows, a total of 561 features were extracted using various signal processing techniques, including time-domain and frequency-domain analysis, such as mean, standard deviation, signal magnitude area, entropy, and correlation between axes. Table 7 summarizes the key parameters of the sensors, their measurement units, and the corresponding human activities captured. These sensor readings are critical for distinguishing subtle variations in movement patterns, particularly between dynamic (e.g., walking) and static (e.g., sitting or lying) activities. The dataset's comprehensive structure and detailed annotation make it an essential benchmark for evaluating HAR algorithms.

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Sensor Type	Parameter	Unit	Measured Activity
Accelerometer	Body acceleration (X, Y, Z)	m/s ²	Walking, Walking Upstairs, Walking Downstairs, Sitting, Standing, Laying
Gyroscope	Body angular velocity (X, Y, Z)	rad/s	Walking, Walking Upstairs, Walking Downstairs, Sitting, Standing, Laying
Accelerometer	Gravity acceleration (X, Y, Z)	m/s ²	Primarily used to separate body motion from gravitational component
Derived Features	Jerk signal (acceleration + gyroscope)	m/s ³ , rad/s ²	Used to enhance detection of rapid transitions between activities
Statistical Features	Mean, Standard Deviation, FFT components	–	All activities; used for classification feature set

TABLE 1: Sensor Parameters, Units, and Measured Activities in the UCI-HAR Dataset

FFT, Fast Fourier Transform; UCI-HAR, University of California Irvine-Human Activity Recognition

Methods applied

Discrete Wavelet Transform

In the preprocessing stage of human activity monitoring using the UCI-HAR Postural Transitions dataset, DWT plays a crucial role in transforming raw sensor signals into a more informative representation. The raw data, typically gathered from sensors like accelerometers and gyroscopes, contain a mix of high- and low-frequency components that correspond to different motion characteristics. The DWT is applied to decompose these time-domain signals into various frequency bands, enabling the extraction of both low-frequency (approximation) and high-frequency (detail) components. This decomposition allows for a multi-resolution analysis of the signal, making it easier to identify distinct patterns associated with different human activities. The wavelet function used in DWT captures localized changes in the signal, providing an efficient representation that preserves temporal information. Mathematically, the DWT decomposes a given signal $f(x)$, using a series of basis functions derived from a mother wavelet $\psi_{i_0,j}(x)$ and a scaling function, resulting in coefficients that represent the signal's structure at different scales. An inverse DWT can then reconstruct the signal from these coefficients, ensuring that no significant information is lost during preprocessing. This process enhances the performance of subsequent ML models by providing noise-reduced, feature-rich inputs that better capture the dynamic nature of human movements [41,42].

Given a discrete signal $f(x)$, the approximation and detail wavelet coefficients are computed as

$$W_{\phi}(i_0, j) = \frac{1}{\sqrt{M}} \sum_{x=0}^{M-1} f(x) \phi_{i_0,j}(x)$$

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$$W_{\psi}(i, j) = \frac{1}{\sqrt{M}} \sum_{x=0}^{M-1} f(x) \psi_{i,j}(x), \quad i \geq i_0 \quad (2)$$

where $W_{\phi}(i_0, j)$ and $W_{\psi}(i, j)$ denote the approximation and detail wavelet coefficients, respectively.

The original signal can be reconstructed using the inverse DWT as

$$f(x) = \frac{1}{\sqrt{M}} \sum_j W_{\phi}(i_0, j) \phi_{i_0,j}(x) + \frac{1}{\sqrt{M}} \sum_{i=i_0}^{\infty} \sum_j W_{\psi}(i, j) \psi_{i,j}(x) \quad (3)$$

where M denotes the signal length, i_0 is the initial decomposition scale, i represents the scale index, j denotes the translation index, and $x = 0, 1, \dots, M-1$ corresponds to the discrete signal samples. In this study, a four-level Daubechies-4 (db4) wavelet decomposition was employed; therefore, the scale index was limited to $i = 0, 1, 2, 3, 4$.

A multi-level DWT decomposition allows splitting the signal into various frequency bands. For example, using a three-level decomposition of a signal sampled at $f_s = 50$ Hz, the frequency bands are as follows:

Detail D1: 12.5-25 Hz (high-frequency motion artifacts)

Detail D2: 6.25-12.5 Hz (dynamic activities like walking or running)

Detail D3: 3.125-6.25 Hz (transitional activities)

Approximation A3: 0-3.125 Hz (postural activities or trends)

These sub-bands, as presented, isolate different types of motion relevant to human activity states, enabling improved feature extraction. Each set of coefficients (D1, D2, D3, A3) can be used to derive statistical features such as mean, energy, entropy, and standard deviation, which can be used to serve as inputs activity classification. By applying DWT, both temporal and spectral features of human movement are captured more effectively compared to traditional Fourier-based techniques that consider only the frequency domain, making it particularly advantageous for analyzing signals with transient or periodic patterns.

Principal Component Analysis

PCA is a widely used DR technique that transforms the original data into a new coordinate system, such that the greatest variance by any projection of the data lies on the first coordinate (called the first principal component), the second greatest variance on the second coordinate, and so on in descending order. The procedural steps for implementing this transformation are outlined in Figure 1. The process starts with a dataset represented as matrix A , where each row corresponds to a data sample and each column corresponds to a feature. The first step is to mean-center the data by subtracting the mean of each feature from the dataset, resulting in a matrix X . Then, the covariance matrix of X is computed to capture the relationships between the variables. Using the spectral decomposition theorem, the covariance matrix is decomposed into eigenvalues and eigenvectors. The principal components are the eigenvectors corresponding to the largest eigenvalues, and the data are projected onto these eigenvectors to obtain the transformed dataset Y . Mathematically, this transformation is often expressed as $Y = XW$, where W contains the top eigenvectors. The explained variance ratio is derived from the eigenvalues and indicates how much information (variance) is retained by each principal component. The cumulative variance helps determine how many components are needed to retain a desired level of information [43]. This makes PCA especially useful in reducing noise and computational complexity when analyzing sensor data from wearable devices in HAR systems.

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-
- Require:** Data matrix $A \in R^{n \times d}$ where n is the number of samples and d is the number of features
- Ensure:** Transformed data Y in reduced dimensional space
- 1: **Step 1:** Center the data
 - 2: Compute the mean vector: $\mu = \frac{1}{n} \sum_{i=1}^n A_i$
 - 3: Subtract the mean from the original data: $X = A - \mu$
 - 4: **Step 2:** Compute the covariance matrix of X :
 - 5: $C = \frac{1}{n-1} X^T X$
 - 6: **Step 3:** Apply spectral decomposition to the covariance matrix:
 - 7: $C = W \Lambda W^T$
 - 8: where W is the matrix of eigenvectors and Λ is the diagonal matrix of eigenvalues
 - 9: **Step 4:** Select the top k eigenvectors corresponding to the k largest eigenvalues
 - 10: $W_k = \text{Top } k \text{ columns of } W$
 - 11: **Step 5:** Project the original data into the new space
 - 12: $Y = XW_k$
 - 13: **Step 6:** Compute explained variance ratio:
 - 14: Explained Variance Ratio $_i = \frac{\lambda_i}{\sum_{j=1}^d \lambda_j}$
 - 15: **Step 7:** Optionally compute cumulative variance to decide on k
-

FIGURE 1: Principal Component Analysis Algorithm

Kernel Principal Component Analysis

KPCA is an advanced DR technique that extends the capabilities of traditional PCA by handling nonlinearly separable data using kernel functions. This method is particularly beneficial for complex datasets like the UCI-HAR Postural Transitions, which contains non-linear patterns due to the nature of human movement. KPCA maps the original data into a high-dimensional feature space H using a nonlinear mapping function ϕ and operates on the dot products between the data points using a kernel function $k(x, x') = \langle \phi(x), \phi(x') \rangle$. The central component in KPCA is the Kernel (Gram) matrix K , which holds the inner products of all data points in the feature space. If the mapped features do not have a zero mean, the Gram matrix is used to compute the covariance matrix in the transformed space. The eigen-decomposition of the centered kernel matrix leads to $K\alpha = \lambda\alpha$, where α are the eigenvectors and λ are the corresponding eigenvalues. These eigenvectors represent the principal components in the kernel-induced space. The nonlinear transformation of the input data using these principal components gives a new representation:

$$KPCA(x) = \sum_{i=1}^n \alpha_i k(x_i, x) \quad (4)$$

where x is a test vector and x_i is the training vectors. This formulation enables KPCA to uncover complex structures in the data that are not captured by standard PCA. When applied in the preprocessing stage of the HAR dataset, KPCA enhances feature extraction by projecting sensor signals (such as accelerometer and gyroscope data) into a nonlinear feature space, enabling more effective activity classification [44]. The detailed procedure of this method is summarized in Figure 2.

How to cite this article:

Require: Training data matrix $X \in R^{n \times d}$, kernel function $K(\cdot, \cdot)$

Ensure: Projected data in kernel space Z

- 1: **Step 1:** Compute the Kernel (Gram) matrix
 - 2: $K_{ij} = K(x_i, x_j)$ for all $i, j = 1$ to n
 - 3: **Step 2:** Center the Kernel matrix
 - 4: $1_n = \frac{1}{n} \mathbf{1} \mathbf{1}^T$
 - 5: $\tilde{K} = K - 1_n K - K 1_n + 1_n K 1_n$
 - 6: **Step 3:** Compute Eigenvalues and Eigenvectors
 - 7: Solve: $\tilde{K} \alpha = \lambda \alpha$
 - 8: **Step 4:** Normalize eigenvectors
 - 9: $\alpha_i = \frac{\alpha_i}{\sqrt{\lambda_i}}$
 - 10: **Step 5:** Project new test vector x into KPCA space
 - 11: **for** each eigenvector $\alpha^{(l)}$ **do**
 - 12: Compute: $z^{(l)} = \sum_{i=1}^n \alpha_i^{(l)} K(x, x_i)$
 - 13: **end for**
 - 14: **return** Projected vector $z = [z^{(1)}, z^{(2)}, \dots, z^{(k)}]^T$
-

FIGURE 2: Kernel Principal Component Analysis Algorithm

Non-Linear Principal Component Analysis

NLPCA extends the traditional linear PCA by capturing non-linear relationships within data, making it particularly suitable for complex datasets such as the UCI-HAR Postural Transitions dataset. While linear PCA assumes that the underlying structure of the data can be explained through linear transformations, NLPCA leverages non-linear functions typically through auto associative neural networks or kernel methods to extract more intricate patterns and dependencies in the data. The preprocessing with NLPCA begins by normalizing the dataset to reduce the absolute magnitudes of the features, ensuring numerical stability and consistency. The method then involves mapping the original data into a higher-dimensional feature space using orthogonal basis functions. These basis vectors, often computed through autoencoders or kernel transformations, help identify the non-linear principal components that best describe the variance in the data. The pattern classifier, denoted as p in the formulation, is trained on these transformed features, enhancing the model's ability to recognize human activities based on complex sensor signals. By capturing hidden, non-linear structures in the data, NLPCA provides a more expressive feature representation than traditional PCA, making it a powerful tool in HAR applications where human motion data can be inherently non-linear [45]. The systematic steps involved in this technique are presented in Figure 3.

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Require: Input data matrix $X \in R^{n \times d}$, number of nonlinear components k
Ensure: Nonlinear projection $Z \in R^{n \times k}$

- 1: **Step 1:** Normalize the input data
 - 2: **for** each feature x_j in X **do**
 - 3: $x_j = \frac{x_j - \mu_j}{\sigma_j}$ ▷ Zero mean and unit variance
 - 4: **end for**

 - 5: **Step 2:** Construct an autoencoder neural network
 - 6: Input layer dimension: d
 - 7: Hidden layer (bottleneck) dimension: k (represents nonlinear components)
 - 8: Output layer dimension: d

 - 9: **Step 3:** Train the autoencoder
 - 10: Minimize reconstruction error: $L = \|X - \hat{X}\|^2$
 - 11: Use backpropagation and gradient descent

 - 12: **Step 4:** Extract nonlinear components
 - 13: $Z = f_{\text{encoder}}(X)$ ▷ Encoded representation from bottleneck layer
 - 14: **return** Z
-

FIGURE 3: Non-Linear Principal Component Analysis Algorithm

Independent Component Analysis

ICA is a statistical method used for separating a multivariate signal into additive and independent components and is especially effective when analyzing complex human activity data. ICA differs from PCA by focusing not just on decorrelation but on statistical independence of the components. In the preprocessing of UCI-HAR Postural Transitions dataset, ICA was typically employed to uncover latent activity-related features that cannot be easily captured through variance-based methods. Let $\mathbf{x}(t)$ represents the observed signal as a set of random variables at time t and let $\mathbf{s}(t)$ denotes the source signals, which are assumed to be statistically independent. ICA models the observed data as a linear mixture of these independent sources:

$$\mathbf{x}(t) = \mathbf{A} \cdot \mathbf{s}(t) \quad (5)$$

where $\mathbf{A}$ is an unknown mixing matrix, and the goal of ICA is to estimate both $\mathbf{A}$ and $\mathbf{s}(t)$ such that the components of $\mathbf{s}(t)$ are as statistically independent as possible. ICA helps to extract latent features that contribute distinctly to different human activities. This is grounded in the central limit theorem, which implies that mixtures of independent sources tend toward a Gaussian distribution. ICA works by inverting this and identifying non-Gaussian signals that represent underlying sources of variation in human movement data [46]. As a result, ICA enhances feature discrimination and supports more accurate classification of human activities by uncovering the hidden, independent signal sources within the complex time-series sensor data. The step-by-step procedure of this technique is presented in Figure 4.

How to cite this article:

Require: Observed mixed signals matrix $X \in R^{n \times T}$ (n signals, T time steps)

Ensure: Estimated source signals matrix $S \in R^{n \times T}$

- 1: **Step 1:** Center the observed data
 - 2: $\mu = \frac{1}{T} \sum_{t=1}^T X[:, t]$
 - 3: $X_{\text{centered}} = X - \mu$
 - 4: **Step 2:** Whiten the centered data (remove correlations)
 - 5: Compute covariance matrix: $C = \frac{1}{T} X_{\text{centered}} X_{\text{centered}}^T$
 - 6: Eigen-decomposition: $C = E D E^T$
 - 7: Whitening matrix: $V = D^{-\frac{1}{2}} E^T$
 - 8: $X_{\text{white}} = V X_{\text{centered}}$
 - 9: **Step 3:** Initialize random unmixing matrix W
 - 10: Initialize $W \in R^{n \times n}$ randomly
 - 11: **Step 4:** Iterate using fixed-point (FastICA) or gradient ascent
 - 12: **while** not converged **do**
 - 13: **for** $i = 1$ to n **do**
 - 14: $w_i^{\text{new}} = E[X_{\text{white}} g(w_i^T X_{\text{white}})] - E[g'(w_i^T X_{\text{white}})] w_i$
 - 15: Normalize: $w_i^{\text{new}} = \frac{w_i^{\text{new}}}{\|w_i^{\text{new}}\|}$
 - 16: **end for**
 - 17: Update $W = [w_1, w_2, \dots, w_n]^T$
 - 18: **end while**
 - 19: **Step 5:** Recover independent sources
 - 20: $S = W X_{\text{white}}$
 - 21: **return** S
-

FIGURE 4: Independent Component Analysis Algorithm

Support Vector Machine

SVM is a supervised machine learning algorithm that has gained prominence due to its effectiveness in solving both binary and multi-class classification problems. Its core principle is to identify an optimal decision boundary, known as a hyperplane, that maximizes the margin between data points of different classes. By maximizing this margin, SVM enhances generalization capability and reduces the likelihood of misclassification, making it particularly well-suited for high-dimensional datasets where traditional classifiers may struggle. In the context of human activity classification, SVM has demonstrated superior performance in classifying human activities derived from wearable sensor data, such as accelerometers and gyroscopes in the UCI-HAR Postural Transitions dataset [47]. Human movement patterns are inherently complex and often produce high-dimensional, overlapping feature spaces. SVM addresses this challenge by

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employing kernel functions (e.g., linear, polynomial and radial basis function), which transform the input feature space into a higher-dimensional representation where the data is more likely to be linearly separable. This kernel trick allows SVM to effectively model non-linear relationships within activity data, thereby improving classification accuracy. For each class k , where for each class $k = 1, \dots, N$ and given a training dataset with labels y_i , a binary classifier is trained to distinguish class k from all others. Let v represent a new input feature vector from the dimensionally reduced dataset (after applying PCA, ICA, or NLPCA). The classifier outputs a decision function $f_k(v)$ for each class. The final predicted class for the input vector is then given by selecting the class with the highest decision value:

$$\hat{y} = \arg \max_k f_k(v)$$

Proposed DWT-DR-SVM human activity recognition framework

The core motivation underlying this study is the formulation of a comprehensive hybrid recognition framework that synergistically integrates DWT for signal denoising and feature extraction, DR for effective feature representation, and SVM for classification of human activities. This DWT-DR-SVM framework aims to enhance recognition accuracy, computational efficiency, and generalization capability when applied to HAR datasets. As depicted in Figure 5, the proposed DWT-DR-SVM framework follows a sequential multi-phase workflow, encompassing data acquisition, preprocessing and transformation, DR, and classification.

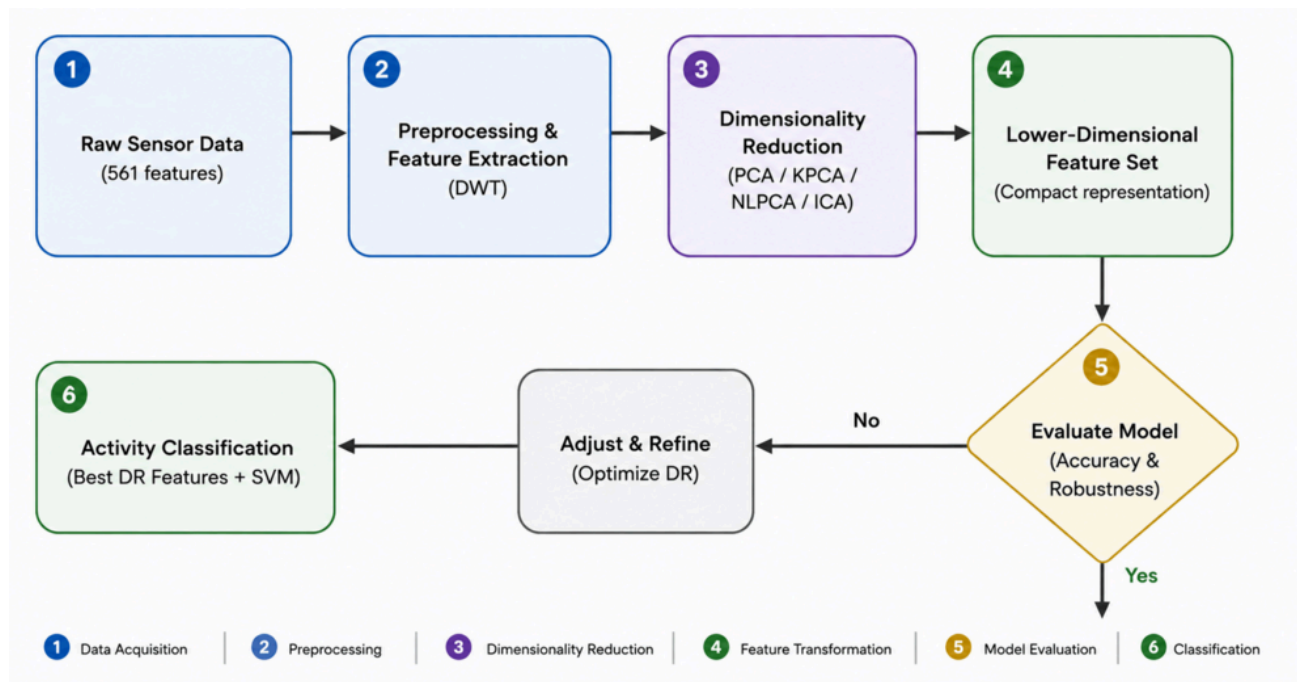


FIGURE 5: Computational Framework for DWT-DR-SVM

DWT, Discrete Wavelet Transform; PCA, Principal Component Analysis; KPCA, Kernel Principal Component Analysis; NLPCA, Nonlinear Principal Component Analysis; ICA, Independent Component Analysis; DR, Dimensionality Reduction; SVM, Support Vector Machine

A step-by-step description of the computational framework is presented as follows:

Data Acquisition: In the UCI-HAR Postural Transitions dataset, the motion data from accelerometers and gyroscopes captured different activities composed of six basic activities: three static postures (standing, sitting, lying) and three dynamic activities (walking, walking downstairs, walking upstairs). The experiment also included postural transitions that occurred between the static postures: stand-to-sit, sit-to-stand, sit-to-lie, lie-to-sit, stand-to-lie, and lie-to-stand. Data are segmented using 5-second windows (50% overlap) and split into 80% training (7352 samples) and 20% testing (2947

samples) following the hold-out cross-validation method. Experimental evaluations in activity recognition emphasize the importance of sufficiently large training sets to capture variability in human motion signals, which are inherently noisy and subject-dependent [48,49]. All signals are normalized to -1 to 1 to ensure uniform feature scaling.

Preprocessing and Feature Extraction: DWT decomposes each signal into approximation (low-frequency) and detail (high-frequency) components, isolating coarse and fine movement patterns. Statistical and spectral features (mean, variance, energy, and entropy) are extracted from each sub-band, followed by redundancy and correlation analysis to retain only informative features for DR.

Dimensionality Reduction: To address the curse of dimensionality and improve computational efficiency, several DR techniques were applied, including PCA, KPCA, NLPCA, and ICA. The number of retained components (10-20) was not arbitrarily selected but determined empirically using a multi-criteria strategy. For PCA, the number of components was chosen based on cumulative explained variance, ensuring retention of over 95% of the total variance while reducing redundancy in the feature space. For nonlinear methods (KPCA and NLPCA), component selection was guided by reconstruction error minimization and observed trends in downstream classification performance on validation data. For ICA, the optimal number of independent components was determined based on stability of the decomposition and class separability under classification performance metrics. Final model selection was therefore guided by comparative evaluation across DR methods, ensuring that the chosen reduced feature representations provide robust class separability and improved computational efficiency for the DWT-DR-SVM framework.

Classification and Validation: The reduced feature sets were subsequently used as input to the SVM classifier for final activity recognition. The SVM constructs an optimal separating hyperplane that maximizes the margin between activity classes, thereby enhancing discriminative capability in high-dimensional feature spaces. During the optimization stage, the learning process is guided by a fitness function defined as:

$$\text{Fitness} = 1 - \text{Accuracy} \quad (7)$$

where accuracy is obtained through k -fold cross-validation on the training dataset. The optimization process terminates when one of the following stopping criteria is satisfied: (i) the maximum number of iterations ($T_{max} = 100$) is reached, or (ii) the improvement in the fitness value between two consecutive iterations is less than 10^{-6} for ten successive iterations, indicating convergence. In addition, the optimization algorithm monitors the best classification accuracy obtained during the search, and the parameter set yielding the minimum fitness value is selected as the optimal solution. Once convergence is achieved, the final SVM model is trained using the optimal parameters and evaluated on the independent testing dataset. The performance of the framework is assessed using standard classification metrics, including accuracy, precision, recall, and F1-score, to provide a comprehensive evaluation of recognition performance across all activity classes.

Model evaluation metrics

To objectively assess the performance and generalization capability of the proposed DWT-DR-SVM framework, multiple quantitative evaluation metrics were employed. These metrics provide comprehensive insight into the model's classification accuracy, robustness, and ability to correctly identify each activity class. The four key performance measures used are Accuracy (Eq. (8)), Precision (Eq. (9)), Recall (Eq. (10)), and F1-Score (Eq. (11)). Accuracy reflects overall model correctness and precision assesses reliability of the predictions. The recall measures sensitivity to actual activities, and the F1-score provides a balanced indicator of classification robustness.

Accuracy: Measures the overall proportion of correctly classified instances among all samples. It reflects the general correctness of the model and is computed as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (8)$$

where TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives, respectively.

Precision: Indicates the proportion of correctly predicted positive observations to the total predicted positives. High precision denotes a low false-positive rate and reliable class discrimination.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (9)$$

Recall: Also referred to as Sensitivity or True Positive Rate, recall quantifies the proportion of actual positives that were correctly identified by the model.

$$\text{Recall} = \frac{TP}{TP + FN} \quad (10)$$

F1-Score: Represents the harmonic mean of precision and recall, providing a balanced measure of the model's ability to avoid both false positives and false negatives.

$$F1\text{-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (11)$$

Results And Discussion

Experimental implementation and processing pipeline

The proposed hybrid DWT-DR-SVM HAR framework was implemented in Python using a Jupyter Notebook environment. All experiments were conducted on a MacBook Pro (M2 Pro, 12-core CPU, 16 GB RAM), which provided sufficient computational resources for training and evaluating the machine learning models using the publicly available UCI-HAR Postural Transitions dataset as explained earlier. Using a higher-performance server or workstation equipped with larger memory capacity, multi-core processors, or GPU acceleration would primarily improve training speed, parallel processing efficiency, hyperparameter optimization time, and scalability for larger datasets. However, it would not necessarily produce significantly higher classification accuracy for the current study because the dataset is relatively moderate in size, and the implemented algorithms (DWT, PCA/KPCA/NLPCA/ICA, and SVM) are deterministic machine learning techniques whose predictive performance depends mainly on feature quality, DR effectiveness, parameter optimization, and data characteristics, rather than hardware specifications alone.

The original dataset was preprocessed using noise filtering and fixed-width sliding windows of 2.56 seconds (128 samples) with 50% overlap. From each window, a total of 561 engineered features were extracted from the time and frequency domains, including statistical, spectral, and signal magnitude measures derived from body acceleration, gravity acceleration, and angular velocity signals. The experiments utilized the predefined training and testing partitions supplied with the dataset. The training set consisted of 7,352 samples, while the test set contained 2,947 samples, resulting in a total of 10,299 activity instances. No additional resampling, balancing, or partitioning procedures were applied to ensure consistency with the benchmark dataset. Figure 6 presents a sample of the wavelet decomposition process, which separates the signal into approximation (low-frequency) and detail (high-frequency) components. This enables the simultaneous representation of global motion trends and localized variations. A four-level Daubechies (db4) wavelet was selected due to its strong time-frequency localization and smoothing properties, facilitating effective noise suppression while preserving transient motion dynamics.

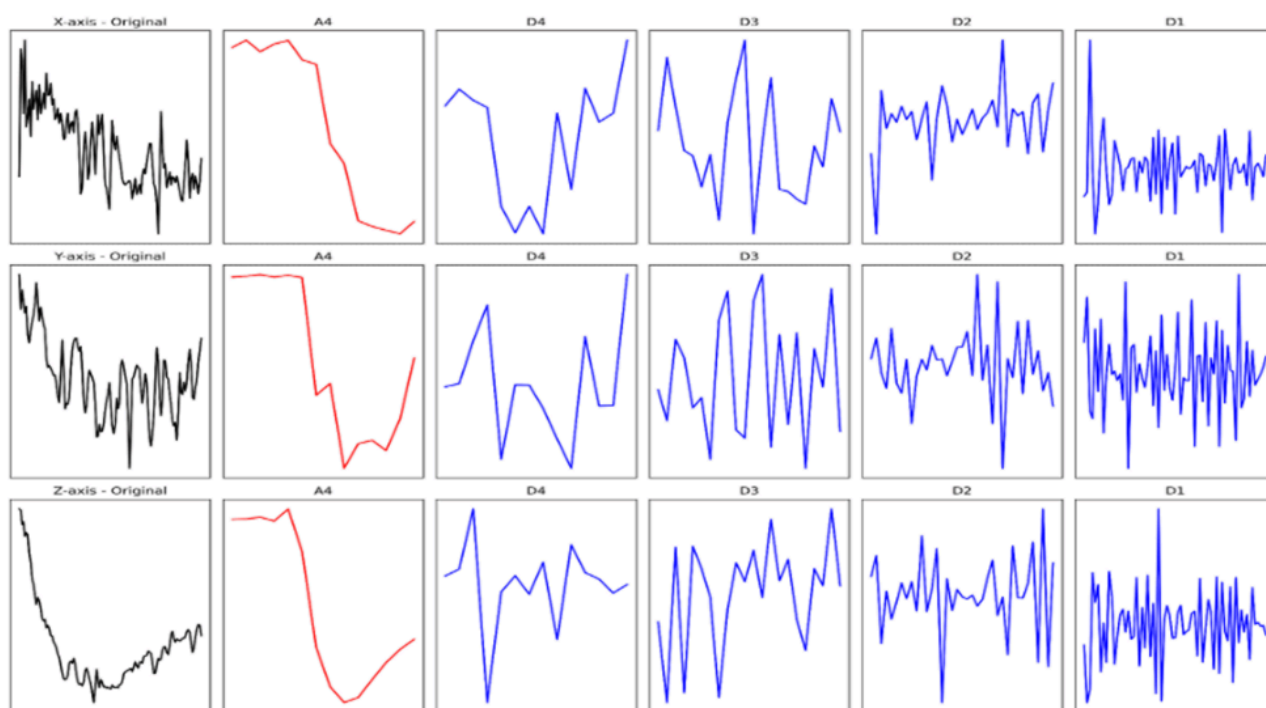


FIGURE 6: Sample Decomposition Results Using DWT

DWT, Discrete Wavelet Transform

Figure 6 illustrates a representative decomposition, where the original signal is separated into approximation coefficient a_4 and detail coefficients d_1 - d_4 . These components capture complementary motion characteristics across multiple temporal scales. The dataset was partitioned using a hold-out strategy: 80% of samples were used for training (7,352 samples, 21 participants) and 20% for testing (2,947 samples, 9 participants). Training data were used for model construction and hyperparameter tuning, while testing data provided independent performance evaluation. All signals were normalized to the range -1 to 1 . Prior to DR, the 561-dimensional feature vectors were processed using a four-level DWT based on the Daubechies-4 (db4) mother wavelet. The decomposition generated approximation and detail coefficients that captured both low-frequency and high-frequency characteristics of human motion signals. The resulting wavelet features formed the input to the dimensionality reduction stage. Four DR techniques were investigated:

- 1) PCA: PCA was implemented using the Scikit-learn library. The number of retained principal components was selected to preserve at least 95% of the cumulative explained variance. This resulted in the retention of 120 principal components from the transformed feature space.
- 2) KPCA: KPCA was implemented using the Scikit-learn KernelPCA module with a Radial Basis Function (RBF) kernel. Kernel parameters were determined through grid-search optimization on the training data. The kernel coefficient (γ) was selected from the range $\{0.001, 0.01, 0.1, 1.0\}$, and the optimal value was retained for all experiments. A total of 120 kernel principal components were retained to maintain consistency with the PCA representation and to provide a comparable feature dimensionality across methods.
- 3) NLPKA: NLPKA was implemented using an autoencoder neural network developed in TensorFlow/Keras. The encoder architecture consisted of fully connected layers of sizes 561-256-128-64, while the decoder mirrored this structure to reconstruct the original input features. Rectified Linear Unit (ReLU) activation functions were used in all hidden layers, with a linear activation function in the output layer. The latent bottleneck layer contained 64 neurons, resulting in a 64-

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dimensional nonlinear feature representation. The model was trained using the Adam optimizer with a learning rate of 0.001, a batch size of 32, and 100 training epochs. Mean Squared Error (MSE) was employed as the reconstruction loss function.

4) ICA: ICA was implemented using the FastICA algorithm available in Scikit-learn. The algorithm employed a maximum of 1,000 iterations and a convergence tolerance of 10^{-4} . The number of independent components was fixed at 120 to ensure consistency with the PCA and KPCA feature spaces. FastICA used the default logarithmic hyperbolic tangent (logcosh) contrast function for estimating statistically independent sources.

The reduced feature representations generated by PCA, KPCA, NLPCA, and ICA were subsequently classified using SVM with hyperparameters optimized via grid search and k-fold cross-validation, as illustrated in Table 2. It is important to note that different kernel functions such as RBF, polynomial and linear were explored. Thus, during model training, multiple candidate values were systematically explored for each tunable parameter using grid search with cross-validation. The range (Table 2) represents the full set of values considered during training, from which the optimal configuration was selected based on validation performance.

Parameter	Symbol	Description	Range and Kernel Function Explored During Training
Kernel Function	$K(x_i, x_j)$	Defines the decision boundary type	{Radial Basis Function, Polynomial, Linear}
Regularization Parameter	(C)	Controls trade-off between margin width and misclassification	{0.1, 1, 10, 100}
Kernel Coefficient	γ	Determines influence of single training examples	{0.001, 0.01, 0.05, 0.1, 0.5}
Tolerance	ϵ	Stopping criterion threshold	{0.01, 0.001, 0.0001}
Cross-Validation	—	Used for parameter optimization	{3-fold, 5-fold, 10-fold}
Max Iterations	—	Upper limit on optimization steps	{1,000; 5,000; 10,000; 20,000}
Scaling	—	Feature normalization range	{[0 to 1] [-1 to 1], z-score standardization}

TABLE 2: SVM Parameter Configuration
SVM, Support Vector Machine

Developed DWT-DR-SVM models

Four hybrid classification models (DWT-PCA-SVM, DWT-KPCA-SVM, DWT-NLPCA-SVM, and DWT-ICA-SVM) were systematically developed and evaluated to determine the optimal configuration for HAR. To ensure optimal classifier performance, a grid-search tuning procedure was implemented to fine-tune the SVM hyperparameters, specifically the

regularization parameter (C) and the kernel coefficient (γ). The tuning process continued iteratively until no further improvement was observed in prediction accuracy across both training and testing datasets, ensuring convergence and model stability. The finalized hyperparameter configurations for each hybrid model with the kernel type are summarized in Table 3.

Model	Kernel Type	Regularization (C)	Kernel Coefficient (γ)	Tolerance (ϵ)	Cross-Validation
DWT-PCA-SVM	RBF	1.0	0.05	0.001	5-fold
DWT-KPCA-SVM	RBF	0.8	0.03	0.001	5-fold
DWT-NLPCA-SVM	RBF	1.2	0.02	0.001	5-fold
DWT-ICA-SVM	RBF	1.0	0.01	0.001	5-fold

TABLE 3: Optimized SVM Hyperparameters for the Developed DWT-DR-SVM Models

DWT, Discrete Wavelet Transform; PCA, Principal Component Analysis; KPCA, Kernel Principal Component Analysis; NLPCA, Nonlinear Principal Component Analysis; ICA, Independent Component Analysis; SVM, Support Vector Machine; RBF, Radial Basis Function

Individual hybrid model performance

DWT-PCA-SVM Model

The class-wise performance of the DWT-PCA-SVM model on the UCI-HAR dataset is presented in Table 4. The results show that the model performs well on steady-state activities, with LAYING ($F1 = 0.85$), WALKING_UPSTAIRS ($F1 = 0.75$), and STANDING ($F1 = 0.73$) achieving the highest scores. WALKING recorded a high recall (0.86) but comparatively lower precision, indicating the presence of false positives. In contrast, transitional activities such as STAND_TO_LIE ($F1 = 0.26$) and LIE_TO_STAND ($F1 = 0.29$) were poorly classified, mainly due to low recall. As illustrated in Figure 7, the confusion matrix shows strong diagonal dominance for static activities, while considerable misclassification occurs among transition classes and closely related posture activities.

ID	Activity	Precision	Recall	F1-Score
1	WALKING	0.61	0.86	0.71
2	WALKING_UPSTAIRS	0.87	0.67	0.75
3	WALKING_DOWNSTAIRS	0.61	0.50	0.55
4	SITTING	0.66	0.46	0.54
5	STANDING	0.64	0.85	0.73
6	LAYING	0.87	0.83	0.85
7	STAND_TO_SIT	0.82	0.39	0.53
8	SIT_TO_STAND	0.86	0.60	0.71
9	SIT_TO_LIE	0.44	0.84	0.57
10	LIE_TO_SIT	0.45	0.52	0.48
11	STAND_TO_LIE	0.47	0.18	0.26
12	LIE_TO_STAND	0.43	0.22	0.29

TABLE 4: DWT-PCA-SVM Classification Result

DWT, Discrete Wavelet Transform; PCA, Principal Component Analysis; SVM, Support Vector Machine

Activity	WALK	W-UP	W-DN	SIT	STND	LAY	STN2SIT	SIT2STN	SIT2LY	LY2SIT	STND2LY	LY2STND
WALKING	406	6	84	0	0	0	0	0	0	0	0	0
WALKING_UPSTAIRS	36	374	61	0	0	0	0	0	0	0	0	0
WALKING_DOWNSTAIR	141	30	249	0	0	0	0	0	0	0	0	0
SITTING	0	0	0	321	163	22	0	0	0	2	0	0
STANDING	2	4	0	75	457	18	0	0	0	0	0	0
LAYING	0	2	0	40	8	495	0	0	0	0	0	0
STAND_TO_SIT	1	8	0	2	0	0	7	0	1	0	4	0
SIT_TO_STAND	0	1	0	1	0	0	1	5	0	0	2	0
SIT_TO_LIE	0	0	0	0	0	0	0	0	26	2	3	1
LIE_TO_SIT	0	0	0	0	0	1	0	0	3	14	0	7
STAND_TO_LIE	0	9	0	1	1	1	0	0	19	3	13	2
LIE_TO_STAND	0	1	0	0	0	0	0	0	0	12	5	9

FIGURE 7: Confusion Matrix of DWT-PCA-SVM

DWT, Discrete Wavelet Transform; PCA, Principal Component Analysis; SVM, Support Vector Machine

DWT-KPCA-SVM Model

Table 5 presents the class-level performance of the DWT-KPCA-SVM model on the UCI-HAR dataset. Overall, the results indicate relatively weak classification performance across most activity classes compared with the other evaluated models. Among the activities, WALKING and STANDING achieved the highest performance, each with an F1-score of 0.44, followed by SITTING (F1 = 0.42) and LAYING (F1 = 0.32). These results suggest that the model was able to capture some patterns associated with basic locomotion and static postures, although the overall discriminative capability remained limited. Moderate recognition was observed for WALKING_UPSTAIRS (F1 = 0.26) and WALKING_DOWNSTAIRS (F1 = 0.24), indicating that the model struggled to differentiate between similar locomotion activities. The relatively low recall values for these classes suggest that many true instances were incorrectly classified as other activities. This behaviour can be attributed to overlapping motion patterns between walking-related activities in the inertial sensor signals. Notably, several transitional activities, including STAND_TO_SIT and SIT_TO_STAND, recorded zero precision, recall, and F1-score values. This indicates that the classifier did not correctly predict any instances belonging to these classes during testing. Such results typically occur when the model fails to learn discriminative features for certain activities, often due to the short duration and subtle motion characteristics associated with transitional movements. In addition, these classes are relatively less represented compared to dominant activities such as walking and sitting, which can further reduce classification reliability. Another contributing factor may be the kernel-based transformation applied in KPCA, which maps the input features into a high-dimensional nonlinear space. In this study, the nonlinear projection appears to have distorted the separability of certain activity patterns derived from the wavelet-transformed features, making it difficult for the SVM classifier to construct effective decision boundaries for transition classes. As illustrated in Figure 8, the confusion matrix shows weak diagonal dominance compared with the other evaluated models, confirming the presence of substantial misclassification across multiple activity classes. Misclassifications are particularly evident among locomotion activities and between static postures and transitional movements, which share similar sensor signal characteristics.

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ID	Activity	Precision	Recall	F1-Score
1	WALKING	0.39	0.51	0.44
2	WALKING_UPSTAIRS	0.25	0.26	0.26
3	WALKING_DOWNSTAIRS	0.26	0.23	0.24
4	SITTING	0.39	0.45	0.42
5	STANDING	0.48	0.41	0.44
6	LAYING	0.32	0.31	0.32
7	STAND_TO_SIT	0.00	0.00	0.00
8	SIT_TO_STAND	0.00	0.00	0.00
9	SIT_TO_LIE	0.00	0.00	0.00
10	LIE_TO_SIT	0.00	0.00	0.00
11	STAND_TO_LIE	0.00	0.00	0.00
12	LIE_TO_STAND	0.00	0.00	0.00

TABLE 5: Classification Report of DWT-KPCA-SVM

DWT, Discrete Wavelet Transform; KPCA, Kernel Principal Component Analysis; SVM, Support Vector Machine

Activity	WALK	W-UP	W-DN	SIT	STND	LAY	STN2SIT	SIT2STN	SIT2LY	LY2SIT	STND2LY	LY2STND
WALKING	250	180	47	0	0	0	1	0	0	0	13	1
WALKING_UPSTAIRS	260	120	90	0	0	0	0	0	0	0	0	0
WALKING_DOWNSTAIRS	110	170	96	0	0	0	0	0	0	0	0	0
SITTING	0	0	4	230	80	190	0	0	0	0	0	0
STANDING	2	0	0	150	230	170	0	0	0	0	0	0
LAYING	1	0	1	200	170	170	0	0	0	0	0	0
STAND_TO_SIT	6	1	13	0	1	2	0	0	0	0	0	0
SIT_TO_STAND	1	0	8	0	0	1	0	0	0	0	0	0
SIT_TO_LIE	1	0	30	0	0	0	0	0	0	0	1	0
LIE_TO_SIT	0	0	25	0	0	0	0	0	0	0	0	0
STAND_TO_LIE	8	6	33	0	1	1	0	0	0	0	0	0
LIE_TO_STAND	2	0	24	0	0	0	0	0	0	0	1	0

FIGURE 8: Confusion Matrix of DWT-KPCA-SVM

DWT, Discrete Wavelet Transform; KPCA, Kernel Principal Component Analysis; SVM, Support Vector Machine

DWT-NLPCA-SVM Model

The DWT-NLPCA-SVM model demonstrates strong recognition of primary activities, with LAYING achieving the highest performance ($F1 = 0.93$), followed by WALKING_UPSTAIRS (0.75), WALKING (0.66), SITTING (0.66), and STANDING (0.63) (Table 6). WALKING_DOWNSTAIRS shows moderate recognition ($F1 = 0.49$), indicating partial discrimination of downward locomotion patterns. In contrast, transitional activities exhibit weak performance. STAND_TO_SIT (0.26), SIT_TO_LIE (0.33), LIE_TO_STAND (0.22), and LIE_TO_SIT (0.11) show low detection accuracy, while SIT_TO_STAND was not detected ($F1 = 0.00$), reflecting the difficulty of modeling short-duration transitions. The confusion matrix (Figure 9) confirms strong correct classification for dominant activities, particularly LAYING and walking-related classes, with most misclassifications occurring among similar locomotion activities and transition movements, as well as between SITTING and STANDING due to similar sensor patterns.

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ID	Activity	Precision	Recall	F1-Score
1	WALKING	0.63	0.69	0.66
2	WALKING_UPSTAIRS	0.80	0.72	0.75
3	WALKING_DOWNSTAIRS	0.47	0.50	0.49
4	SITTING	0.60	0.72	0.66
5	STANDING	0.73	0.55	0.63
6	LAYING	0.90	0.96	0.93
7	STAND_TO_SIT	0.50	0.17	0.26
8	SIT_TO_STAND	0.00	0.00	0.00
9	SIT_TO_LIE	0.30	0.38	0.33
10	LIE_TO_SIT	0.17	0.08	0.11
11	STAND_TO_LIE	0.40	0.39	0.40
12	LIE_TO_STAND	0.22	0.22	0.22

TABLE 6: Classification Report of DWT-NLPCA-SVM

DWT, Discrete Wavelet Transform; NLPCA, Nonlinear Principal Component Analysis; SVM, Support Vector Machine

Activity	WALK	W-UP	W-DN	SIT	STND	LAY	STN2SIT	SIT2STN	SIT2LY	LY2SIT	STND2LY	LY2STND
WALKING	360	29	110	0	0	0	0	0	0	0	0	0
WALKING_UPSTAIRS	64	370	39	0	0	0	0	0	0	0	0	0
WALKING_DOWNSTAIRS	160	40	220	0	0	0	0	0	0	0	0	0
SITTING	0	1	0	400	77	33	0	0	0	0	0	0
STANDING	2	5	0	160	380	8	1	0	0	0	1	0
LAYING	0	0	0	10	4	530	0	0	0	0	1	0
STAND_TO_SIT	0	8	2	0	0	1	3	0	2	0	7	0
SIT_TO_STAND	0	1	0	1	0	0	0	0	0	0	8	0
SIT_TO_LIE	0	0	1	0	0	0	0	0	17	1	8	5
LIE_TO_SIT	0	0	0	0	0	1	0	0	0	3	2	19
STAND_TO_LIE	5	3	1	0	1	0	2	0	10	4	21	2
LIE_TO_STAND	1	0	1	0	0	3	0	0	0	3	4	15

FIGURE 9: Confusion Matrix of DWT-NLPCA-SVM

DWT, Discrete Wavelet Transform; NLPCA, Nonlinear Principal Component Analysis; SVM, Support Vector Machine

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DWT-ICA-SVM Model Result

As presented in Table 7, the DWT-ICA-SVM model achieved strong performance for locomotion activities, with WALKING (F1 = 0.96), WALKING_UPSTAIRS (F1 = 0.96), and WALKING_DOWNSTAIRS (F1 = 0.95). The LAYING activity is classified almost perfectly (F1 = 1.00), while SITTING (F1 = 0.90) and STANDING (F1 = 0.92) also show high recognition accuracy. In contrast, transitional activities exhibit lower recall and F1-scores due to their brief duration and similarity to neighbouring postures, such as STAND_TO_SIT (F1 = 0.72), SIT_TO_LIE (F1 = 0.69), and LIE_TO_SIT (F1 = 0.74). Figure 10 (confusion matrix) supports these results, showing strong diagonal dominance for locomotion and static activities, indicating correct predictions. Most misclassifications occur among transition activities and their corresponding static states.

ID	Activity	Precision	Recall	F1-Score
1	WALKING	0.95	0.98	0.96
2	WALKING_UPSTAIRS	0.99	0.93	0.96
3	WALKING_DOWNSTAIRS	0.92	0.98	0.95
4	SITTING	0.91	0.88	0.90
5	STANDING	0.91	0.93	0.92
6	LAYING	0.99	1.00	1.00
7	STAND_TO_SIT	1.00	0.57	0.72
8	SIT_TO_STAND	1.00	0.90	0.95
9	SIT_TO_LIE	0.72	0.66	0.69
10	LIE_TO_SIT	0.81	0.68	0.74
11	STAND_TO_LIE	0.81	0.69	0.75
12	LIE_TO_STAND	0.73	0.70	0.72

TABLE 7: Classification Report of DWT-ICA-SVM

DWT, Discrete Wavelet Transform; ICA, Independent Component Analysis; SVM, Support Vector Machine

Activity	WALK	W-UP	W-DN	SIT	STND	LAY	STN2SIT	SIT2STN	SIT2LY	LY2SIT	STND2LY	LY2STND
WALKING	490	0	10	0	0	0	0	0	0	0	0	0
WALKING_UPSTAIRS	23	440	9	0	0	0	0	0	0	0	0	0
WALKING_DOWNSTAIRS	3	4	440	0	0	0	0	0	0	0	0	0
SITTING	0	0	3	450	52	4	0	0	0	0	0	0
STANDING	0	0	0	38	520	0	0	0	0	0	0	0
LAYING	0	0	0	0	0	540	0	0	0	0	0	0
STAND_TO_SIT	1	1	3	2	2	0	13	0	0	0	1	0
SIT_TO_STAND	0	0	1	0	0	0	0	9	0	0	0	0
SIT_TO_LIE	0	0	4	1	0	0	0	0	21	0	6	0
LIE_TO_SIT	0	0	0	0	0	0	0	0	0	17	1	7
STAND_TO_LIE	1	0	4	1	0	1	0	0	8	0	34	0
LIE_TO_STAND	0	0	3	1	0	0	0	0	0	4	0	19

FIGURE 10: Confusion Matrix of DWT-ICA-SVM

DWT, Discrete Wavelet Transform; ICA, Independent Component Analysis; SVM, Support Vector Machine

Overall Classification Model Results

Table 8 presents the comparative overall classification performance of the evaluated hybrid models (DWT-PCA-SVM, DWT-KPCA-SVM, DWT-NLPCA-SVM, and DWT-ICA-SVM) using precision, recall, F1-score, and overall accuracy. These metrics provide a comprehensive evaluation of the models by assessing not only the correctness of predictions but also the balance between correctly identifying activity instances and minimizing misclassification. The results reveal clear performance variations among the four evaluated hybrid models. Among them, the DWT-ICA-SVM model achieved the best overall classification performance across all evaluation metrics. The model obtained a precision, recall, and F1-score of 0.89, 0.83, and 0.85, respectively, with an overall accuracy of 94%. The superior performance of the model can be attributed to the ability of ICA to extract statistically independent latent sources from multivariate sensor signals. Consequently, the ICA stage isolates underlying motion components that correspond more closely to distinct human activities, thereby producing a feature space with improved class separability for the SVM classifier. In contrast, the DWT-PCA-SVM model demonstrated moderate performance, achieving a precision of 0.64, a recall of 0.58, and an F1-score of 0.58, with an overall accuracy of 69%. Although the model was able to classify several activities reasonably well, its overall performance was lower than that of the DWT-ICA-SVM model, suggesting that PCA-based dimensionality reduction was less effective in preserving the most discriminative activity information. Since PCA maximizes overall variance rather than class discrimination, some activity-relevant characteristics may have been compressed or discarded during DR, resulting in reduced feature separability in the transformed space.

Similarly, the DWT-NLPCA-SVM model achieved a precision of 0.48, a recall of 0.45, and an F1-score of 0.45, with an overall accuracy of 67%. While NLPCA is designed to capture nonlinear relationships within data, the nonlinear transformations introduced may have altered the intrinsic structure of the wavelet-derived features without providing additional discriminatory information. This likely increased class overlap within the reduced feature space, thereby limiting the ability of the SVM classifier to establish effective decision boundaries. The findings indicate that nonlinear feature extraction did not provide a significant advantage for the activity patterns contained in the dataset. The DWT-KPCA-SVM model produced the lowest overall performance among the evaluated models, achieving a precision of 0.17, a recall of 0.18, and an F1-score of 0.18, with an overall classification accuracy of 35%. The substantially lower performance suggests that the kernel-based projection was less effective in preserving activity-discriminative characteristics from the wavelet-transformed signals. Since the effectiveness of KPCA depends heavily on the suitability of the kernel transformation and the resulting feature representation, the projected feature space may have introduced excessive class overlap and

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reduced separability between activity classes. These findings demonstrate that more complex nonlinear transformations do not necessarily yield superior performance when the underlying feature structure is already adequately represented by the wavelet features.

Model	Precision	Recall	F1-Score	Accuracy
DWT-PCA-SVM	0.64	0.58	0.58	0.69
DWT-KPCA-SVM	0.17	0.18	0.18	0.35
DWT-NLPCA-SVM	0.48	0.45	0.45	0.67
DWT-ICA-SVM	0.89	0.83	0.85	0.94

TABLE 8: Overall Classification Performance of DWT-DR-SVM Models

DWT, Discrete Wavelet Transform; PCA, Principal Component Analysis; KPCA, Kernel Principal Component Analysis; NLPCA, Nonlinear Principal Component Analysis; ICA, Independent Component Analysis; DR, Dimensionality Reduction; SVM, Support Vector Machine

Table 9 presents a comprehensive comparison of the classification performance of all developed DWT-DR-SVM pipelines, with DWT-SVM serving as the baseline model. The results clearly demonstrate the effect of the chosen dimensionality reduction technique on the final recognition performance. The baseline DWT-SVM achieved strong performance (accuracy = 0.91), confirming that discrete wavelet decomposition effectively extracts discriminative time-frequency features suitable for SVM classification. Although PCA is widely recognized for its effectiveness in reducing redundancy while preserving variance, its application in the wavelet-transformed domain inadvertently suppresses discriminative transient components that are critical for HAR. Since DWT already performs strong signal compression and decorrelation, the subsequent application of PCA into the pipeline (DWT-PCA-SVM) improved class separability for some activities but resulted in a reduced accuracy of 0.69 due to excessive information loss, particularly for short-duration transitional activities. This explains the observed reduction in classification accuracy for the DWT-PCA-SVM model relative to the baseline DWT-SVM model. A further drop in performance was observed in the DWT-KPCA-SVM pipeline (accuracy = 0.35), suggesting that kernel mappings in the transformed wavelet feature space induced over-complex representations and information redundancy, limiting discriminative capability. That is, KPCA projects data into a high-dimensional feature space using kernel functions, which, when applied after multi-resolution wavelet decomposition, introduce excessive redundancy and amplify noise. Furthermore, the eigen-decomposition of large Gram matrices is susceptible to numerical instability, particularly when kernel parameters are sub-optimally tuned. These effects lead to distorted feature representations and degraded class separability, thereby significantly reducing classification performance. The nonlinear autoencoder-based NLPCA pipeline achieved moderate improvement (accuracy = 0.67) relative to KPCA, but still lagged the baseline, highlighting the sensitivity of deep nonlinear mappings to parameter tuning and dataset size. This discrepancy arises from the sensitivity of autoencoder-driven DR to hyperparameter selection, architectural design, and training sample size, which significantly affects feature stability and generalization. As a result, the DWT-SVM framework exhibited superior robustness and discriminative power. In contrast, the proposed DWT-ICA-SVM model achieved the highest performance across all metrics (accuracy = 0.94, precision = 0.89, recall = 0.83, and F1-score = 0.85). A diagrammatic illustration of the reported results is shown in Figure 11. ICA proved highly effective in separating independent latent sources within the wavelet-transformed space, suppressing noise and redundancy while preserving discriminative class features. This led to significant performance gains over DWT-SVM and large improvements over PCA/KPCA/NLPCA-based variants. Overall, the results demonstrate that ICA provides the most suitable post-wavelet

decorrelation strategy for SVM-based HAR, significantly improving classification robustness and generalization capability. This confirms the proposed DWT-ICA-SVM model as the optimal configuration for the UCI machine learning repository HAR-specific dataset used in this study.

Model	Precision	Recall	F1-Score	Accuracy
DWT-SVM	0.83	0.79	0.80	0.91
DWT-PCA-SVM	0.64	0.58	0.58	0.69
DWT-KPCA-SVM	0.17	0.18	0.18	0.35
DWT-NLPCA-SVM	0.48	0.45	0.45	0.67
DWT-ICA-SVM	0.89	0.83	0.85	0.94

TABLE 9: Comparison Between DWT-SVM and DWT-DR-SVM Models

DWT, Discrete Wavelet Transform; PCA, Principal Component Analysis; KPCA, Kernel Principal Component Analysis; NLPCA, Nonlinear Principal Component Analysis; ICA, Independent Component Analysis; DR, Dimensionality Reduction; SVM, Support Vector Machine

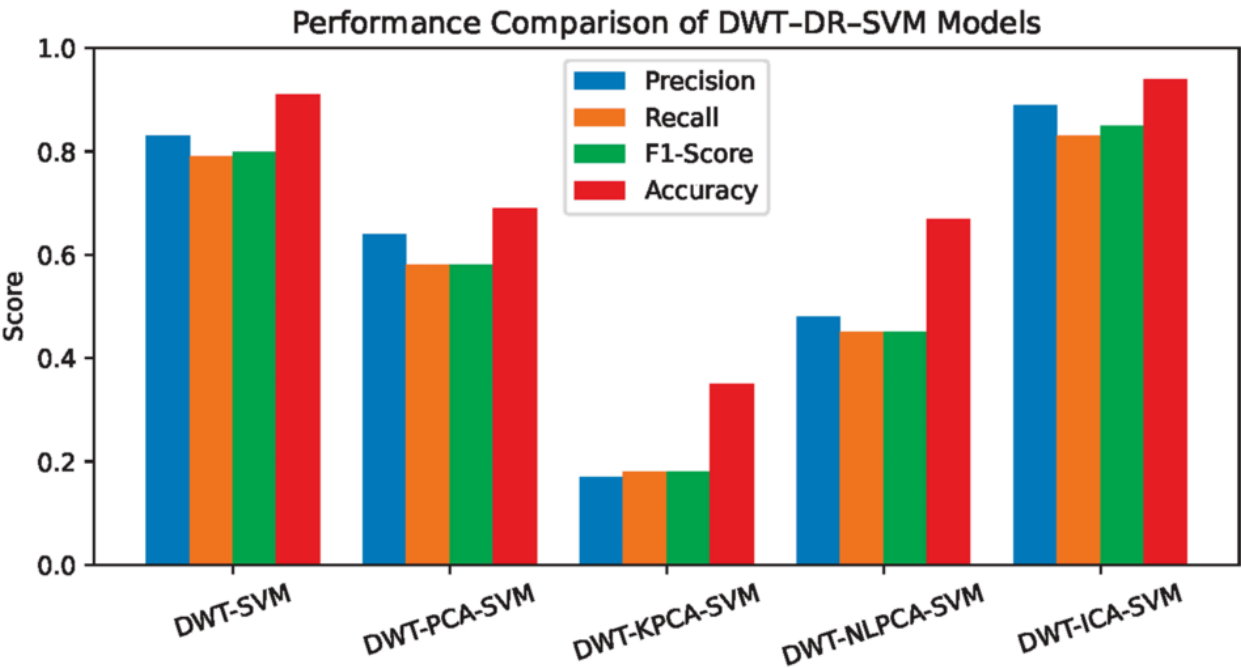


FIGURE 11: Performance Comparison of DWT-DR-SVM Models
DWT, Discrete Wavelet Transform; PCA, Principal Component Analysis; KPCA, Kernel Principal Component Analysis; NLPCA, Nonlinear Principal Component Analysis; ICA, Independent Component Analysis; DR, Dimensionality Reduction; SVM, Support Vector Machine

Validation of DWT-ICA-SVM model results with literature

The performance of the proposed DWT-ICA-SVM model was validated by comparing its results with representative studies reported in the HAR literature, as summarized in Table 10. In HAR research, classification performance is commonly evaluated using indicators such as accuracy, precision, recall, and F1-score, which together provide a balanced assessment of classification effectiveness [48,49]. However, direct comparison across studies must be interpreted carefully because experimental conditions vary considerably in terms of datasets, feature extraction methods, and evaluation protocols. Different datasets used in HAR research, such as UCI-HAR, PAMAP2, and SisFall, present varying levels of activity complexity, sensor modalities, and participant diversity [50,51]. These differences significantly influence the reported performance of classification models. In addition, evaluation strategies adopted in previous studies may affect performance outcomes. For example, several works reporting very high accuracies (often exceeding 97%) employ random k-fold cross-validation or window-based validation strategies, which may produce optimistic estimates due to overlap between training and testing data segments [52]. When models are evaluated using subject-independent validation protocols, which better reflect real-world deployment scenarios, the reported performance typically becomes more conservative.

Under the experimental conditions adopted in this study, the proposed DWT-ICA-SVM model achieved an overall classification accuracy of 94%, with precision, recall, and F1-score of 0.89, 0.83, and 0.85, respectively, on the UCI-HAR dataset. These results demonstrate competitive performance relative to many classical machine learning approaches reported in the literature. The effectiveness of the model can be attributed to the complementary integration of DWT and (ICA for feature extraction) [53]. Ablation analysis conducted during model development further demonstrated that incorporating the ICA stage improved classification performance by approximately 2.5 percentage points in overall

accuracy, while simultaneously reducing redundant features in the transformed feature space. This improvement enhances both the compactness and discriminative power of the extracted features, thereby enabling the SVM classifier to construct more effective decision boundaries for activity classification.

Overall, the comparative analysis with existing HAR studies (Table 10) indicates that the proposed DWT-ICA-SVM model achieved competitive and reliable performance while maintaining relatively low computational complexity compared with deep learning-based approaches. The integration of time-frequency signal decomposition with independent component-based feature separation significantly enhances activity classification capability. These findings support the suitability of the proposed DWT-ICA-SVM model for practical human activity monitoring applications, particularly in mobile and wearable sensing environments where computational efficiency and classification reliability are critical.

Author (Year)	Paper (short)	Method applied	Validation results
[54]	A Robust Deep Feature Extraction Method for HAR Using a Wavelet-Based Spectral Visualisation Technique	CWT, scalograms, deep feature extractor (ResNet-101, etc.), classifier (softmax/SVM baselines)	Recall = 97.0%, Precision = 98.2%, F1-score = 97.6%, Accuracy = 98.4%
[55]	Quantitative Analysis of Mother Wavelet Selection For Wearable-Sensor HAR	WPT/wavelet packet features + classifiers (SVM among tested)	Accuracy = 98.64%, F1-score = 0.97
[56]	Transfer Learning Approach for HAR Based on CWT (Scalograms)	CWT scalograms + pre-trained CNNs (DenseNet, ResNet, etc.); SVM baseline comparisons	Accuracy = 97.48%, F1-score = 97.52%, Precision = 97.62%, Recall = 97.41%
[57]	A Novel Deep-Learning Model for Human Activity Recognition Based on Continuous Wavelet Transform	WPT features + feature selection (GA/other) + classical ML (SVM baseline)	Accuracy = 97.48%, F1-score = 97.52%
[58]	CNN-SVM Learning Approach Based Human Activity Recognition	CNN feature extractor + SVM classifier (hybrid)	Accuracy = 99.92%, Precision = 98.77%, Recall = 99.79%, F1-score = 99.28%
[59]	Human Activity Recognition from Accelerometry, Based on a Radius of Curvature Feature	Time-domain engineered feature + ANN/SVM baselines	Accuracy = 95%, Recall: Not explicitly reported, Precision: Not explicitly reported, F1-score: Not explicitly reported
[60]	Wavelet-Based Temporal Forecasting Models of Human Activities for Anomaly Detection	Wavelet/time-frequency features → SVM/classifiers	Precision = 94.0%, Recall = 93.9%, Accuracy = 89.2%, F1 score = 94.0%
[61]	Human-Assisted vs. Deep Learning Feature Extraction: An Evaluation of ECG Features Extraction Methods for Arrhythmia Classification Using Machine Learning.	Wavelet temporal modelling + ML classifiers (SVM among baselines)	Accuracy = 92.00%, F1-score = 91.54, Recall = 94.20%, Precision = 89.04%
Proposed model	Performance Evaluation of Hybrid Intelligent Models for Human Activity Recognition	DWT-ICA-SVM	Accuracy = 94%, Recall = 83%, Precision = 89%, F1-score = 85%

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TABLE 10: Comparison of DWT-ICA-SVM Model and Some Established Literature Results

DWT, Discrete Wavelet Transform; PCA, Principal Component Analysis; KPCA, Kernel Principal Component Analysis; NLPCA, Nonlinear Principal Component Analysis; ICA, Independent Component Analysis; DR, Dimensionality Reduction; SVM, Support Vector Machine; HAR, Human Activity Recognition; CWT, Continuous Wavelet Transform; WPT, Wavelet Packet Transform; CNN, Convolutional Neural Network; GA, Genetic Algorithm; ML, Machine Learning; ANN, Artificial Neural Network

Limitations of the study

Despite the promising performance achieved by the proposed DWT-ICA-SVM framework, the study only utilized the UCI-HAR dataset, which was collected under controlled laboratory conditions with a single smartphone placement at the waist. While widely used as a benchmark for HAR studies, the dataset may not fully represent real-world variability such as differences in sensor placement, user behaviour, environmental noise, and device heterogeneity. Consequently, further validation using more diverse datasets, including PAMAP2, WISDM, and mHealth, is necessary to confirm the generalizability of the proposed framework. Additionally, the study examined four DR techniques that include PCA, KPCA, NLPCA, and ICA. Exploring other advanced representation learning methods, such as autoencoders, variational autoencoders, or manifold learning approaches, may provide richer feature representations and further contribute to the HAR studies.

Conclusions

The study presented a comprehensive investigation of a hybrid DWT-ICA-SVM framework for Human Activity Recognition (HAR) using inertial motion sensor data. The proposed model was designed to leverage the complementary strengths of wavelet-based time-frequency feature extraction, statistical feature separation, and robust nonlinear classification. Through systematic experimentation, the DWT-ICA-SVM model demonstrated a strong balance between classification accuracy, generalization capability, and computational efficiency. The proposed framework was benchmarked against four established approaches, namely DWT-SVM, DWT-PCA-SVM, DWT-KPCA-SVM, and DWT-NLPCA-SVM, under identical experimental conditions and evaluation criteria. The results showed that the DWT-ICA-SVM model achieved an overall accuracy of 94%, outperforming the baseline DWT-SVM model (91%) as well as all DR-based alternatives. The observed performance improvement indicates that ICA was more effective in preserving and enhancing activity-discriminative information extracted from the wavelet-transformed signals. By decomposing the feature space into statistically independent latent components, ICA reduced feature redundancy and produced a representation with improved class separability, enabling the SVM classifier to construct more discriminative decision boundaries. In contrast, the PCA-, KPCA-, and NLPCA-based models achieved lower classification performance, suggesting that variance-preserving and nonlinear projection techniques were less effective in retaining the most informative characteristics of the wavelet-derived features for activity recognition. The particularly poor performance of the KPCA-SVM model further indicates that increased transformation complexity does not necessarily translate into improved discrimination when the underlying activity patterns are already adequately represented in the transformed feature space. The findings demonstrate that the integration of DWT and ICA provides a highly effective feature representation for HAR tasks, yielding superior recognition performance compared with conventional linear and nonlinear DR approaches. The results therefore validate the suitability of the DWT-ICA-SVM framework as a reliable and efficient solution for inertial sensor-based human activity recognition applications.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

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Human subjects: All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

Data Availability Statements

The data supporting this study are openly available in UCI Machine Learning Repository at <https://doi.org/10.24432/C54S4K>.

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