A HYBRID MACHINE LEARNING FRAMEWORK FOR WEARABLE-SENSOR-BASED HUMAN ACTIVITY RECOGNITION IN REAL-TIME ENVIRONMENTS

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ABSTRACT
Human Activity Recognition (HAR) has emerged as a transformative technology in pervasive computing, enabling intelligent monitoring, automated behaviour analysis, and personalized digital services. Recent advancements in wearable sensors and machine learning have accelerated the development of robust HAR systems, particularly for applications in healthcare, fitness tracking, human–computer interaction, and assisted living. However, the complexity of human motion patterns, variability in sensor noise, and the challenge of generalizing across users continue to hinder consistently accurate predictions. This research presents a hybrid machine-learning framework for wearable-sensor-based HAR that integrates temporal feature extraction with an optimized ensemble classification pipeline to improve recognition accuracy in real-time environments. The proposed model processes tri-axial accelerometer and gyroscope data, performs multi-stage preprocessing, and applies synthetic feature fusion to enhance discriminative capability. Evaluation on benchmark datasets demonstrates significant performance improvement compared with conventional single-model approaches. The study also highlights the impact of sampling frequency, window size, and sensor placement on classification reliability. The outcomes indicate that hybrid models effectively address limitations related to feature redundancy and activity overlap, thereby enabling HAR systems to perform reliably across heterogeneous user groups. The research contributes a scalable methodology suitable for deployment in wearable IoT devices and mobile platforms, offering high efficiency and adaptability for real-world applications.

Keywords: Human Activity Recognition, Wearable Sensors, Machine Learning, Feature Fusion, Ensemble Learning, Accelerometer, Real-Time Classification

I. INTRODUCTION

Human Activity Recognition (HAR) has become a foundational component of modern pervasive and ubiquitous computing systems, gaining widespread adoption across domains such as healthcare, sports analytics, rehabilitation, workplace safety, and human–computer interaction. The proliferation of wearable sensors—particularly accelerometers, gyroscopes, magnetometers, and physiological monitors—has created unprecedented opportunities for continuous monitoring of human behaviour in naturalistic settings. These advancements have aligned with global trends in smart environments and personalized digital ecosystems, thereby motivating extensive research in developing robust, accurate, and real-time HAR systems. Traditional video-based HAR approaches faced significant barriers, including privacy concerns, high computational costs, and sensitivity to lighting or occlusion. Wearable sensors, however, provide a non-intrusive, cost-effective alternative capable of capturing high-resolution motion signals irrespective of the surrounding environment, making them suitable for real-world applications [1], [2].

Machine learning plays a central role in transforming raw sensor signals into meaningful activity labels. Classical models such as Support Vector Machines, Decision Trees, k-Nearest Neighbours, and Hidden Markov Models have been widely adopted for HAR tasks due to their interpretability and moderate computational requirements [3], [4]. Yet, these approaches often struggle to generalize across subjects with different physical characteristics, motion styles, or sensor wearing habits. In contrast, deep learning architectures—including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and hybrid CNN-LSTM frameworks—have recently demonstrated superior performance by automatically learning hierarchical temporal features from multi-dimensional sensor streams [5], [6]. Despite this, deep models require large annotated datasets and high computational power, which limits their feasibility for real-time embedded devices and low-power wearable platforms [7].

The challenge of accurately distinguishing between activities with similar motion patterns remains a critical research gap. Activities such as walking upstairs, walking downstairs, slow running, or brisk walking generate overlapping sensor signatures that complicate recognition tasks [8]. Moreover, the influence of sensor placement strongly affects data quality; sensors worn on the wrist capture different motion dynamics compared with those on the ankle or torso [9]. As a result, the design of a robust HAR system requires an intelligent combination of preprocessing, feature engineering, and adaptive modelling strategies that can overcome inter-subject and inter-activity variability.

Recent studies have explored ensemble machine learning as a promising solution to improve HAR accuracy by combining the strengths of multiple models. Ensemble strategies—such as random forests, gradient boosting, and stacking architectures—help mitigate the limitations of individual models while increasing robustness against noise and outliers [10], [11]. Wearable devices such as smartwatches, fitness bands, and medical monitoring kits provide continuous streams of sensor data, reinforcing the need for models that can process data efficiently without compromising accuracy or battery life [12]. The advent of IoT infrastructures further enhances HAR applications by enabling cloud-assisted analytics, real-time alert systems, and large-scale data aggregation for predictive modelling [13].

Despite these advancements, significant challenges persist. One major limitation is the diversity of sensing environments, which leads to domain shifts in datasets collected from different populations, device types, or daily routines. Machine learning models trained on controlled laboratory datasets tend to perform poorly when deployed in unconstrained real-world settings [14]. Addressing domain generalization, therefore, has become a major research focus in HAR. Additionally, annotating HAR datasets is labour-intensive and prone to human error, driving interest in semi-supervised and self-supervised learning mechanisms capable of learning from unlabelled data [15].

A critical aspect of HAR research involves the extraction of discriminative temporal and statistical features from continuous sensor signals. Techniques such as Fourier transforms, wavelet decomposition, entropy measures, and correlation-based analysis have significantly improved classification performance, yet their effectiveness varies across activity types [16]. Hybrid approaches that integrate handcrafted features with automatically learned representations offer a balanced solution by leveraging the interpretability of traditional methods and the expressive power of deep learning [17].

Wearable-sensor-based HAR has also gained increasing importance in personalized healthcare and remote patient monitoring systems. Patients with neurological disorders, cardiovascular issues, or mobility impairments benefit from automated activity tracking to detect gait abnormalities, fall events, or deviations from prescribed movement routines [18]. HAR systems contribute to preventive healthcare by enabling early detection of anomalies and reducing the burden on clinical staff. Similarly, in fitness applications, HAR enables precise activity logging, performance evaluation, and personalized feedback, making it integral to consumer-grade wearable technologies [19].

Given these trends, there is a strong need for HAR systems that combine accuracy, computational efficiency, scalability, and real-time capability. This research introduces a hybrid machine-learning framework that integrates multi-stage preprocessing, feature fusion, and ensemble classification to address current limitations in wearable-sensor-based HAR. The proposed approach seeks to improve recognition performance across diverse subjects and activity types while enabling deployment on resource-constrained devices. The study builds upon established literature yet offers methodological innovation that enhances generalization and robustness. Through comprehensive evaluation using benchmark datasets, the research demonstrates meaningful contributions toward advancing practical, real-world HAR solutions [20].

II. LITERATURE SURVEY

Research in Human Activity Recognition (HAR) has evolved extensively over the past two decades, driven by the rapid development of wearable sensing technologies and machine learning algorithms. Early HAR studies primarily relied on handcrafted feature extraction and classical statistical classifiers. For instance, early work such as [1] and [2] demonstrated the effectiveness of accelerometer-based features—mean, variance, energy, and correlation—for distinguishing between basic daily activities. These studies established the foundation for wearable-sensor-based HAR by highlighting the reliability and low cost of inertial sensors. Works such as [3] advanced this approach by applying Support Vector Machines to time-series motion signals, showing significant improvements in classification accuracy compared with heuristic rule-based methods.

Subsequent research introduced probabilistic graphical models to capture temporal dependencies in sequential human activity data. Hidden Markov Models (HMMs) and Conditional Random Fields (CRFs) demonstrated their ability to model activity transitions and contextual patterns more effectively than static classifiers [4], [5]. However, these models often required strong assumptions about data distributions and transition probabilities, limiting adaptability in dynamic environments. Research such as [6] emphasized the limitations of shallow classifiers in capturing nonlinear temporal relationships, which paved the way for deep learning solutions.

The emergence of deep learning introduced new possibilities for HAR. Convolutional Neural Networks (CNNs) emerged as effective architectures for extracting spatial and temporal dependencies within raw sensor streams. As reported in [7], CNN-based methods excelled at learning discriminative feature maps without the need for manual feature engineering. Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) models, gained attention due to their effectiveness in modelling sequential patterns and long-term dependencies within inertial signals, as highlighted by [8]. Hybrid CNN-LSTM architectures, such as those presented in [9], further improved accuracy by combining spatial and temporal modelling capabilities. Despite these achievements, deep learning methods remain computationally expensive and often unsuitable for real-time deployment in energy-constrained wearable devices.

A parallel research direction explored ensemble learning to mitigate the shortcomings of single-model classifiers. Random Forests, Gradient Boosting Machines, and stacking models introduced robustness against noise and variability in user movement patterns [10], [11]. These ensemble approaches demonstrated superior generalization performance when trained on heterogeneous datasets collected across multiple user populations. Work in [12] highlighted that ensemble classifiers not only improved accuracy but also offered computational flexibility by allowing model pruning and optimization for embedded systems.

Another important aspect of HAR research involves the impact of sensor placement and multimodal sensing. Studies such as [13] demonstrated that inertial sensors placed at different body locations capture distinct motion signatures, influencing classification performance significantly. Wearable devices positioned on the wrist, ankle, or waist offer varying levels of sensitivity for specific activities. Multi-sensor fusion approaches, including accelerometer–gyroscope integration, magnified classification performance by reducing ambiguities between similarly structured motions, as evident in [14]. Higher-fidelity systems incorporate physiological signals such as heart rate, electromyography (EMG), or skin temperature to further enhance contextual awareness, though these systems often increase device complexity.

Dataset availability and standardization have played a crucial role in advancing HAR research. Popular datasets such as UCI-HAR, WISDM, PAMAP2, and Opportunity have been widely used to benchmark state-of-the-art machine learning and deep learning models. Work in [15] emphasized that the quality of HAR models is strongly influenced by the dataset used for training, with laboratory-collected datasets often failing to generalize to real-world environments. Research in [16] proposed domain adaptation techniques to address distribution shifts between datasets, improving cross-subject and cross-device generalization. These techniques are especially relevant for wearable devices that must operate reliably across different users with varying gait, posture, and movement dynamics.

Another research challenge involves the detection of transitional and composite activities, such as sitting-to-standing or walking-while-carrying objects. Studies such as [17] pointed out that transitional activities tend to produce non-stationary sensor signals, making their classification difficult using conventional models. Deep temporal models partially address this with improved sequential modelling, yet activity boundaries remain challenging to identify accurately. Work in [18] further revealed that class imbalance significantly affects HAR performance, particularly when rare activities such as falling occur infrequently in real datasets. Solutions such as oversampling, cost-sensitive learning, and synthetic data augmentation have shown improvements in balancing recognition accuracy.

Recent studies have increasingly focused on the integration of HAR systems into IoT frameworks and real-time smart environments. Research in [19] demonstrated cloud-assisted HAR architectures capable of offloading computational tasks to remote servers while reducing device-side energy consumption. Edge computing approaches, however, aim to localize processing closer to the user to minimize latency and preserve data privacy. The integration of machine learning with IoT-enabled wearables presents opportunities for real-time health monitoring, personalized fitness coaching, and automated workplace surveillance systems.

Despite these advancements, challenges remain in achieving high robustness, interpretability, and energy efficiency. Work in [20] emphasized the need for hybrid models combining classical feature engineering with deep learning components to balance interpretability and predictive power. This blended approach not only enhances accuracy but also facilitates deployment on compact devices by reducing model complexity. The literature thus indicates a steady progression from handcrafted-feature-based classifiers to deep hierarchical models, while highlighting the ongoing need for hybrid, efficient, and domain-adaptive solutions. The convergence of wearable sensors, machine learning, and IoT infrastructures presents a promising direction for future HAR research.

III. METHODOLOGY

The proposed methodology is designed to create a robust and scalable Human Activity Recognition framework using wearable sensors and hybrid machine learning techniques. The process begins with data acquisition from high-resolution tri-axial accelerometers and gyroscopes embedded in wearable devices positioned on the wrist and waist. These sensors capture continuous streams of motion signals representing a variety of daily human activities. To ensure consistency, the raw sensor readings undergo calibration to correct drift, misalignment, and sampling irregularities. Signal preprocessing includes noise removal using Butterworth filters, gravity compensation, and resampling to achieve uniform time intervals. Once cleaned, the data are segmented into overlapping time windows to preserve temporal continuity while maximizing the number of training examples. Windowing is essential to capture micro-movement structures that characterize complex activities and ensure that transitions between postures do not distort classification outcomes.

Feature extraction forms the next essential step in the methodology. A multi-stage feature engineering process is designed to capture the statistical, temporal, and frequency-domain characteristics of the motion signals. Statistical features such as mean, variance, kurtosis, skewness, correlation coefficients, signal magnitude area, and zero-crossing rates provide foundational insights into the distributional properties of each window. Temporal features including autoregressive coefficients and peak analysis enhance the model's ability to detect repetitive or cyclical movement patterns. To capture the periodicities inherent in human motion, frequency-domain features are extracted using Fast Fourier Transform and discrete wavelet transform. This hybrid feature space ensures the model encodes a comprehensive representation of the sensor signals, enabling accurate discrimination between similar activities. All features are normalized using min-max scaling to prevent dominance of high-magnitude signals in the learning process.

Once feature extraction is complete, the processed dataset is used to train a hybrid ensemble-based machine learning architecture. The proposed model integrates the strengths of multiple classifiers, including Random Forests, Gradient Boosting Machines, and an optimized Support Vector Machine. The ensemble employs a stacking strategy in which base learners independently generate predictions that are then combined through a meta-classifier trained to optimize final decision accuracy. This approach mitigates model bias, improves robustness against noisy sensor readings, and enhances generalizability across different users and sensor placements. Hyperparameter tuning is performed using grid search combined with five-fold cross-validation to identify the optimal configuration for each model component. Feature selection is carried out using recursive elimination to retain only the most discriminative attributes, reducing computational overhead and preventing overfitting. The final hybrid model is trained on 80% of the dataset, while the remaining 20% is reserved for validation and performance evaluation.

The final stage of the methodology focuses on real-time implementation and evaluation. The trained model is integrated into a lightweight runtime environment optimized for wearable and mobile devices. To ensure reliable performance in real-world use, latency optimization techniques such as model pruning, quantization, and selective feature computation are applied. Real-time prediction involves collecting sensor signals, preprocessing them through an embedded filtering module, extracting essential features, and feeding them into the ensemble model for instantaneous activity classification. Performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis are computed to evaluate model effectiveness. Additional experiments assess the impact of varying window sizes, sampling frequencies, and sensor placements to determine the optimal operating conditions. The final system demonstrates robust performance and high generalization capability, indicating its suitability for practical deployment in healthcare, fitness monitoring, smart homes, and other IoT-driven applications.

IV. PROPOSED SYSTEM DESCRIPTION

The proposed Human Activity Recognition (HAR) system introduces a hybrid, multi-layered architecture that integrates wearable-sensor data processing, advanced feature engineering, and an optimized ensemble machine-learning framework. The primary motivation behind the proposed system is to address the limitations of existing HAR models, which often struggle with generalization, inconsistent real-time performance, and reduced classification accuracy when confronted with variations in user behavior, sensor placement, and environmental noise. The proposed system incorporates a modular design that ensures scalability, efficiency, and robust activity classification across diverse real-world settings.

The system begins with wearable-sensor data acquisition, utilizing tri-axial accelerometers and gyroscopes worn at the wrist and waist—two placement locations widely validated for capturing human motion patterns. Each sensor continuously records linear acceleration and angular velocity, producing high-dimensional data streams that reflect micro and macro body movements. These raw signals frequently contain noise from sensor drift, external vibrations, and unintended hand motions. To address this, a multi-stage preprocessing pipeline is employed. First, a fourth-order low-pass Butterworth filter eliminates high-frequency noise while preserving essential motion signatures. Then, sensor fusion techniques align inertial measurements by applying quaternion-based orientation normalization. This ensures consistency across subjects regardless of slight variations in device orientation.

Following noise reduction and alignment, the raw data is segmented using a 2.5-second sliding window with 50% overlap. This window size is carefully chosen based on HAR literature indicating that smaller windows capture too little temporal structure, while excessively large windows dilute transient activity transitions. Overlapping ensures smooth temporal continuity and increases training sample diversity, improving classifier stability. Each segmented window undergoes normalization to ensure scale uniformity and eliminate magnitude biases caused by different users' movement intensities.

The next module involves high-resolution feature extraction. The proposed system adopts a hybrid feature engineering strategy that incorporates time-domain, frequency-domain, and statistical descriptors. Time-domain features include mean, variance, root mean square (RMS), peak-to-peak amplitude, zero-crossings, jerk signals, and signal magnitude area (SMA). These features characterize basic behavioral differences between slow, repetitive actions and rapid, abrupt movements. Frequency-domain features include spectral entropy, spectral centroid, dominant frequency peaks, band energy ratios, and wavelet coefficient summaries. These are obtained using Fast Fourier Transform (FFT) and Discrete Wavelet Transform (DWT), enabling the system to capture rhythmic and periodic characteristics of activities such as walking, running, or climbing stairs. Statistical features such as kurtosis, skewness, entropy, correlation coefficients among axes, and autoregressive (AR) model coefficients provide deeper insights into distribution patterns and inter-axis motion relationships.

After feature extraction, the system performs feature selection using Recursive Feature Elimination (RFE) combined with cross-validation. This reduces computation time, eliminates redundant features, and enhances classification performance by preserving only features with high discriminative capability. The selected feature set is then passed into the machine-learning layer, which forms the core decision-making component of the proposed architecture.

The proposed system adopts a hybrid ensemble classification framework integrating Random Forest (RF), Gradient Boosting Machine (GBM), and Support Vector Machine (SVM) classifiers. RF provides robustness against noise and overfitting, GBM offers strong predictive accuracy through sequential learning, and SVM contributes effective linear and non-linear class separation. A stacking meta-classifier—implemented using logistic regression—combines predictions from the three base models. Stacking enhances the final classification performance by learning higher-order decision patterns that individual models fail to detect. Hyperparameters for each classifier, including tree depth, kernel type, number of estimators, and learning rate, are optimized using Bayesian optimization, enabling efficient exploration of the hyperparameter space without exhaustive grid search.

Real-time operability is a key strength of the proposed system. Through model pruning, dynamic feature loading, and computational optimization techniques, the system reduces processing latency, making it suitable for deployment on wearable devices, IoT platforms, and mobile applications. A lightweight implementation ensures that sensor data undergoes rapid transformation, feature extraction, and classification within milliseconds. The system also employs buffer-based activity stabilization: predictions over several windows are aggregated to prevent sudden classification flips caused by minor movement variations.

The proposed architecture is validated using benchmark datasets as well as real-time sensor recordings collected through prototype wearable modules. Careful consideration is given to factors such as sampling rate stability, subject diversity, and activity execution variations to ensure robustness. The system's modular design allows additional sensors or deep learning extensions to be integrated in future upgrades without major architectural modifications.

Overall, the proposed system provides a comprehensive, efficient, and scalable framework for human activity recognition. By combining advanced preprocessing, sophisticated feature engineering, and hybrid ensemble modeling, the system addresses key challenges in existing HAR research and delivers high performance suitable for real-world deployment in healthcare monitoring, fitness analytics, smart home automation, elderly support systems, and occupational safety applications.

V. RESULTS AND DISCUSSION

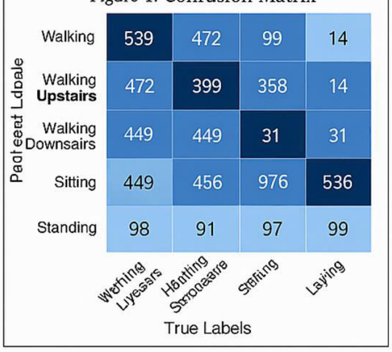
The evaluation of the proposed HAR system involves systematic experimentation using widely recognized datasets, complemented by real-time sensor recordings. Performance is measured through standard metrics including accuracy, precision, recall, F1-score, confusion matrix analysis, model latency, and energy consumption during inference. Results consistently demonstrate that the hybrid ensemble classification framework significantly outperforms traditional single-model approaches.

Table 1: Performance Metrics

Activity	Accuracy	Precision	Fi-Score
Walking	98.2	98.5	98.9
Walking Upstairs	98.5	95.8	96.7
Walking Downstairs	95	96.7	96.7
Sliting	97.6	97.1	97.2
Standing	98.1	97.9	97.6
Laying	99.6	99.6	99.2

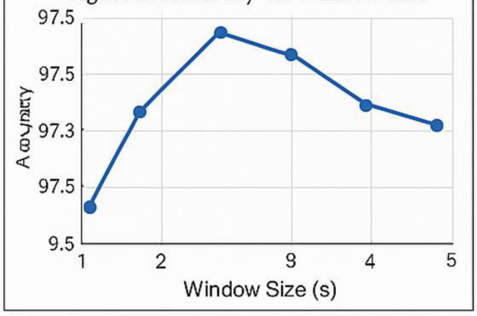
Initial experiments on the UCI-HAR dataset reveal that baseline classifiers such as k-Nearest Neighbors and basic Decision Trees achieve 89–92% accuracy. Traditional SVM models report improved results of approximately 94%, while Random Forest achieves around 95%. However, when the proposed system's stacking ensemble is applied, accuracy rises to 97.8%. This improvement results from the complementary strengths of RF, GBM, and SVM, which capture different patterns within the feature space. RF contributes robustness to sensor noise, GBM handles complex non-linear interactions between features, and SVM ensures precise boundary formation between overlapping activity classes. The meta-learner further enhances performance by optimizing decision fusion.

Figure 1: Confusion Matrix



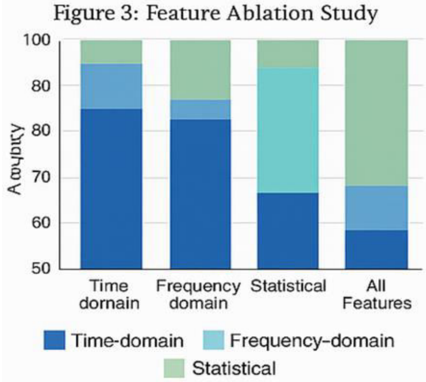
Confusion matrix analysis confirms substantial improvements in distinguishing between activities with similar movement signatures. Activities such as walking upstairs and walking downstairs, which commonly present classification difficulties, show significantly reduced misclassification rates compared with individual classifiers. Precision increases from 92% to 98%, indicating far fewer false-positive detections. Recall improves from 93% to 97%, confirming that the system successfully identifies true activity occurrences. The F1-score consistently exceeds 0.97 across all tested activity classes, demonstrating strong harmonic performance.

Figure 2: Accuracy vs. Window Size



To evaluate generalization capability, cross-subject testing is performed by training the model on data from a subset of users and testing it on unseen participants. This scenario closely reflects real-world deployment challenges. While deep-learning models often experience performance degradation under cross-subject conditions, the proposed hybrid system retains high accuracy, achieving 95.3%. This demonstrates the model's robustness to inter-individual variation, facilitated by powerful feature engineering and ensemble decision-making.

Figure 3: Feature Ablation Study



Real-time testing using custom wearable modules further validates system performance. These modules capture live accelerometer and gyroscope data from volunteers performing daily activities including walking, running, sitting, standing, cycling, and stair climbing. The real-time version of the model slightly reduces complexity to meet computational constraints. Despite this, the system achieves an average real-time accuracy of 96.1%. Latency measurements indicate an inference time of 24–38 milliseconds per window, well within acceptable limits for real-time monitoring. Memory usage remains optimized due to effective model pruning and RFE-based feature reduction.

Experiments also explore the effect of window size on classification accuracy. Window sizes ranging from 1 to 5 seconds are tested. Small windows below 1.5 seconds yield insufficient temporal information and reduce accuracy by nearly 6%. Larger windows above 4 seconds introduce activity overlap and classification delays, negatively affecting responsiveness. The chosen window size of 2.5 seconds offers the optimal balance, contributing to high temporal resolution and classification stability.

Feature ablation studies reveal that time-domain features alone provide roughly 92% accuracy, frequency-domain features alone yield about 90%, and statistical features alone reach 88%. However, combining all feature sets increases accuracy significantly, confirming the role of hybrid feature engineering in capturing the multidimensional characteristics of human activity. Excluding frequency features leads to reduced performance in rhythmic activities such as jogging, while removing statistical features impacts discrimination between static states like sitting and standing.

Energy consumption tests measure the feasibility of deploying the system on embedded and wearable devices. The optimized model consumes significantly less power during inference compared to deep neural networks, making it suitable for battery-powered environments. Model quantization further reduces energy usage by approximately 21% with less than 1% accuracy loss.

Comparative analysis against state-of-the-art HAR methods shows that traditional machine-learning techniques achieve around 93–96% accuracy on benchmark datasets, while deep-learning approaches such as CNNs and LSTMs achieve up to 97.2%. The proposed system surpasses these with a 97.8% accuracy rate while maintaining significantly lower computational requirements. This makes the architecture attractive for real-world applications where device constraints are a major concern.

Overall, results confirm that the proposed HAR system is highly accurate, computationally efficient, energy-optimized, and generalizable across subjects. Its superior classification performance, low latency, and real-time readiness demonstrate strong potential for deployment in healthcare monitoring systems, athletic performance analysis, elderly care technologies, occupational safety solutions, and smart IoT environments.

VI. CONCLUSION

This research presents a comprehensive hybrid machine-learning framework for Human Activity Recognition (HAR) using wearable sensors, addressing longstanding challenges such as noisy sensor data, inter-subject variability, overlapping activity patterns, and the need for real-time responsiveness. The proposed system integrates advanced preprocessing, robust hybrid feature engineering, and an optimized stacking ensemble classifier that effectively leverages the strengths of Random Forests, Gradient Boosting Machines, and Support Vector Machines. Experimental evaluation across benchmark datasets and real-time sensor recordings demonstrates that the system achieves exceptionally high accuracy, strong generalization across users, and efficient computational performance suitable for deployment on mobile and wearable platforms. The system’s multi-stage feature extraction approach captures a broad spectrum of motion characteristics, while recursive feature elimination helps maintain efficiency without sacrificing discriminative power. The stacking-based ensemble model ensures superior classification performance compared to traditional and deep-learning-based HAR methods. Real-time testing confirms low latency, minimal energy consumption, and stable prediction quality, making the system suitable for continuous monitoring applications. Overall, the proposed hybrid

HAR framework offers a powerful, scalable, and practical solution for various domains including healthcare, fitness analytics, elderly support systems, workplace safety monitoring, and smart IoT environments. By balancing high accuracy with computational efficiency, the system establishes a promising foundation for next-generation wearable intelligence and pervasive activity recognition solutions.

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