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iJIM International Journal of Interactive Mobile Technologies

iJIM | eISSN: 1865-7923 | Vol. 18 No. 24 (2024) | OPEN ACCESS

https://doi.org/10.3991/ijim.v18i24.48785

PAPER

Multi-Approach Learning with Embedded Sensors Application in Gesture Recognition

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ABSTRACT

The increased attention to human daily activities in academic circles has proven highly valuable, serving various specific needs and producing desired outcomes across different fields. Evaluating human activity data opens up numerous possibilities for researchers, facilitating personalized support options such as timely stress interventions, real-time feedback mechanisms, and applications for assisting individuals with disabilities or monitoring mental health. This paper presents a comprehensive approach integrating multiple sensors to recognize human body movements, applicable to real-life scenarios such as classrooms, driving, and kitchen-related activities. Our focus is to enhance the precision of motion classification and improve motion classification rates by merging acceleration and rotation signals and analyzing an enhanced array of features using various high-caliber machine-learning models. This methodology achieves exceptional performance and flexibility, with accuracy rates ranging between 96% and 98%, substantiating activity recognition within diverse contexts. It aims to reduce system recognition errors, improve the classification process, and promote the advanced utilization of artificial intelligence algorithms in signal processing and in controlling and enhancing bionic hands.

KEYWORDS

wearable sensors, vehicle control tasks, kitchen activities, educational activities, machine learning, deep and ensemble learning

1 INTRODUCTION

The advancement of dynamic technologies and the proliferation of vast amounts of sensor-type data have positioned human-computer interaction (HCI) as a focal point of extensive global research. Central to these research endeavors is human activity recognition (HAR), which involves discerning and identifying human actions through the analysis of physical observations and environmental parameters from diverse sensor sources [1]. Within this context, the monitoring and analysis of activities of daily living (ADLs) have gained prominence due to technological advancements

Lamsellak, O., Hdid, J., Benlghazi, A., Chetouani, A., Benali, A. (2024). Multi-Approach Learning with Embedded Sensors Application in Gesture Recognition. *International Journal of Interactive Mobile Technologies (iJIM)*, 18(24), pp. 51–81. https://doi.org/10.3991/ijim.v18i24.48785

Article submitted 2024-02-27. Revision uploaded 2024-09-13. Final acceptance 2024-09-23.

and the reduction in equipment costs. The HAR community has increasingly favored sensor-based solutions over vision-based methods due to cost efficiency and privacy concerns [2]. This trend highlights the practical utilization of wearable sensors, which are cost-effective and highly effective in monitoring human behavior during routine activities [3]. Wearable sensor-based activity recognition has occupied a central position in an extensive body of research, augmenting the depth of scientific inquiry and affording added avenues for data integration and aggregation. These sensors encompass a variety of internal sensor types, including accelerometers, gyroscopes, magnetometers, and GPS, among others. These sensors are conducive to simultaneous utilization, facilitating the delivery of contextually sensitive and adaptable services tailored to individuals' immediate contexts and circumstances [4].

A review of various research projects indicates that the data fusion approach is currently gaining traction for many reasons [5], [6]. To reach an elevated level of understanding human activities and obtain high-accuracy results, researchers are now fusing a variety of technologies in a hybrid method, concurring that the combination of sensors is essential in order to create innovative forms and patterns of information that complement the convoluted nature of people's movements and facilitate their identification and classification [7], [8]. Four key stages have potentially been distinguished for the development of HAR [9]. They, according to [10] are: 1. Sensor Selection and Implementation: In the initial phase, meticulous consideration is given to the selection and strategic deployment of sensors. This stage holds pivotal significance, as it determines the breadth and quality of data acquisition. 2. Sensor Data Capture: Subsequent to the selection process, data capture ensues, wherein the designated sensors collect information relevant to human activities. 3. Data Processing and Feature Extraction: The journey then proceeds to a critical juncture where the data undergoes comprehensive processing and relevant features are extracted. This process is pivotal in distilling meaningful insights from the raw data and facilitating substantive analysis. 4. Selection and Adoption of a Machine Learning Algorithm for Activity Interpretation and Deduction: The culmination of this process involves the judicious selection and deployment of machine learning algorithms. These algorithms are instrumental in interpreting and deducing human activities based on the processed data.

The objective of this study is to develop an advanced activity recognition system capable of offering evolutionary functionalities to its users. By analyzing data generated by sensors during various everyday activities in different contexts and circumstances, the system leverages diverse machine learning algorithms to gain a deep understanding of human activities. This facilitates the development of sophisticated, adaptable solutions to enhance interactive human-computer systems and e-health applications. This project is centered on the development of an activity recognition system designed to achieve a notably high degree of accuracy for multiple contexts of daily activities. The primary emphasis of this study is the detection and monitoring of human behavior, with specific applications aimed at optimizing vehicle control, analyzing kitchen-related behaviors for performance improvements, and enhancing educational activity recognition for educators and students in real-world experiences. The objectives include developing supervised learning systems that explore driver gestures and behaviors to optimize vehicle responses and enhance safety and performance; creating a deep learning model for kitchen environments where actions and practices are examined for productivity and prevention improvements; and implementing an ensemble learning approach that recognizes and interprets gestures in educational settings to tailor educational content and teaching approaches to individual learning styles and provide real-time feedback and personalized learning experiences.

By focusing on these objectives, the research seeks to leverage gesture recognition innovations to improve vehicle control, kitchen efficiency, and the multifaceted educational process, thereby contributing to the fields of intelligent environments and automation technology. The model development process encompasses a comprehensive consideration of multiple critical factors, including the diversification of activities, user privacy (non-visual contexts), and the effective deployment and accessibility of sensors in terms of their combination and positioning. These factors are recognized as the cornerstone elements essential for the realization of a successful ADL recognition system. The fundamental techniques and objectives underpinning our activity recognition system are visually depicted in Figure 1. This study paper contributes significantly to the field in several key aspects:

- Propose an activity recognition approach utilizing cost-effective, non-intrusive wrist-worn sensors to identify ADLs across diverse age groups.
- Establish a feature combination methodology that emphasizes the collective performance of a variety of features as opposed to individual features. Analysis of Variance (ANOVA) is employed to identify the optimal feature combinations for each dataset while continuously assessing model accuracy.
- Validate two distinct approaches: A1: Demonstrate that the proposed method compares favorably to prior research, attaining over 95% classification accuracy. A2: Highlight the potential to boost activity classification accuracy by integrating accelerometer and gyroscope data with a multi-approach learning strategy, which could be beneficial for timely stress interventions and the development of assistive technologies.

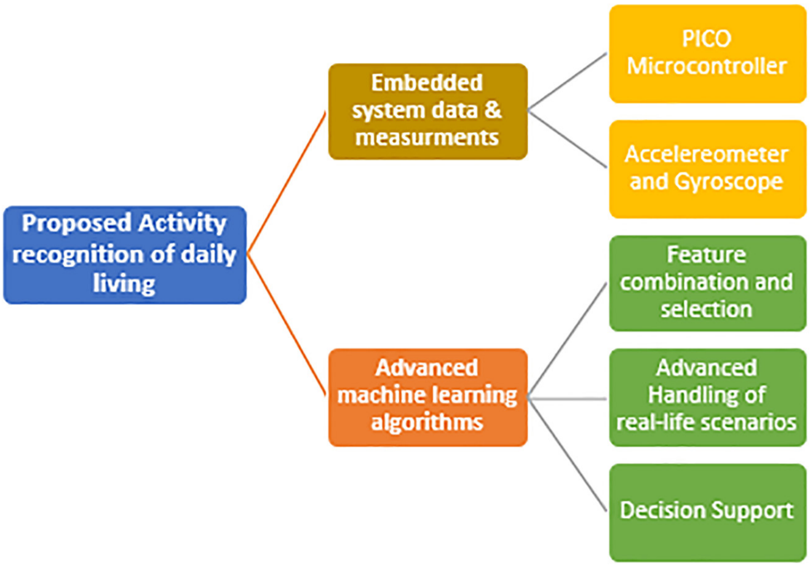

Fig. 1. Core elements of proposed activity recognition: Techniques and methodology

2 RELATED WORK

Human activity recognition constitutes a multifaceted challenge within the domains of artificial intelligence and sensor-based technologies. The intricacy of this challenge stems from the inherent diversity in human behaviors, which manifests in various forms, durations, and contextual settings (refer to Table 1). One of the primary challenges in this endeavor revolves around the inherent variability and contextual nuances associated with human activities. Activities of daily living, encompassing a wide spectrum of behaviors and postures, pose a considerable challenge in accurately identifying and categorizing them, given the inherent variations in their execution, environmental factors, and individual preferences.

In the pursuit of addressing these challenges, noteworthy research contributions have emerged in the field. Notably, Mi-So, Lee, and Kyung-Won Kim in [11] introduced a hand gesture recognition system employing inertial sensors. Their work elucidated a novel approach to hand gesture recognition, utilizing a wrist-mounted three-axis accelerometer, gyroscope, and magnetometer. This system was precisely designed to discriminate between six distinct hand gestures, including gestures denoting upward, downward, leftward, rightward, single-click, and double-click actions. Furthermore, Chun Zhu and Weihua Sheng in [12] directed their research efforts towards the realm of natural human-robot interaction (HRI) within the context of a smart assisted living (SAIL) system tailored for elderly and disabled individuals. Their study addressed two pivotal HRI challenges: hand gesture recognition and daily activity recognition. To surmount these challenges, the authors proposed an innovative multi-sensor fusion scheme that meticulously analyzed motion data collected from both the foot and waist regions of human subjects.

In addition to these endeavors, Hongnian Yu and Anthony Atkins in [13] contributed to the field by devising an activity recognition system capable of discerning nine common daily activities performed by elderly individuals. Their approach was distinguished by its comprehensive consideration of both technical and practical aspects. Notably, the recognition system relied upon a suite of compact, cost-effective, and unobtrusive sensors, including an accelerometer, a temperature sensor, and an altimeter, seamlessly integrated into a wristwatch form factor. These sensors collectively served as inputs for the activity recognition process.

The second paramount challenge in the realm of recognizing human activities resides in the quality and diversity of sensor data. An inherent limitation arises when reliance is placed on a solitary type of sensor, leading to a restricted comprehension of human activities. This limitation is particularly pronounced in the case of complex activities that encompass multi-modal cues. It is evident that restricting the selection of sensors curtails the system's ability to encapsulate the complete contextual intricacies of an activity. Notably, diverse sensors exhibit distinctive strengths and weaknesses. Thus, a salient strategy is to harness a diverse array of sensors to mitigate the inherent limitations of individual sensor types, thereby augmenting the overall accuracy of activity recognition. Real-world activities are inherently intricate and often entail subtle cues that elude detection by a single sensor. For instance, the recognition of culinary activities necessitates the amalgamation of visual, auditory, and olfactory cues. It is the amalgamation of multiple sensors that offers a comprehensive perspective on the activity. For an exhaustive exploration of this domain, Lara and Labrador in [14] have conducted extensive work in the realm of activity recognition using wearable sensors. Their contribution encompasses an in-depth scrutiny of the design considerations within HAR systems. These considerations span sensor and attribute selection, data collection protocols, recognition performance metrics, data processing methodologies, and energy consumption optimizations. The research categorically classifies extant studies into three primary categories: supervised online systems, supervised offline systems, and semi-supervised offline systems.

Additionally, Cornacchia et al., [15] have offered a comprehensive survey that stratifies previous research into two principal domains: global body motion activities, which involve holistic body movements such as walking and running, and local interaction activities, which encompass finer extremity movements linked to object manipulation. Furthermore, this survey provides a nuanced classification based on sensor types and their anatomical placement on the human body, including waist- and chest-mounted sensors. The authors delve into various techniques leveraging sensors such as gyroscopes, accelerometers, magnetometers, wearable cameras, and hybrid sensor systems.

In a parallel vein, Mijovic and Popovic [16] have modeled a two-link system mechanism. Their endeavor entails the estimation of motion trajectories, with a particular focus on the upper arm and forearm during vertical arm movements. This estimation relies on the measured angular accelerations utilizing dual-axis accelerometers. Notably, their work incorporates the utilization of a dataset comprising reaching synergies from able-bodied individuals, serving as the foundational dataset for training a radial basis function artificial neural network with upper arm and forearm tangential angular accelerations.

The concluding point we intend to highlight within this related work is the integration of a diverse array of machine learning algorithms, along with the utilization of deep learning models. This approach, often referred to as ensemble learning or hybrid modeling, has become a prevalent strategy in the development of resilient and versatile AI systems. The primary objective behind this technique is to capitalize on the strengths of various algorithms, thereby enhancing overall performance, mitigating issues of overfitting, and augmenting the system's capacity for generalization.

The selection of machine learning and deep learning models for integration is contingent on several factors, including the specific problem at hand, the availability of data, and computational resources, and the desired balance between accuracy and interpretability. Wang et al., [17] have underscored the significance of diverse deep learning strategies in the context of HAR using sensor data. Their research places particular emphasis on sensor modality, various deep model types, and application domains. The crux of their investigation revolves around the implementation and fusion of an assortment of deep model architectures, encompassing discriminative, generative, and hybrid models. Concerning application domains, their study delves into a spectrum of areas such as activities of daily living, sleep monitoring, sports analytics, and health-related applications.

In a study conducted by Jindong Wang and Yiqiang Chen in [18], the focal point is the latest advancements in deep learning techniques for sensor-based activity recognition. In contrast to traditional pattern recognition methods, deep learning significantly reduces the necessity for manually engineered feature extraction and achieves superior performance by automatically extracting high-level representations from sensor data. Moreover, Tai-hoon Kim and Debnath Bhattacharyya in [19] have set multiple objectives for their research. Firstly, they provide an exhaustive examination of neural networks, with a special focus on the neural network family frequently employed for pattern classification tasks. Secondly, their article aims to showcase approaches for harnessing the fundamental attributes of neural networks and their potential for integration with other models. This includes their ability to comprehend complex nonlinear input-output relationships, their utilization of sequential training techniques, and their adaptability to diverse sensor data sources.

Table 1. Summary of the works presented for gesture recognition

Reference	Sensor Type	#Features	#Subject	#Activity	Recognition Methods	Varied Context Environment	Multiple Model Recognition
Chun Zhu & Weihua Sheng, 2011	A	3	–	8	Neural network, Hidden Markov model	No	Yes
Atkins & Hong, 2013	A, T, Alt	13	5	9	SVM, Neural network	No	Yes
Nattawut & Choksuriwong, 2015	C, P, PIS, Ac	Statistical	–	6	Fuzzy logic	Yes	No
Mi-So Lee & Kyung-Won Kim, 2016	A, G, M	–	8	6	–	No	–
Joyeeta & Amarjit, 2016	C	44	–	40	NN, SVM, kNN	No	Yes
Jie Yang & Roman Kusche, 2017	A, EMG, MMG	2	6	4	SVM	No	No
Shuman & Duric, 2017	A, EMG	11	5	47	HMM, RF	Yes	Yes
Zuocai Wang & Bin Chen 2018	A, G, M	16	–	10	BP-NN	No	No
Oguntala et al., 2019	Rf	–	4	12	Multi-variant Gaussian	No	No
Webber & Fernandez, 2021	A, G	7	66, 19, 10, 30	4	Bagging and Stacking	No	yes
Liron & Adi, 2023	EMG	2	8	8	Neural network	No	No
Yongfeng & Shuyan Chen, 2023	A, G	10	1	4	LSTM network	No	No

Notes: (A = accelerometer, Alt = altimeter, Ac = Acoustic, M = magnetometer, G = gyroscope, C = camera, Rf = RFID tag, P = pressure, T = temperature sensor, PIS = passive infrared sensors, EMG = myoelectric, MMG = echanomyography).

3 SYSTEM AND MATERIALS

To attain a more profound comprehension of ADL tasks, the implementation of the data fusion process, encompassing the amalgamation of diverse data sources, facilitates a more comprehensive and lucid conceptualization of the inherent characteristics and properties of each physical movement. This scholarly article elucidates the systematic procedure commencing with the initial collection of physical data measurements, advancing to the ultimate phase of artificial intelligence algorithm classification and prediction, all facilitated through an electronic data acquisition system.

3.1 Sensors

The review of numerous study results reveals that a higher level of accuracy and reliability in HAR measurement and in-depth knowledge of human organ motion in six degrees of freedom (DOF) are achieved by incorporating both the features of a 3-axis accelerometer and a gyroscope [20]. One of the most frequently used sensors in HAR is the accelerometer. This electromechanical tool can contemporaneously measure static and dynamic acceleration forces applied to the sensor, offering precise information to identify patterns of movement. Specifically, a 3-axis accelerometer provides three-dimensional data along the X, Y, and Z axes, ensuring extensive examination of movements in all directions. This capability is key for capturing the complete range of human motion and recognizing various sorts of activities.

Another vital sensor in HAR research is the gyroscope. It detects angular velocity, or the rate of rotation around the three axes (pitch, roll, and yaw) (see Figure 2), providing essential information about the orientation and rotational movements of body extremities. When combined with accelerometer data, the gyroscope's measurements enable a comprehensive understanding of both linear and rotational movements, increasing the overall precision and reliability of HAR systems. This combination of sensors allows for accurate tracking of complex activities and movements, making it an integral aspect of advanced HAR research and applications.

We have chosen to employ our accelerometer and gyroscope sensors in two types of placements according to the environmental context and activity specificity, as illustrated in Figure 3. For instance, for activities that depend on finger movements, such as handwriting or mouse clicking, we utilized dorsal finger sensing. Conversely, for activities that rely on hand orientation and rotation, such as car gearbox transmission, student engagement in classrooms, and certain kitchen activities, we employed surface hand sensing.

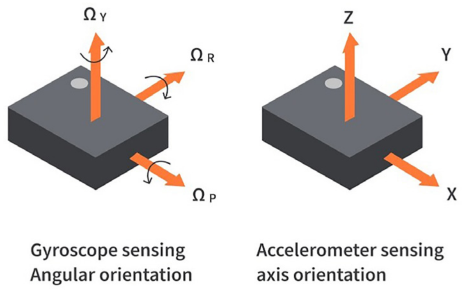

Fig. 2. 3-axis gyroscope and 3-axis accelerometer

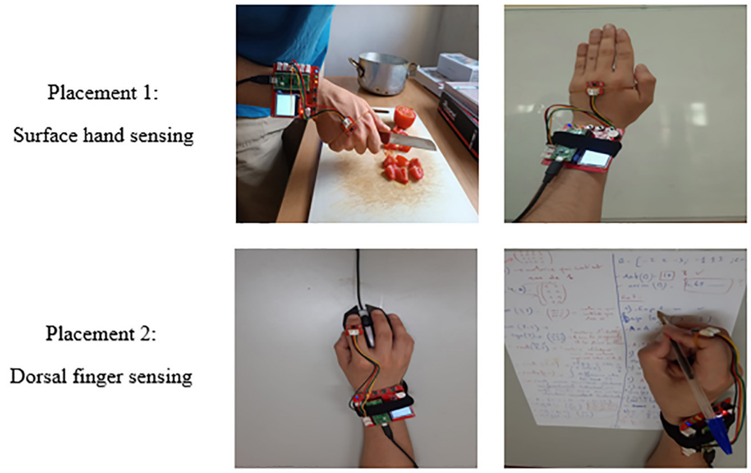

Fig. 3. Strategic sensor placement

3.2 Embedded system: PICO microcontroller

Previously, computing systems for monitoring daily activities were created using a microprocessor combined with several peripheral chips. This required supplementary components such as memory, input-output interfaces, timers, and interrupt circuitry, leading to a complicated technological infrastructure and design that intensified power consumption. Consequently, this architecture restricted the effectiveness and accuracy of HAR, and the analysis of activities of daily living (ADLs).

On the other hand, our observations utilize the high-performance Raspberry Pi Pico microcontroller, purpose-built for physical computing. It is designed to execute single processes, making it ideal for rapid real-time control and monitoring applications. The Pico features a robust dual-core ARM Cortex-M0 + RP2040 chip with a clock speed up to 133 MHz, 2 MB of flash memory, and 264 KB of SRAM. It offers a substantial number of GPIO pins and various peripheral interface modules (see Figure 4), including SPI, I2C, UART, PWM, and precision timing modules. The Raspberry Pi Pico stands out for its cost-effectiveness, expanded memory capacity, and precise timing modules, providing significant advantages over other microcontroller options.

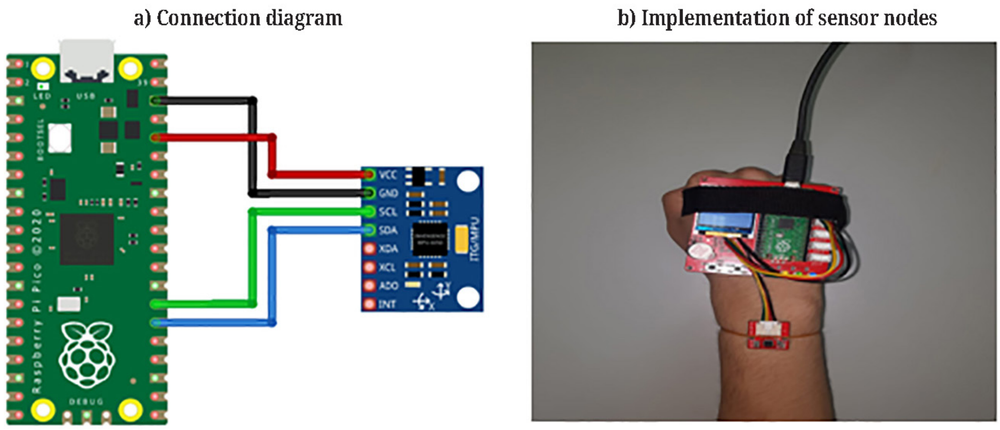

Fig. 4. The Raspberry Pi Pico and the Inertial Measurement Unit (IMU) connection diagram

3.3 Communication protocol: Interfacing sensors with Raspberry Pi Pico

The Inter-Integrated Circuit (I2C) protocol serves as a straightforward and commonly employed communication mechanism within the sector of microcontroller-based sensor connectivity. It establishes a bidirectional bus that lends itself to straightforward implementation across various integrated circuit (IC) platforms. This bus architecture streamlines the overall connection process, minimizing both the quantity of connections required and the temporal demands associated with communication. In the I2C communication protocol, a master-slave framework is adopted. Within this hierarchy, the master entity assumes the role of bus controller, taking charge of addressing individual slave devices and facilitating the exchange of data with or from the registers located within these slave devices.

3.4 Transmission program

This section explains how to retrieve data from the accelerometer and gyroscope sensors on the Raspberry Pi Pico. The Pico has internal accelerometer and gyroscope sensors connected to pins known as Analog-to-Digital Converters (ADCs). The Pico addresses these sensors to acquire data by examining READ/WRITE instructions and receiving an acknowledgment bit from the sensors, indicating their readiness for data transmission. After acknowledgment, the sensor takes control of the Serial Data (SDA) line to send data to the microcontroller. The data is then transferred to a nearby computer via a COM port and stored in a CSV file. Initially, the Pico collects the sensor data and sends it through the serial port to the PC. A Micro Python script on the PC reads and collates this serial data, specifying technical parameters like data acquisition frequency and duration, which will be detailed later. These gathered values will be used for AI-based analysis and processing.

4 RECOGNITION SYSTEM DESCRIPTION

Activities Recognition systems are an interdisciplinary field, continually evolving and submitting new challenges, including challenges related to scalability and adaptability. As they continue to be integrated into various aspects of modern life, they hold the potential to revolutionize our interaction with data, offering heightened clarity and more effective decision-making support. The architectural design of a recognition system capable of handling three distinct contexts of activities represents an innovative and complex challenge in the field of artificial intelligence and machine learning. Our architecture incorporates the development of an advanced model that can effectively recognize and differentiate activities within different environments (see Figure 5). These three context-specific domains, often characterized by unique features and challenges, encompass vehicle control tasks, kitchen-related behaviors, and educational activities.

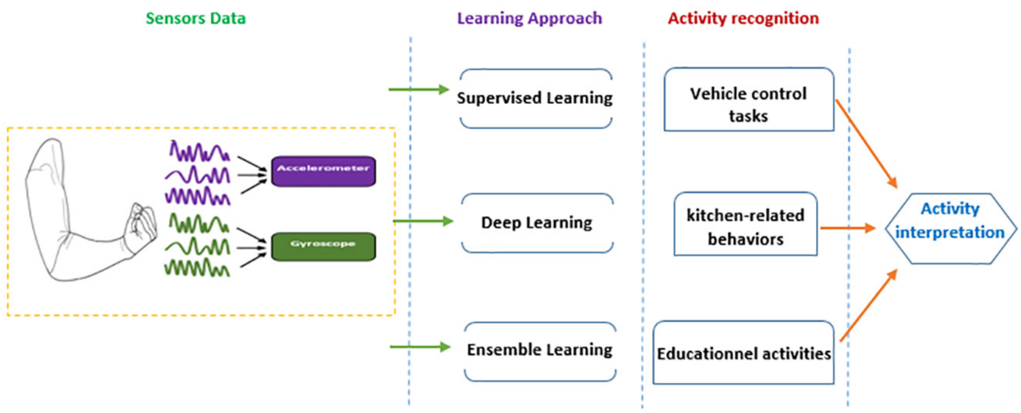

Fig. 5. Proposed architecture

4.1 Optimizing vehicle control: The role of recognition activities

a) **Data acquisition: Subjects and activities:** To assess the effectiveness of the acquired signals in advancing research within the fields of human-machine interaction and transportation research. An experiment involving data collection was conducted with 10 participants in the age range of 20 and 40 years of diverse genders (five men and five women). Every participant was assigned the task of executing a predetermined sequence comprising 10 distinct gesture classes that are widely recognized and prevalent within the field of automobiles, as shown in Table 2. Each set of movements was meticulously recorded in a continuous manner. To maintain the independence of each action, a designated two-second interval was introduced between successive actions. The dual sensors employed consist of a 6-axis motion tracking device that integrates a tri-axial gyroscope and a tri-axial accelerometer. Subsequently, the files containing the recorded signals were subject to analysis and direct processing on the workstation, utilizing the MATLAB software library.

Table 2. List of vehicle control gestures

Gesture ID	Gestures Name	Hand Position
1	1st Gear	Standard
2	2st Gear	Standard
3	3st Gear	Standard
4	4st Gear	Standard
5	5st Gear	Standard
6	Reverse Gear	Standard
7	Neutral Gear	Standard
8	Steering wheel	Left & right
9	Hand Break	Enable & disable
10	No control	Free hand & non-dominant hand

b) **Signal pre-processing:** A comprehensive scrutiny of the amassed acceleration signals transpired, wherein the acceleration data spanning the commencement and termination intervals of the respective gestures was systematically categorized in accordance with the nomenclature assigned to each gesture. At a sampling frequency of 10 Hz, discrete samples were acquired at a rate of one per 100 milliseconds. Each participant contributed data encompassing a temporal extent ranging from 6000 to 6500 seconds, leading to an aggregate of 3,900,000 three-dimensional acceleration and data samples.

The signal computed for each specific activity necessitates a preliminary windowing procedure as a crucial step in readiness for subsequent processes related to feature extraction [21]. Following this, a classification decision will be synthesized for each of these windows. As a direct consequence of this method, the signal was partitioned into two-second windows, each containing 20 samples, with an overlap of 10 samples.

c) **Feature extraction and selection:** In the pursuit of pattern recognition, a pivotal endeavor within this phase is the imperative differentiation of the key signal attributes embedded within the segmented data. This phase, situated within our project design, assumes a critical role in the endeavor to reduce the dimensionality of the data by purging superfluous information and discerning essential characteristics from the input data, thus concomitantly elevating the precision of the trained models. The features harnessed in this investigation emanate from the temporal domain. To elucidate our philosophy of feature extraction and provide a comprehensive understanding of our signal extraction prototype, we have focused on extracting a diverse set of measures. These measures are categorized into central tendency, dispersion, energy, and higher-order statistics, each offering unique insights into the characteristics of the signal, thus facilitating a holistic analysis. These parameters have been widely adopted in the realm of machine learning-based time series analysis [22]. Following an exhaustive review and comparative analysis of numerous pertinent studies [23]–[24], the integration of accelerometer and gyroscope sensors was deployed to compile a feature vector comprising 10 statistical metrics, as elucidated in Table 3.

After applying the necessary feature extraction processes to the accelerometer and gyroscope sensor signals (Ax, Ay, Az for the accelerometer and Gx, Gy, Gz for the gyroscope), we obtained a feature matrix for each sensor dimension. Each matrix consists of vectors with 128 readings per window and 9014 observations. Finally, we constructed the final matrix of the extracted features, incorporating 60 variables from all sensor axes. The selection of these features can be facilitated by employing feature selection methods that predicate their choices on discriminative criteria that are largely disassociated from classification. Several methods encompass elementary correlation coefficients, while others encompass mutual information or statistical tests. In this particular investigation, we have opted to utilize ANOVA techniques as a method for selecting features [25], an approach aimed at discerning the most salient features conducive to class differentiation and the elimination of superfluous attributes. From the initial set of 60 features, 49 were selected based on their high importance scores (> 70%) to determine the characterization of each activity window, as shown in Table 4.

Table 3. Summary of extracted features with their mathematical representations

Statistical Features	Signification	Mathematical Equation
Arithmetic mean-Mean	The average measurement on every axis over a set time interval.	$(\mu) = (\Sigma xi)/n$ (μ) is the average of the data points. Σxi represents the sum of all data points; n is the number of data points.
Root mean square-RMS	To characterize the signal's pattern and identify its most recurrent form.	$RMS = \sqrt{[(1/n) * \Sigma(xi^2)]}$ n is the number of data points. $\Sigma(xi^2)$ represents the sum of the squares of individual data points (xi).
Standard deviation-STD	This variable represents the disparity between each signal window and its mean value.	$(\sigma) = \sqrt{[(1/n)] * \Sigma(xi - \mu)^2}$ (σ) is the measure of the spread or variability of the data. n is the number of data points. $\Sigma(xi - \mu)^2$ represents the sum of the squared differences between each data point (xi) and the mean (μ).
Principal component analysis-PCA	To reduce the dimensionality of the information set and observe correlations.	$\mu = (1/n) * \Sigma xi$ $\Sigma = (1/n) * \Sigma(xi - \mu)(xi - \mu)T$ $\Sigma * v = \lambda * v$ Σ is the covariance matrix; v is the eigenvector; λ is the eigenvalue.
Max & min-value	Highest and lowest values within each window.	$\max = \max(xi)$ $\min = \min(xi)$
Minmax value-Minmax	This discrepancy between the max and min values.	–
Energy-VAR	The fluctuation within a specified timeframe.	$(Var) = (1/n) * \Sigma(xi - \mu)^2$ n is the number of data points. $\Sigma(xi - i)^2$ represents the sum of the squared differences between each data point (xi) and the mean (μ).
Kurtosis-Kurt	To ascertain the weight distribution of tails.	$(Kurt) = [(1/n) * \Sigma(xi - \mu)^4]/s^4$ $\Sigma(xi - \mu)^4$ represents the sum of the fourth power of the differences between each data point (xi) and the mean (μ). s is the sample standard deviation.
Skewness-Sk	It assesses the symmetry of the distribution.	$(Sk) = (1/n) * \Sigma(xi - \mu)^3/s^3$ n is the number of data points. $\Sigma(xi - \mu)^3$ represents the sum of the cubed differences between each data point (xi) and the mean (μ). s is the sample standard deviation.

Table 4. Summary of extraction and selection techniques

Type	Methods	Features Number	Anova Discarded Features (< 70%)
Central tendency measures	Arithmetic mean (Mean)	6	Wmean_AZ Wmean_GY
	Root mean square (RMS)	6	0
Dispersion measures central	Standard deviation (STD)	6	Wstd_AY
	Minmax value (Minmax)	6	WPEAK2peak_AX WPEAK2peak_GZ
	Maximum and minimum value	12	MAX_AY/MAX_GX MIN_AX/MIN_GX
Higher-Order Statistics	Kurtosis (Kurt)	6	KURTOSIS_GZ
	Skewness (Sk)	6	WSWEKNESS_AY WSWEKNESS_GY
Energy Measures	Energy (VAR)	6	0
Data transformation	Principal component analysis (PCA)	6	0

d) **Classification of data:** The incorporation of supervised learning techniques in the construction of recognition models tailored for the identification of daily motion constitutes a substantial advancement within the fields of artificial intelligence and machine learning. This methodology capitalizes on the utilization of meticulously labeled data, facilitating the precise annotation of daily activities and their corresponding sensor patterns. By applying supervised learning, these models can be refined to discriminate effectively among a diverse spectrum of activities, thereby achieving a notable level of precision. In our process of classification, we partitioned the signals into training and testing sets, aiming to leverage artificial intelligence methodologies. A wide array of automated classification methods [26]–[28], comprising linear discriminant analysis (LDA), support vector machines (SVM), neural networks (NN), decision trees (DT), and the K-nearest neighbor algorithm (KNN), were examined within the scope of this investigation.

In this study, a neural network algorithm was customized with specific learning parameters and a normalization method. The dataset was divided into 70% for training and 30% for testing, ensuring robust model evaluation. The NN comprised three hidden layers with 30 neurons each, enabling the extraction of intricate patterns. A maximum of 100 iterations were set for training, balancing computational efficiency and convergence. For the remaining machine learning algorithms, a comprehensive summary of key techniques and configurations will be presented in Table 5. The focus predominantly lies on critical parameters such as the regularization parameter, iteration number, quality measure, and pertinent techniques employed in data analysis. This structured analysis aims to provide a comparative insight into the intricacies of each algorithm's configuration, facilitating a nuanced understanding of their respective methodologies and performance attributes.

Table 5. Technical details of the five employed classifiers

Algorithm	Partitioning	Normalization	Learning Parameters
Neural Network	70% Train data 30% Test data	Min-Max Normalization	Maximum Number of Iteration: 100 Number of Hidden Layers: 3 Number of Hidden Neurons Per Layer: 30
Support Vector Machine			Kernel Type: Radial Basis Function (RBF) Regularization Parameter (C): 1.0 Gamma (for RBF Kernel): 0.01
K Nearest Neighbor			Number of Neighbors to Consider (k): 5
Decision Tree			Quality Measure: Gini index Minimum Number Records Per Node: 10000 Number Threads: 4
Linear Discriminant Analysis			Prior Probabilities: Estimated Priors Solver Type: SVD (Singular value decomposition) Number of Components: 9 Maximum Iterations: 1000 Shrinkage: Automatic

e) **Performance metrics:** This section outlines the accuracy metric of a classification model, denoting the ratio of correct predictions made by the classifier among the total number of predictions. Subsequent to the training phase, a series of tests were conducted to evaluate the recognition performance of individual gestures. This involved the application of various classifiers to the compiled dataset. A confusion matrix can be established for a binary dataset in order to scrutinize the performance of a classifier. This facilitates the assessment of critical performance metrics, encompassing the *TPR* (True Positive Rate) and *FNR* (False Negative Rate).

$$TPR = \frac{TP}{(TP + FN)} \tag{1}$$

$$FNR = \frac{FN}{TP + FN} \tag{2}$$

Where *TP* represents the count of true positives and *FN* denotes the count of false negatives.

f) **Results and discussion:** In this section, we elucidate the predominant metric for assessing the efficacy of the classification model, detailing the ratio of accurate predictions in relation to the overall predictions rendered by the classifier (refer to Table 6). Following the culmination of the training protocol, a series of tests were conducted to gauge the recognition effectiveness of each gesture. Various classifiers were applied to the amassed data. Notably, the neural network emerged as the foremost performer across all participants (refer to Table 7), exhibiting an admirable accuracy rate of 97.5%. Simultaneously, securing the second position in classification accuracy, SVM demonstrated a commendable rating with results that closely mirrored the leading outcome. In contrast, outcomes from alternative classifiers manifested a marginal disparity.

Table 6. Classification accuracy for different participants with five classifiers

Clasifiers	Accuracy (%)
Neural Network	97.50%
Support Vector Machine	93.25%
K Nearest Neighbor	91.87%
Decison Tree	89.40%
Linear Discriminant Analysis	84.10%

Table 7. Performance metrics of different participants with neural network

	Neural Network
TPR	97.54%
FNR	24.60%

The classifiers underwent training and assessment based on the derived features, employing a 10-fold cross-validation approach [29]. To enhance clarity, we have chosen to present the error rates of the NN using 10-fold cross-validation, as demonstrated in Table 8. For our dataset containing 36,000 samples, we opted for 10-fold cross-validation with random sampling enabled. This method ensures that each fold accurately represents the entire dataset, thereby avoiding biases that may arise from sequential data splitting. This approach balances computational efficiency with reliable performance estimates. Consequently, we created 10 folds of 3,600 samples each, which allows the model to train on 32,400 samples and test on 3,600 samples in each iteration. The error rates for the neural network algorithm exhibit slight variability, ranging from 2.30% to 2.70%, corresponding to accuracy spanning from 97.30% to 97.70%. This consistency across folds suggests uniform performance across diverse subsets of the dataset. Notably, the narrow range of error rates indicates stable model behavior. The observed low error rates and high accuracies underscore the algorithm's efficacy in classifying instances within the dataset. An average overall accuracy of approximately 97.43% further corroborates the model's robust performance, highlighting its ability to accurately classify the majority of instances in the test sets.

Table 8. 10-fold cross-validation errors rate of neural network

10-Fold ID	Error in %	Set Size of Test Set	Error Count
1	2.40	3600	86
2	2.55	3600	92
3	2.35	3600	85
4	2.60	3600	94
5	2.50	3600	90
6	2.45	3600	88
7	2.70	3600	97
8	2.30	3600	83
9	2.55	3600	92
10	2.35	3600	85

In the conclusive phase of result validation, our emphasis is directed towards the exposition of the confusion matrix and the corresponding percentages of precise classification for each specific class, encompassing true positive rates and false negative rates (refer to Table 9). This pursuit aims to facilitate the expeditious validation of results and to conduct a comprehensive analysis of the machine learning classification performance. Gesture recognition poses a significant challenge when distinguishing between hand gestures associated with these vehicle control gesture groups {1st Gear = FiG, 3st Gear = TG, 5st Gear = FG}, {2st Gear = SG, 4st Gear = FoG, Reverse Gear = RG} and {Steering wheel control = SWC, Steering wheel no control = SWnC}, as these gestures exhibit identical hand orientation and direction. The overlap in hand orientation and direction between these vehicle control tasks, along with the distinct muscle responses of our participants shaped by factors such as age, gender, physical condition, and emotional state, highlights the complexity of the gesture recognition problem. This complexity demands further adaptation and development in data collection and calibration protocols to ensure consistency and accuracy in the gathered data. Achieving this is crucial for reliable analysis and facilitates the application of sophisticated machine learning approaches for accurate differentiation. Addressing these challenges is crucial for the seamless implementation of gesture-based control systems, particularly in scenarios where precise identification of gear positions is paramount.

The integration of our model gesture recognition system into automotive systems focuses on motion detection in real-world driving scenarios. This emphasis aims to enhance the system's proficiency, enabling it to rectify, identify, and forecast behaviors exhibited by drivers. The implementation of gesture recognition holds promise for fortifying road safety and facilitating efficient traffic management. Simultaneously, in the realm of security, this intelligent model extends to the discernment and identification of aberrant behaviors. These functionalities are expected to significantly improve overall performance and safety in practical driving situations. For instance, the detection leads to conclusions regarding potential driver health challenges. In response to the aforementioned circumstances, our recognition mechanism can seamlessly integrate into forthcoming developments in human-machine interaction interfaces. This integration endeavors to cultivate an intuitive and easily comprehensible interaction experience, amalgamating diverse modes to ensure adaptability and inclusivity for users possessing varied abilities and preferences. This improvement is achieved by processing real gestures and comparing them with typical actions related to wheel steering control and gear transmission. It culminates in assessing the similarity of activities and delivering guidance to enhance proficiency and various aspects of car-driving actions. This holistic approach significantly contributes to overall driving quality and the maintenance of the vehicle's mechanical status.

Table 9. Confusion matrix of the neural network classifier for 'All participants'

	Predicted Class										TPR %	FNR %
	FiG	**SG**	**TG**	**FoG**	**FG**	**RG**	**NG**	**HB**	**SWC**	**SWnC**		
FiG	884		10		7					7	97.4	2.6
SG		888		4		6		2			98.7	1.3
TG	11		883							6	98.1	1.9
FoG		12		878		10					97.6	2.4
FG	3		13		884						98.2	1.8
RG		6		9		881		4			97.9	2.1
NG	7				4	4	870		8	7	96.7	3.3
HB				7		8	3	873		9	97	3
SWC							9	2	881	8	97.9	2.1
SWnC	3		2		5		5	10	12	869	95.5	4.1

4.2 Kitchen related behaviors: Analyzing related behaviors for performance improvements

Activity recognition in the kitchen, an appealing and dynamically evolving field, places emphasis on leveraging the latest advancements in technology to comprehensively understand and analyze human actions, particularly within the intricate domains of eating and food preparation. As modern scientific advances keep redefining several aspects of our daily lives, it becomes increasingly evident that the kitchen, as a pivotal space for human sustenance and cultural expression, is not insulated from this ground-breaking wave [30], [31].

Deep learning architecture. The widespread implementation of machine learning techniques, especially multi-layer perceptron's (MLPs), in the field of HAR holds immense relevance, with an exclusive focus on activities that involve the kitchen [32]. Recognizing human behaviors in kitchen-related activities is vital for enhancing various aspects of daily life, including health monitoring, lifestyle analysis, and assisted living. MLPs, representing a subtype of feedforward NN, exhibit the capacity to identify intricate patterns and correlations within data, making them particularly well-suited for discerning nuanced activities within kitchen settings [33]. They are especially recommended for interpreting acceleration and rotation data captured by accelerometers and gyroscopes and prove profitable in pattern recognition endeavors [34]. The present study delves into the importance of employing MLPs in HAR, elucidating their potential to unravel and recognize the complicated nature of kitchen-related behaviors, thereby contributing to advancements in human-centric analytics, behavioral biometrics, and real-time feedback mechanisms.

a) **MLP feedforward network: learning configurations summary:** This study presents the development and evaluation of a multi-layer perceptron (MLP) feedforward network designed to process data generated by accelerometer and gyroscope sensors. The experiment involved collecting sensor data from twenty participants at a sampling frequency of 50 Hz, resulting in samples acquired every 20 milliseconds. The proposed MLP architecture incorporates six distinct shape features {Ax, Ay, Az, Gx, Gy, Gz} as inputs to the network's input layer, capturing nuanced patterns derived from accelerometer and gyroscope measurements. These patterns are crucial for recognizing activities depicted in Figure 6, such as eating, drinking, kitchen-specific gestures, and knife recognition activities.

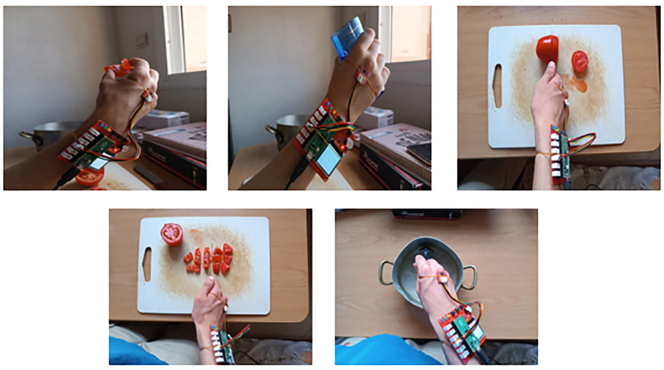

Fig. 6. Participants engage in kitchen-related activities

Before discussing the technical details (refer to Table 10) of our neural network (see Figure 7), it's important to highlight the significance of the data-preprocessing phase.

We have implemented Z-score normalization as a crucial step to standardize and center the distribution of our input features. This statistical method ensures that every measure has a mean of zero and a standard deviation of one, supporting a more consistent and comparable scale across all features. By subtracting the mean and dividing by the standard deviation for each data point, we appropriately transform our input data into a standardized form. The execution of Z-score normalization is aimed at upgrading the convergence and success rate of our NN during training [35], as well as promoting a more dependable and regenerative learning process across different features. The complex and lengthy data generated by accelerometer and gyroscope sensors, along with the imperative to capture targeted and nuanced patterns inherent in human activities, required an advanced model design [36]. To optimize the performance of the MLP feedforward network for processing the collected data, a thorough investigation into hidden layer configurations was carried out. Initial experiments using one and two hidden layers demonstrated a shortfall in achieving the desired classification accuracy. The decision to utilize three hidden layers proved pivotal in rectifying the deficiencies identified in earlier configurations. The heightened model depth facilitated a more nuanced representation of intricate patterns within the data [37], resulting in a significant enhancement in classification accuracy. The intricate nature of the accelerometer and gyroscope data, inherently characterized by complex dimensions and spatial dependencies, necessitated a deeper network architecture to aptly capture and learn the underlying features. Incorporating the Rectified Linear Unit (ReLU) activation function into our network's hidden layers plays a crucial role in enhancing its capacity to learn and represent complex patterns in the data. By introducing non-linearity through ReLU, our model gains the ability to capture sophisticated connections between input and output data, which is essential for the successful processing of accelerometer and gyroscope-generated data.

The simplicity and computational efficiency of ReLU contribute to the effectiveness of our network. It replaces negative values in the input with zero, addressing some famous phenomena, including the vanishing gradient problem, and fostering faster convergence during training [38]. Another benefit is that ReLU promotes the sparsity of activations, optimizing computational resources and improving the efficiency of our network. Incorporating the Softmax activation function into the output layer of our neural network is fundamental for converting the raw model outputs into valuable probability distributions, mostly in cases requiring multiclass classification [39]. This activation function transforms the network's final layer into a set of probabilities, granting a clear indication of the likelihood of each class. The Softmax activation ensures that the sum of these probabilities across all classes equals 1, making the output interpretable as a probability distribution. Mathematically, for each class *i*, the Softmax function is expressed as:

$$s(xi) = \frac{e^{xi}}{\sum_{j=1}^{n} e^{xj}} \tag{3}$$

e^{xi} represents the exponential function applied to the raw output score for class *i*, and the denominator is the sum of the exponential values for all classes.

This mathematical transformation ensures that the output probabilities are well calibrated and provides a reliable basis for decision-making in multiclass classification operations. By adopting Softmax in the output layer, our network is fitted to deliver coherent and adjusted probability predictions, boosting the interpretability and convenience of the model's outputs in scenarios where class probabilities serve as critical for decision-making. The inclusion of the categorical cross-entropy loss function in the training of our NN is mandatory for optimizing its performance in multiclass classification processes. By taking advantage of this loss function, we provide the network with a clearly defined goal: to minimize the dissimilarity between its predicted probability distributions and the true probability distributions corresponding to the actual class labels. Mathematically, for a single training example, the categorical cross-entropy loss is given by:

$$L(y, \hat{y}) = \sum_i y_i \; log(\hat{y}_i) \tag{4}$$

L is the categorical cross-entropy loss, y_i represents the true probability of class $\hat{y}_i$ represents the predicted probability of class i as output by the neural network.

During the training process, our NN dynamically refines its parameters by exploiting the Adam optimization algorithm, a strategic choice made to reduce the categorical cross-entropy loss across all training examples. The iterative process of this optimization, assisted by Adam's adaptive learning rates and momentum mechanisms, plays a prominent role in directing the network to acquire durable and precise models of the input data [40]. This is particularly applicable in scenarios where each input correlates with precisely one class, as the flexible architecture of Adam contributes to the network's adaptability as well as accuracy in refining its parameters for greatest effectiveness in multiclass classification tasks.

Table 10. Summary of neural network learning configurations

Input Layers	Hidden Layers	Size of Output Layer	Activation of Output Layer	Optimization Function
Shape = 6 (All Accelerometer and Gyroscope features: AX, AY, AZ, GX, GY, GZ)	3 layer: – First Layer: Units = 16 – Second Layer: Units = 16 – Third Layer Units = 16	Unit = 7 • Eating (1) • Drinking (1) • Kitchen specific gestures (2) • Knife recognition activity (3)	SOFTMAX	ADAM

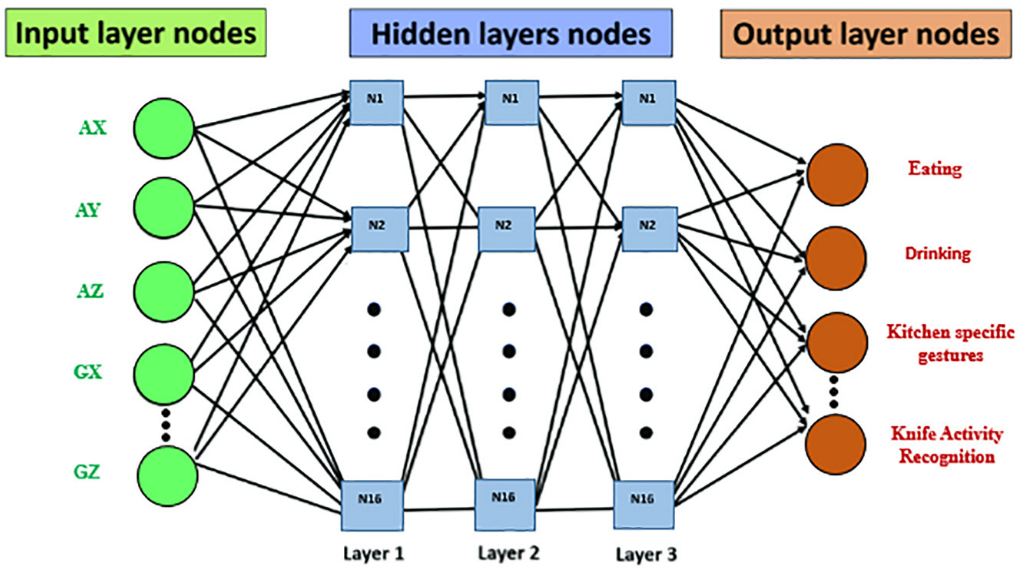

Fig. 7. MLP feedforward network architecture

b) MLP feedforward network: Results and examinations

i) Training progress: In the evaluation of the MLP Feedforward Network's performance, notable metrics were obtained during the learning process. The accuracy achieved on the training dataset reached 98% (see Figure 8), indicating the model's proficiency in categorizing instances within this set. The corresponding loss function value, a crucial indicator of the disparity between predicted and real values, demonstrated a minimal value of 0.05% (see Figure 9), affirming the network's effectiveness in minimizing prediction errors.

The training process spanned 20 epochs, reflecting the number of complete passes through the entire training dataset. Implementing a batch size of 100 instances per iteration, the network iteratively updated its parameters to optimize performance. With a total of 3600 batches executed during training, each batch comprising 100 instances, it is noteworthy that the learning rate exhibited a significant increase, especially from batch 250. This increase in the learning rate contributed to an enhanced adaptation of the model's parameters. Notably, the learning rate stabilized beyond batch 500, showcasing a refined and enduring learning process. These metrics collectively highlight the fruitful convergence and learning quality of our MLP feedforward network during the training phase. The high accuracy, accompanied by a low loss function value, attests to the model's ability to capture complicated shapes within the data and make precise projections. The aforementioned suited configurations attributed to the number of epochs and batch size lead to a comprehensive assessment of the network's learning dynamics, providing relevant inferences into its training progression and reliability.

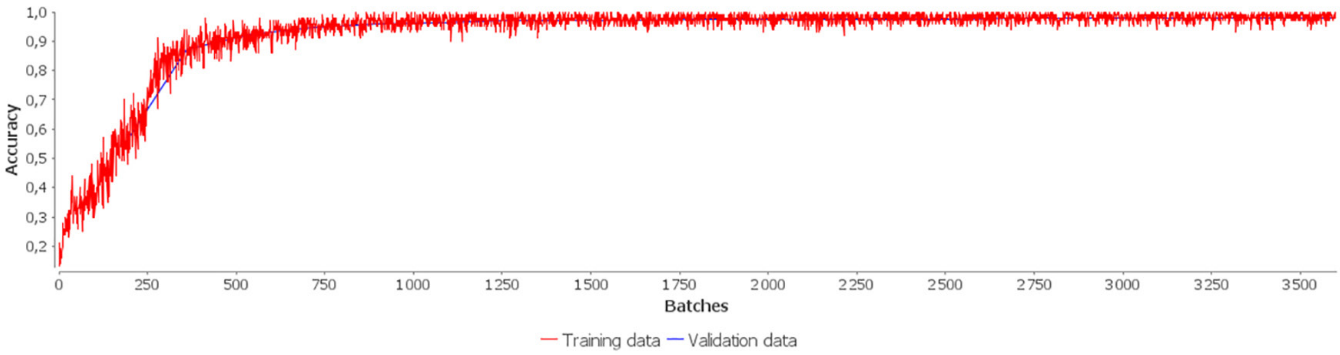

Fig. 8. MLP learning process accuracy

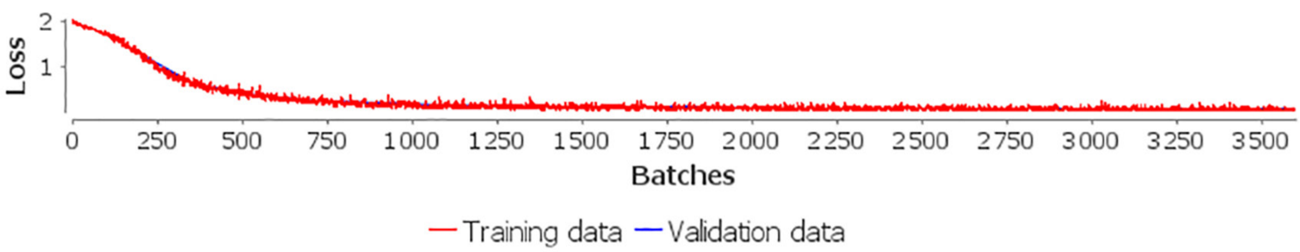

Fig. 9. MLP loss function

ii) Test results and confusion matrix analysis: The confusion matrix of our MLP feedforward network presents valuable insights into the model's performance across various classes (refer to Table 11). Notably, some noteworthy observations emerge from the matrix, shedding light on specific challenges encountered by the network in recognizing certain activities. One noteworthy aspect is the slight confusion observed between the classes of eating and drinking. This can be attributed to the similarity in the vertical direction of hand movements involved in these activities. The network may encounter challenges in distinguishing these actions, particularly when they share common characteristics of hand motion. This limitation is inherent in accelerometer and gyroscope sensors. To address this, the inclusion of additional sensors is necessary. Specifically, incorporating electromyography (EMG) signals can help interpret finger movements, while pressure sensors are able to supply specific information about the force and pressure exerted by the hand during these activities, which are abilities beyond the scope of acceleration and rotation sensors. Addressing the confusion between atypical knife activity and other gestures, like successive cutting and stirring, presents a challenge; the model faces difficulties in distinguishing these actions due to the nuanced nature of movement. Variations in hand movements linked to knife-related actions, including diverse techniques and movement velocity, pose obstacles for accurate detection. Wearable sensors, while useful, may be uncomfortable and restrict natural movements, resulting in a variety of motion patterns and occasional misclassifications. Overcoming these limitations requires future adjustments in scale factor and cross-axis sensitivity to accurately capture rapid and precise movements. Additionally, there is a slight confusion between stirring clockwise and stirring counter-clockwise. This ambiguity may arise from the symmetrical nature of stirring motions, making it challenging for the network to consistently discern the specific direction of stirring. To further strengthen the performance evaluation, we implemented a comprehensive set of accuracy statistics, as illustrated in Table 12, across multiple experimental activities. The key performance metrics assessed include true positives, false positives, true negatives, false negatives, recall, precision, specificity, F-measure, accuracy, and Cohen's kappa. The model displays distinguished results, with high values in key parameters like precision, recall, specificity, and F-measure. These metrics prove the model's impact in accurately identifying both positive and negative cases with minimal errors. The considerable accuracy score additionally confirms the model's overall ability to perform classification tasks. On top of that, Cohen's Kappa points out powerful agreement between the model's predictions and actual findings, clarifying the model's reliability beyond coincidence.

This study in deep learning aims to advance the field of gesture recognition, with a specific focus on actions inherent in daily kitchen activities. Consequently, through the analysis of hand-to-mouth motions, our activity recognition model can discern eating and drinking habits. This information proves valuable for individuals' seeking insights into their dietary patterns or for health professionals monitoring nutritional intake [41]. Moreover, the recognition of kitchen-specific activities plays a pivotal role in the development of intelligent assistive technologies and contributes significantly to the broader field of HCI. The system we propose can be trained to identify atypical knife activities, such as unsafe cutting practices or irregular motions. This is particularly crucial for ensuring kitchen safety, as it enables the system to provide real-time alerts or warnings when unusual behaviors are detected. This functionality allows for the development of adaptive assistance systems, which can guide users in correcting their techniques, preventing accidents, and promoting safer cooking practices [42]. Furthermore, our exploration of activity recognition extends beyond the general to the realm of specific gestures, including actions like stirring clockwise or counter-clockwise. The implications are far-reaching, particularly in the context of smart kitchen devices equipped with sensors [43]. These devices can interpret such gestures, providing a seamless, hands-free control mechanism for various kitchen appliances. Overall, our neural network aims to contribute valuable insights to the intersection of deep learning and human activity recognition, with practical applications extending to diverse domains for the enhancement of daily life. This includes real-time feedback mechanisms, behavioral biometrics, and context-aware systems [44]. It outperforms other studies presented in Table 13 by correctly identifying seven distinct actions, whereas those studies typically only distinguish two or three activities. Our approach achieves an impressive 98% accuracy rate, significantly higher than the typical 88% to 94% accuracy range seen in other works. This exceptional performance can be attributed to several factors discussed in previous sections, including data preprocessing techniques, optimization strategies, and network configurations. Despite facing challenges in identifying a broad range of activities, our algorithm demonstrates remarkable efficacy and reliability.

Table 11. Confusion matrix of the MLP feedforward network

Act/Pred	Eating	Drinking	Cutting	Successive Cutting	Atypical Knife Activity	Stirring Clockwise	Stirring Counter-Clockwise	TPR %
Eating	762	3	0	0	0	0	0	99.6
Drinking	3	808	0	0	1	0	0	99.5
Cutting	0	0	762	0	0	0	0	100
Succ Cutting	0	0	1	831	3	0	0	99.5
Atyp Knife Activity	1	4	3	15	739	10	17	93.6
Stirring CW	0	0	0	0	2	821	10	98.5
Stirring CCW	0	0	3	0	5	13	783	97.3

Table 12. Accuracy statistics

Activities	TP	FP	TN	FN	Recall	Precision	Specificity	F Measure	Accuracy	Cohen's Kappa
Eating	762	4	4831	3	99%	99%	99%	99%		
Drinking	808	7	4781	4	99%	99%	99%	99%		
Cutting	762	6	4832	0	100%	99%	99%	99%		
Succ cutting	831	15	4750	4	99%	98%	99%	98%		
Atyp knife activity	739	11	4800	50	93%	98%	99%	96%		
Stirring CW	821	24	4743	12	98%	97%	99%	97%		
Stirring CCW	783	27	4769	21	97%	96%	99%	97%		
Overall									98%	98%

Table 13. Comparison with existing state-of-the-art

Team	Year	Activities Recognized	Methods	Sensors	Accuracy
Schrader and Vargas	2020	Eating, Drinking	Supervised Learning	Inertial Sensors Stationary cameras	90.5%
Kimiaki Shirahama	2021	Cutting, Wiping	LSTM	Inertial Sensors, Gravity Sensors	88.9%
Cunyi and Xiren	2022	Eating-habits Washing Cleaning	Deep Learning Methods	Infrared Array Sensor	92.4%
Yang and Guanci	2023	Cleaning Maintenance Food-Prepa	CNN	Inertial Sensors	87.9%
Patrica and arza	2024	Cutting, Stirring Washing Cleaning	Ensemble Learning	Cameras, Force Sensors	91.5%

4.3 Educational activities: Enhancing activity recognition with ensemble learning

This segment explores the implementation of activity recognition systems in educational environments, specifically focusing on classrooms. The integration of sensors into educational processes has opened new avenues for understanding and refining learning practices. Traditionally centered on artificial intelligence and signal processing, activity recognition holds the potential to revolutionize learning methodologies and enhance student engagement. Using sensor technology, machine learning, and data analytics, educators and researchers have the opportunity to gather insights into the dynamics of the learning environment. This, in turn, facilitates the evolution of tailored and adaptive educational strategies [45], [46].

Data collection and methodology. In the pursuit of comprehending and enhancing educational interactions and processes, this study initiates a comprehensive data collection phase involving 30 participants. During this phase of our study, sensor data were collected at a sampling frequency of 100 Hz, with each sample acquired at intervals of 10 milliseconds. This setup enabled the detailed capture of movements and activities with high temporal resolution. Employing cutting-edge sensor technologies, specifically accelerometers and gyroscopes, participants are equipped with wearable devices tailored to capture diverse hand movements within the educational context. This comprehensive methodology endeavors to unveil the intricacies of activities within educational routines. It spans diverse elements (see Figure 10), including interactions between students and teachers, writing activities undertaken by both educators and students, levels of engagement, mouse control, and practices linked to the utilization of the blackboard. The study aspires to contribute to a holistic understanding of the dynamic interactions and practices inherent in educational environments, paving the way for informed improvements and targeted interventions.

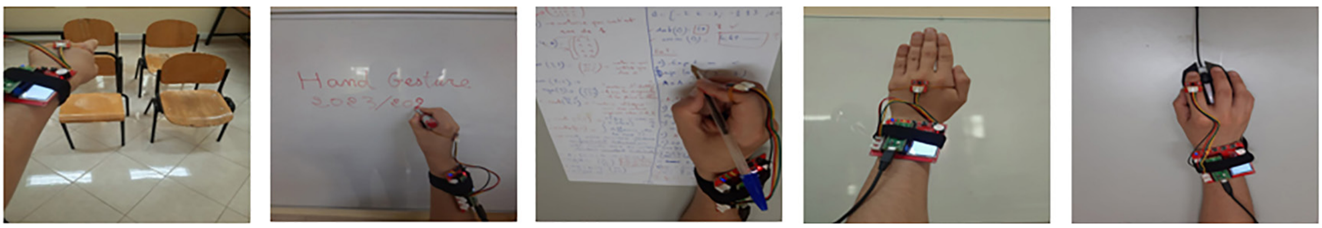

Fig. 10. Teachers and students carry out educational activities

Ensemble learning and machine learning methods. Ensemble learning, a method that integrates predictions from multiple models, holds considerable significance in enhancing the recognition of activities within educational environments. Its importance lies in its capacity to overcome the inherent limitations of individual models [47], resulting in heightened accuracy, robustness, and adaptability. Within educational contexts, ensemble learning excels at capturing intricate patterns such as student-teacher interactions, writing activities, and engagement forms. The method's flexibility is crucial for handling the dynamic properties of classrooms, while its ability to filter data irregularities and noise contributes to more reliable outcomes [48]. Ultimately, ensemble learning stands as a transformative approach to activity recognition within the learning environment, offering valuable perspectives for educators to develop unique interventions and enhance the learning experience. In the implementation of activity recognition within an educational context, we will apply the same combination of classifiers utilized in the initial chapter. Following this, a comparative analysis of the results will be conducted, elucidating outcomes relevant to this initial phase. In the subsequent stage of our study, our objective is to showcase the effectiveness of the bagging technique in enhancing algorithm performance. This involves presenting necessary comparisons and highlighting all observed improvements across all classifiers. In the final stage of our investigation, maintaining a persistent focus on enhancing model classification accuracy, we will employ stacking techniques. The presentation will feature combinations of classifiers that yield optimal outcomes, thereby demonstrating the potential for improved accuracy through advanced ensemble methodologies.

- **Experience 1:** The section elucidates the outcomes derived from employing the aforementioned five learning methods (DT, KNN, LDA, MLP, and SVM) separately. The primary performance metrics scrutinized in this investigation are classification accuracy. Additionally, the computed error metrics, which comprise accuracy, precision, recall, and the F1 score, are listed in Table 14.

Table 14. Error metrics: Accuracy, Precision, Recall, and F1-Score based on ML algorithms (DT, KNN, LDA, MLP, and SVM)

Classifiers	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
DT	94.67%	95.07%	95.78%	95.01%
KNN	61.78%	83.70%	61.53%	62.72%
LDA	65.13%	68.76%	95.62%	65.23%
MLP	96.47%	96.68%	98.69%	96.27%
SVM	85.01%	92.18%	89.52%	95.30%

Upon scrutinizing the overall statistics presented in Table 15, it becomes apparent that three classifiers emerged prominently: DT, MLP, and SVM. Notably, MLP demonstrated superiority, correctly classifying 3782 out of 3995 testing samples, resulting in an accuracy rate of 96.27%. A mere 141 samples were misclassified, corresponding to a classification error rate of 3.53%. Conversely, DT and SVM achieved accuracy rates of 94.67% and 85.01%, respectively, indicating satisfactory performance. In contrast, KNN and LDA yielded less favorable outcomes in terms of classification accuracy. For instance, KNN correctly classified 2468 out of 3995 samples, yielding an accuracy rate of 61.78% with a corresponding misclassification rate of 38.22%. LDA exhibited somewhat similar results.

Table 15. Overall statistics

Classifiers	Overall Accuracy	Overall Error	Correctly Classified	Incorrectly Classified
DT	94.67%	5.33%	3782	213
KNN	61.78%	38.22%	2468	1527
LDA	65.13%	34.87%	2602	1393
MLP	96.47%	3.53%	3854	141
SVM	85.01%	14.99%	3396	599

- **Experience 2:** To enhance the outcomes of the previous experience, both bagging and stacking bolster ensemble learning by capitalizing on the cognitive capabilities of multiple models [49], thereby yielding heightened predictive accuracy and adaptability. Bagging entails training numerous iterations of the identical learning algorithm on diverse subsets of the training dataset. These subsets are generated using bootstrapping, which involves sampling with replacement. A multitude of models are trained independently based on these constructed samples, and their predictions are merged for regression or classification tasks [50]. We explored the potential of bagging techniques to improve estimation performance according to our experimental results. Figure 11 demonstrates the enhancement in accuracy for certain classifiers through bagging. In this regard, SVM improved from 85.01% to 87.54%, while notably, KNN and LDA saw increases from 61.78% to 86.21% and 65.13% to 88.92%, respectively. MLP and the remaining classifiers experienced only marginal improvements, maintaining their accuracy at similar levels.

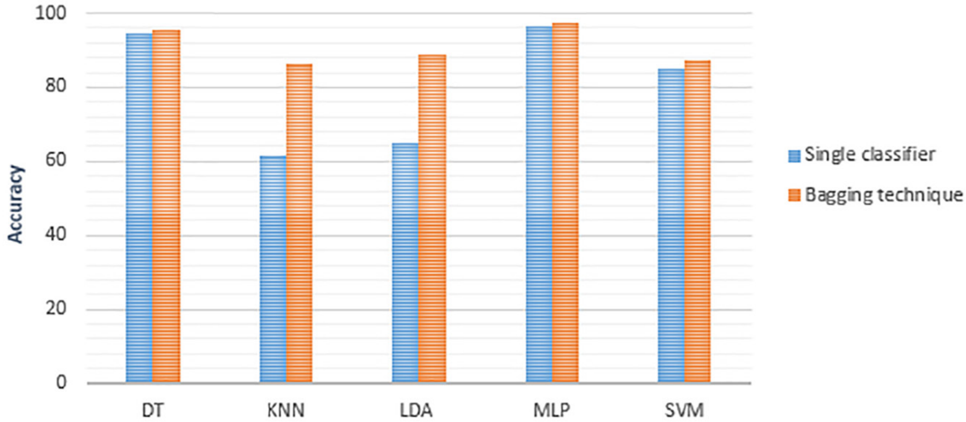

Fig. 11. The precision of different methods employing the bagging approach

In the continuous pursuit of reaching the most effective method to discern human activities, stacking introduces a higher level of model diversity and a meta-model to optimize the combination of individual model outputs [51]. These techniques have proven effective in various machine learning applications, including activity recognition within educational environments [52]. Utilizing stacking in our study entails the integration of multiple aforementioned techniques, employing logistic regression as an aggregation approach. Table 16 illustrates that the highest accuracy is attained through the combination of DT, MLP, and SVM (98.75%).

Table 16. The results achieved through the application of the stacking method

Classifiers	Accuracy (%)
DT – KNN – LDA	82.31%
DT – KNN – MLP	91.66%
DT – KNN – SVM	89.83%
MLP – LDA – DT	92.42%
SVM – LDA – DT	87.37%
DT – MLP – SVM	98.75%
LDA – KNN – MLP	85.39%
KNN – LDA – SVM	80.89%
KNN – MLP – SVM	86.66%
LDA – MLP – SVM	88.77%

The experimental results show that among the tested classifiers, MLP achieved the highest accuracy at 96.47%, while KNN had the lowest accuracy at 61.78%. Following the implementation of bagging, KNN and LDA demonstrated the most substantial improvement, with accuracies of 86.21%, and 88.92% respectively, highlighting their superior enhancement through the use of the bagging technique. Additionally, our stacking approach validated that a combination of DT, MLP, and SVM yielded the highest accuracy, scoring 98.75%. These findings underscore the potential of ensemble techniques for enhancing classification performance in large, sensitive, and complex datasets.

5 FUTURE WORK

In our future research directions, driven by our aspiration to address specific challenges in real-world deployment, we aim to make significant contributions to the medical field, particularly in remote surgeries employing bionic hands. By proposing new prototypes and technical improvements in human-robot interaction and the development of control systems for bionic hands, we seek to enhance the present state of the art. To achieve the aforementioned goals, we recognize the key importance of incorporating additional sensor modalities. Following an extensive review of numerous research projects, we have elected to focus on EMG signals [53]–[55], which are essential for assessing and interpreting the electrical activity generated by skeletal muscles [56]. A scrutinized diagnostic procedure accompanied by these signals should be adopted to measure the state of the muscles and motor neurons that send electrical signals inducing muscle contractions and convert these electrical responses into graphs, sounds, or numerical data for specialists to analyze. By incorporating EMG signals into our ongoing research, we intend to enhance the performance, intelligence, and adaptability of prosthetic devices. Additionally, this integration will assist physicians in conducting complex surgeries remotely by leveraging hand motion, rotation, and EMG signals. This approach, described in Figure 12, is designed to ensure that these devices more closely align with the natural hand and finger movements and intentions of their users.

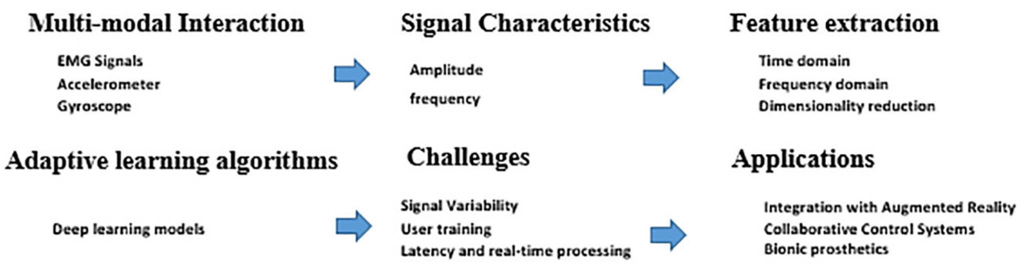

Fig. 12. Multi-modal prototype for future bionic hand control

6 CONCLUSION

In summary, our investigation into human gesture recognition spanning diverse contexts such as driving cars, kitchen-related tasks, and educational environments has produced encouraging results. By leveraging all technical processes and communication protocols between the Raspberry Pi Pico and accelerometers and gyroscopes, the meticulous data collection process engaged the active involvement of 60 volunteers, thereby securing precise and dependable datasets for analysis. Through the utilization of hybrid models that blend supervised learning, deep learning, and ensemble learning techniques, our study has attained commendable accuracy rates across the spectrum of contexts explored, with models consistently achieving an average accuracy of 96% and 98% across all datasets. These findings underscore the potential of gesture recognition technology to enhance safety, efficiency, and interaction across a diverse spectrum of applications. The implications of this study extend widely, encompassing enhancements in automotive safety, facilitation of educational interactions, and automation of kitchen tasks. Moreover, the success of the hybrid model approach underscores the significance of harnessing diverse learning methodologies to address intricate real-world challenges and creating more functional and responsive assistive devices for individuals with limb differences. Looking forward, the incorporation of signals such as EMG in conjunction with existing accelerometer and gyroscope data presents a promising avenue for advancing the sophistication of activity recognition models. Integration of EMG signals in future endeavors stands to enhance precision and complexity, thereby paving the way for more seamless and intuitive control of bionic hands.

7 REFERENCES

[1] A. M. Khan, A. Tufail, A. M. Khattak, and T. H. Laine, "Activity recognition on smartphones via sensor-fusion and KDA-based SVMs," *International Journal of Distributed Sensor Networks*, vol. 10, no. 5, 2014. https://doi.org/10.1155/2014/503291

[2] A. Bayat, M. Pomplun, and A. Tran, "A study on human activity recognition using accelerometer data from smartphones," *Procedia Computer Science*, vol. 34, pp. 450–457, 2014. https://doi.org/10.1016/j.procs.2014.07.009

[3] B. Guo *et al.*, "Mobile crowd sensing and computing: The review of an emerging human-powered sensing paradigm," *ACM Computing Surveys*, vol. 48, no. 1, pp. 1–31, 2015. https://doi.org/10.1145/2794400

[4] K.-C. Liu, C.-Y. Yen, L.-H. Chang, C.-Y. Hsieh, and C.-T. Chan, "Wearable sensor-based activity recognition for housekeeping task," in *2017 IEEE 14th International Conference on Wearable and Implantable Body Sensor Networks (BSN)*, 2017, pp. 67–70. https://doi.org/10.1109/BSN.2017.7936009

[5] M. Webber and R. F. Rojas, "Human activity recognition with accelerometer and gyroscope: A data fusion approach," *IEEE Sensors Journal*, vol. 21, no. 15, pp. 16979–16989, 2021. https://doi.org/10.1109/JSEN.2021.3079883

[6] C. Chen, R. Jafari, and N. Kehtarnavaz, "A survey of depth and inertial sensor fusion for human action recognition," *Multimed. Tools Appl.*, vol. 76, pp. 4405–4425, 2017. https://doi.org/10.1007/s11042-015-3177-1

[7] A. Alam, A. Das, M. S. Tasjid, and A. A. Marouf, "Leveraging sensor fusion and sensor-body position for activity recognition for wearable mobile technologies," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 15, no. 17, pp. 141–155, 2021. https://doi.org/10.3991/ijim.v15i17.25197

[8] E. Debie *et al.*, "Multimodal fusion for objective assessment of cognitive workload: A review," *IEEE Trans. Cybern.*, vol. 51, no. 3, pp. 1542–1555, 2021. https://doi.org/10.1109/TCYB.2019.2939399

[9] C. Chen, R. Jafari, and N. Kehtarnavaz, "A real-time human action recognition system using depth and inertial sensor fusion," *IEEE Sensors Journal*, vol. 16, no. 3, pp. 773–781, 2016. https://doi.org/10.1109/JSEN.2015.2487358

[10] G. Bhat, R. Deb, V. V. Chaurasia, H. Shill, and U. Y. Ogras, "Online human activity recognition using low-power wearable devices," in *IEEE/ACM International Conference on Computer-Aided Design (ICCAD)*, 2018, pp. 1–8. https://doi.org/10.1145/3240765.3240833

[11] M.-S. Lee, K.-W. Kim, M. Ryu, and J.-N. Kim, "Hand gesture recognition with inertial sensors and a magnetometer," *Sensors and Materials*, vol. 28, pp. 655–660, 2016. https://doi.org/10.18494/SAM.2016.1221

[12] C. Zhu and W. Sheng, "Wearable sensor-based hand gesture and daily activity recognition for robot-assisted living," *IEEE Transactions on Systems, Man, and Cybernetics, Part A: Systems and Humans*, vol. 41, pp. 569–573, 2011. https://doi.org/10.1109/TSMCA.2010.2093883

[13] S. Chernbumroong, S. Cang, A. Atkins, and H. Yu, "Elderly activities recognition and classification for applications in assisted living," *Expert Systems with Applications*, vol. 40, no. 5, pp. 1662–1674, 2013. https://doi.org/10.1016/j.eswa.2012.09.004

[14] O. D. Lara and M. A. Labrador, "A survey on human activity recognition using wearable sensors," *IEEE Communications Surveys & Tutorials*, vol. 15, no. 3, pp. 1192–1209, 2013. https://doi.org/10.1109/SURV.2012.110112.00192

[15] M. Cornacchia, K. Ozcan, Y. Zheng, and S. Velipasalar, "A survey on activity detection and classification using wearable sensors," *IEEE Sensors Journal*, vol. 17, no. 2, pp. 386–403, 2017. https://doi.org/10.1109/JSEN.2016.2628346

[16] F. M. Petrini *et al.*, "Enhancing functional abilities and cognitive integration of the lower limb prosthesis," *Sci. Transl. Med.*, vol. 11, p. eaav8939, 2019. https://doi.org/10.1126/scitranslmed.aav8939

[17] S. Gupta, "Deep learning based human activity recognition (HAR) using wearable sensor data," *Int. J. Inf. Manage. Data Insights*, vol. 1, no. 2, p. 100046, 2021. https://doi.org/10.1016/j.jjimei.2021.100046

[18] J. Wang, Y. Chen, S. Hao, X. Peng, and L. Hu, "Deep learning for sensor-based activity recognition: A survey," *Pattern Recognition Letters*, vol. 119, pp. 3–11, 2018. https://doi.org/10.1016/j.patrec.2018.02.010

[19] D. Bhattacharyya, Th. Kim, and Gs. Lee, "Use of artificial neural network in Bengali character recognition," in *Signal Processing, Image Processing and Pattern Recognition*, in Communications in Computer and Information Science, vol. 260, Th. Kim, H. Adeli, C. Ramos, and BH. Kang, Eds., SIP 2011, Berlin, Heidelberg: Springer, 2011, pp. 140–152. https://doi.org/10.1007/978-3-642-27183-0_15

[20] A. Jalal, M. A. K. Quaid, S. B. u. d. Tahir, and K. Kim, "A study of accelerometer and gyroscope measurements in physical life-log activities detection systems," *Sensors*, vol. 20, no. 22, p. 6670, 2020. https://doi.org/10.3390/s20226670

[21] R. Ahmed Bhuiyan, N. Ahmed, M. Amiruzzaman, and M. R. Islam, "A robust feature extraction model for human activity characterization using 3-axis accelerometer and gyroscope data," *Sensors (Basel)*, vol. 20, no. 23, p. 6990, 2020. https://doi.org/10.3390/s20236990

[22] S. U. Jan, Y.-D. Lee, J. Shin, and I. Koo, "Sensor fault classification based on support vector machine and statistical time-domain features," *IEEE Access*, vol. 5, pp. 8682–8690, 2017. https://doi.org/10.1109/ACCESS.2017.2705644

[23] A. K. Singh and S. Krishnan, "ECG signal feature extraction trends in methods and applications," *BioMed Eng OnLine*, vol. 22, no. 22, 2023. https://doi.org/10.1186/s12938-023-01075-1

[24] S. Small *et al.*, "Impact of reduced sampling rate on accelerometer-based physical activity monitoring and machine learning activity classification," *Journal for the Measurement of Physical Behaviour*, vol. 4, no. 4, pp. 298–310, 2021. https://doi.org/10.1123/jmpb.2020-0061

[25] O. Lamsellak, A. Benlghazi, A. Chetouani, and A. Benali, "Hand gesture recognition using machine learning for bionic applications: Forearm case study," in *Digital Technologies and Applications*, vol. 668, S. Motahhir and B. Bossoufi, Eds., Cham: Springer, 2023, pp. 193–204. https://doi.org/10.1007/978-3-031-29857-8_16

[26] J. Singha, A. Roy, and R. H. Laskar, "Dynamic hand gesture recognition using vision-based approach for human–computer interaction," *Neural Comput. & Applic.*, vol. 29, pp. 1129–1141, 2018. https://doi.org/10.1007/s00521-016-2525-z

[27] A. Soofi and A. Awan, "Classification techniques in machine learning: Applications and issues," *Journal of Basic & Applied Sciences*, vol. 13, pp. 459–465, 2017. https://doi.org/10.6000/1927-5129.2017.13.76

[28] Q. An, S. Rahman, J. Zhou, and J. J. Kang, "A comprehensive review on machine learning in healthcare industry: Classification, restrictions, opportunities and challenges," *Sensors*, vol. 23, no. 9, p. 4178, 2023. https://doi.org/10.3390/s23094178

[29] A. Subasi, K. Khateeb, T. Brahimi, and A. Sarirete, "Human activity recognition using machine learning methods in a smart healthcare environment," in *Next Generation Technology-Driven Personalized Medicine and Smart Healthcare*, M. D. Lytras and A. Sarirete, Eds., Cambridge, MA, USA: Academic Press, 2020, pp. 123–144. https://doi.org/10.1016/B978-0-12-819043-2.00005-8

[30] F. Bozkurt, "A comparative study on classifying human activities using classical machine and deep learning methods," *Arab J Sci. Eng.*, vol. 47, pp. 1507–1521, 2022. https://doi.org/10.1007/s13369-021-06008-5

[31] K. H. Liland, J. Skogholt, and U. G. Indahl, "A new formula for faster computation of the K-fold cross-validation and good regularisation parameter values in ridge regression," *IEEE Access*, vol. 12, pp. 17349–17368, 2024. https://doi.org/10.1109/ACCESS.2024.3357097

[32] M. Schroth, D. Birkenmaier, and W. Stork, "Towards a modular machine learning architecture for human activity recognition," in *2024 IEEE Sensors Applications Symposium (SAS)*, Naples, Italy, 2024, pp. 1–6. https://doi.org/10.1109/SAS60918.2024.10636463

[33] J. DelPreto *et al.*, "ActionSense: A multimodal dataset and recording framework for human activities using wearable sensors in a kitchen environment," in *Neural Information Processing Systems (NeurIPS) Track on Datasets and Benchmarks*, 2022. [Online]. Available: https://action-sense.csail.mit.edu

[34] S. Zolfaghari, T. Stoev, and K. Yordanova, “Enhancing kitchen activity recognition: A benchmark study of the rostock KTA dataset,” *IEEE Access*, vol. 12, pp. 14364–14384, 2024. https://doi.org/10.1109/ACCESS.2024.3356352

[35] H. M. Balaha and A. E. S. Hassan, “Comprehensive machine and deep learning analysis of sensor-based human activity recognition,” *Neural Computing and Applications*, vol. 35, pp. 12793–12831, 2023. https://doi.org/10.1007/s00521-023-08374-7

[36] E. Sansano, R. Montoliu, and Ó. Belmonte Fernández, “A study of deep neural networks for human activity recognition,” *Computational Intelligence*, vol. 36, no. 3, pp. 1113–1139, 2020. https://doi.org/10.1111/coin.12318

[37] M. Fahim, S. M. A. Kazmi, and A. M. Khattak, “ApplianceNet: A neural network-based framework to recognize daily life activities and behavior in smart home using smart plugs,” *Neural Comput. & Applic.*, vol. 34, pp. 12749–12763, 2022. https://doi.org/10.1007/s00521-022-07144-1

[38] O. M. Igwe *et al.*, “Human activity recognition in smart environments employing margin setting algorithm,” *J. Ambient Intell. Human Comput.*, vol. 13, pp. 3669–3681, 2022. https://doi.org/10.1007/s12652-020-02229-y

[39] D. Singh and B. Singh, “Investigating the impact of data normalization on classification performance,” *Appl. Soft Comput.*, vol. 97, p. 105524, 2020. https://doi.org/10.1016/j.asoc.2019.105524

[40] G. Bhat, N. Tran, H. Shill, and U. Y. Ogras, “w-HAR: An activity recognition dataset and framework using low-power wearable devices,” *Sensors*, vol. 20, no. 18, p. 5356, 2020. https://doi.org/10.3390/s20185356

[41] D. J. Benkendorf and C. P. Hawkins, “Effects of sample size and network depth on a deep learning approach to species distribution modeling,” *Ecological Informatics*, vol. 60, p. 101137, 2020. https://doi.org/10.1016/j.ecoinf.2020.101137

[42] B. Olimov, S. Karshiev, E. Jang, S. Din, A. Paul, and J. Kim, “Weight initialization based-rectified linear unit activation function to improve the performance of a convolutional neural network model,” *Concurrency Computat. Pract. Exper.*, vol. 33, p. e6143, 2021. https://doi.org/10.1002/cpe.6143

[43] D. C. Marcu and C. Grava, “The impact of activation functions on training and performance of a deep neural network,” in *2021 16th International Conference on Engineering of Modern Electric Systems (EMES)*, Oradea, Romania, 2021, pp. 1–4. https://doi.org/10.1109/EMES52337.2021.9484108

[44] S. H. Haji and A. M. Abdulazeez, “Comparison of optimization techniques based on gradient descent algorithm: A review,” *PalArch's Journal of Archaeology of Egypt/Egyptology*, vol. 18, no. 4, pp. 2715–2743, 2021. https://archives.palarch.nl/index.php/jae/article/view/6705

[45] Y. Liu, “Design and optimization of human-computer interaction system for education management based on artificial intelligence,” *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 18, no. 7, pp. 107–124, 2024. https://doi.org/10.3991/ijim.v18i07.48337

[46] N. C. Tay, T. Connie, T. S. Ong, A. B. J. Teoh, and P. S. Teh, “A review of abnormal behavior detection in activities of daily living,” *IEEE Access*, vol. 11, pp. 5069–5088, 2023. https://doi.org/10.1109/ACCESS.2023.3234974

[47] D. Bouchabou, S. M. Nguyen, C. Lohr, B. LeDuc, and I. Kanellos, “A survey of human activity recognition in smart homes based on IoT sensors algorithms: Taxonomies, challenges, and opportunities with deep learning,” *Sensors*, vol. 21, no. 18, p. 6037, 2021. https://doi.org/10.3390/s21186037

[48] S. Shamshirband, M. Fathi, A. Dehzangi, A. T. Chronopoulos, and H. Alinejad-Rokny, “A review on deep learning approaches in healthcare systems: Taxonomies, challenges, and open issues,” *J. Biomed. Inform.*, vol. 113, p. 103627, 2021. https://doi.org/10.1016/j.jbi.2020.103627

[49] F.-C. Lin, H.-H. Ngo, C.-R. Dow, K.-H. Lam, and H. L. Le, "Student behavior recognition system for the classroom environment based on skeleton pose estimation and person detection," *Sensors*, vol. 21, no. 16, p. 5314, 2021. https://doi.org/10.3390/s21165314

[50] C. Pabba and P. Kumar, "An intelligent system for monitoring students' engagement in large classroom teaching through facial expression recognition," *Expert Systems*, vol. 39, no. 1, p. e12839, 2022. https://doi.org/10.1111/exsy.12839

[51] S. Xu, Q. Tang, L. Jin, and Z. Pan, "A cascade ensemble learning model for human activity recognition with smartphones," *Sensors*, vol. 19, no. 10, p. 2307, 2019. https://doi.org/10.3390/s19102307

[52] H. D. Nguyen, K. P. Tran, X. Zeng, L. Koehl, and G. Tartare, "An improved ensemble machine learning algorithm for wearable sensor data based human activity recognition," in *Reliability and Statistical Computing*, H. Pham, Ed., Cham: Springer, 2020, pp. 207–228. https://doi.org/10.1007/978-3-030-43412-0_13

[53] N. N. Unanyan and A. A. Belov, "Low-price prosthetic hand controlled by EMG signals," *IFAC-PapersOnLine*, vol. 54, no. 13, pp. 299–304, 2021. https://doi.org/10.1016/j.ifacol.2021.10.463

[54] S. F. Yatsun, A. V. Malchikov, and A. N. Rukavitsyn, "Development of a hand prosthesis control system with tactile feedback," *Biomed. Eng.*, vol. 58, pp. 10–13, 2024. https://doi.org/10.1007/s10527-024-10356-5

[55] H. R. Schone *et al.*, "Should bionic limb control mimic the human body? Impact of control strategy on bionic hand skill learning," *bioRxiv, preprint*, 2023. https://doi.org/10.1101/2023.02.07.525548

[56] K. S. Park, "Electrical signals from the muscles and nerves," in *Humans and Electricity*, Cham: Springer, 2023, pp. 199–222. https://doi.org/10.1007/978-3-031-20784-6_9

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