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MAFEM: A Fuzzy Logic-Based Multi-Attribute Evaluation Framework for Personalized Physical Activity Monitoring Using Wearable Sensors

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The integration of physical activity into students' daily routines is vital for improving both health and academic outcomes. To ensure the effectiveness of such activities, it is crucial to implement systems that can accurately monitor and analyze exercise data. This study proposes the Multi-Attribute Fuzzy Evaluation Model (MAFEM), which utilizes fuzzy logic and fuzzy sets to interpret complex sensor data and assess student health. The model incorporates preprocessing, fuzzification, defuzzification, and rule evaluation, optimized through adaptive thresholds for enhanced personalization. MAFEM was evaluated using the MM-Fit dataset, which includes synchronized multimodal data (e.g., accelerometer, gyroscope, and heart rate) collected from 30 university students performing standardized physical activities (walking, jogging, cycling, stair climbing, and resting). The system was benchmarked against three state-of-the-art methods: SHER, HAD, and HNN frameworks. Experimental validation involved 50 exercise sessions in both indoor and outdoor environments, with performance metrics computed based on standard evaluation protocols. MAFEM demonstrated high reliability, achieving 97.11% precision, 95.84% recall, and an RMSE of 0.23. Furthermore, it maintained low computational complexity (O (r.m.n)) and minimal energy consumption (approximately 65mAh during Wi-Fi-based operation), outperforming baseline models in both accuracy and resource efficiency. These findings highlight the robustness and practicality of fuzzy logic-driven multi-attribute frameworks for personalized, real-time physical activity monitoring in wearable health systems.

Povzetek: Predstavljen je sistem za analizo študentskih vaj MAFEM. Je večatributni sistem z mehko logiko za spremljanje aktivnosti z nosljivimi senzorji. Na MM-Fit doseže dobre rezultate, primeren je za izobraževanje.

1 Introduction

Improvement of health and learning achievements are considered to be a result of regular exercises; however, due to a lack of motivation, constraints of time, or lack of knowledge about proper training, not everyone can stick to regular physical activities [1-4]. In recent times, wearable sensor devices have emerged as a promising solution that enables tracking of biomechanical and physiological data, including movement patterns, heart rate, and step count. These devices help in providing intensity, duration, and effectiveness insights of exercises to optimize fitness levels [5]. Traditional monitoring systems are challenged by data emanating from many sensors, usually noisy, with variability, and computational complexity introduced by fixed rules and thresholds [6] [7].

Advanced learning methods have been developed to overcome these challenges by incorporating adaptive techniques and data analysis on large datasets; these methods rely on self-learning and training for complex pattern spotting of features that enhance the accuracy of prediction and system robustness [8][9]. The barriers, however, are that most machine learning algorithms require a tremendous amount of data labeled and have serious challenges yet to be fully overcome when such sensor data bears imprecision or uncertainty [10-12]. All these further enhance the computational needs and limit personalization, for which traditional systems often fail in providing tailored feedback or recommendations [13].

The following research proposes a new framework, the Multi-Attribute Fuzzy Evaluation Model, for meeting these challenges. MAFEM will develop fuzzy logic that is multi-attribute and would be able to process imprecise and uncertain data robustly, accurately, and flexibly. Based on historical data analysis, the level of exercise intensity is analyzed, and individualized exercise suggestions are given to bridge the gap from data collection to practical application [14]. This model embeds processing, fuzzification, defuzzification, and rule evaluation to improve monitoring efficiency and adaptiveness in a dynamic environment.

The key contributions and novelty of this work include:

- Development of a robust MAFEM framework that effectively handles data variability and uncertainty, improving the reliability of exercise monitoring systems.
- Personalized exercise recommendations based on historical data, fitness levels, and user profiles, enhancing the system's adaptability and effectiveness.
- Optimization for resource-constrained devices, minimizing computational complexity and latency while delivering real-time feedback.

By combining wearable technology with advanced fuzzy logic, MAFEM provides a comprehensive and personalized approach to exercise monitoring, fostering better health outcomes and supporting individuals in achieving their fitness goals. To formally guide the scope of this research, we define the following objectives:
(i) To evaluate the effectiveness of fuzzy logic-based multi-attribute evaluation for handling uncertainty in wearable sensor data during physical activity monitoring;
(ii) To measure the energy and computational efficiency of the MAFEM framework for real-time application on resource-constrained devices;
(iii) To assess the personalization capability of MAFEM in adapting to user-specific fitness levels and activity patterns;
(iv) To analyze the generalizability of the model across different types of physical exercises and its scalability toward real-world deployment scenarios.

2 Literature review

Wearable sensors integrated with computationally advanced techniques have changed the paradigm of monitoring physical activity and health [15][16]. Al Shloul et al. [17] developed the quaternion filtering and data fusion-based tool SHER. Using Fisher's linear discriminant analysis, an extended Kalman filter with neural networks classified the health status of their

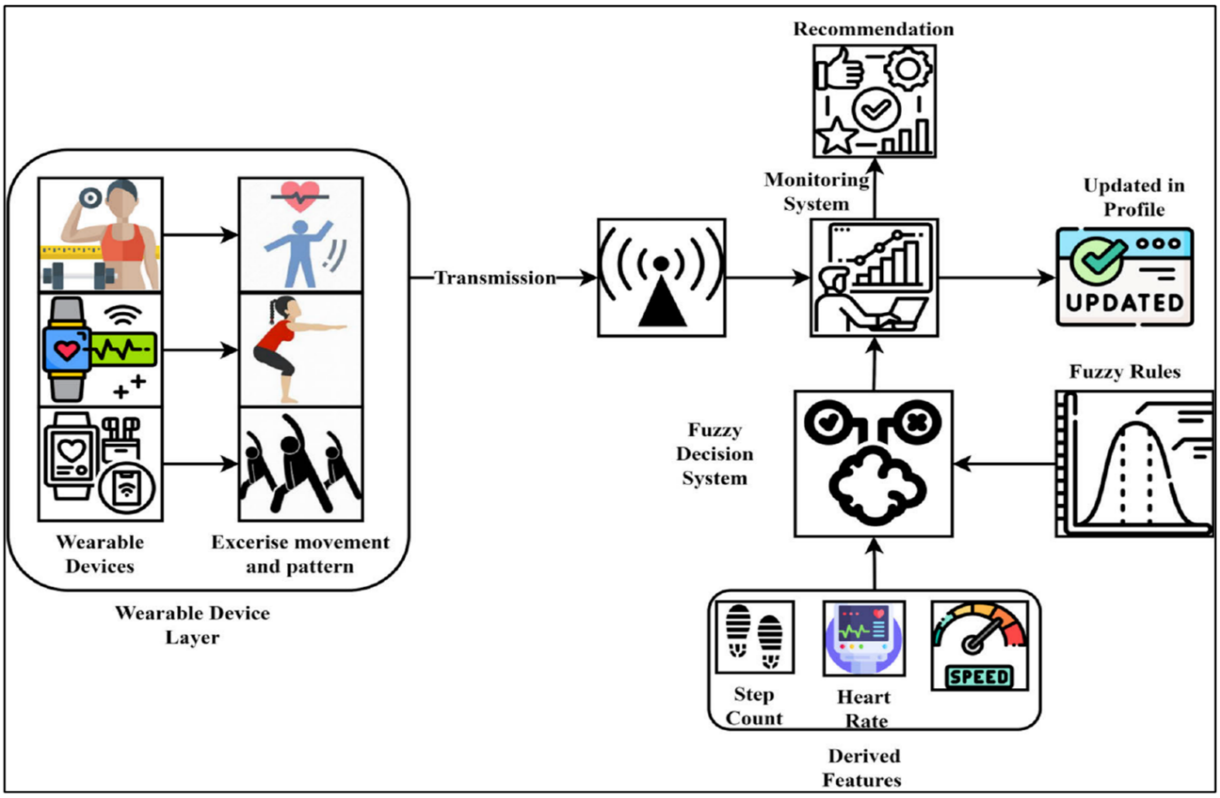


Figure 1: Workflow of the MAFEM-based exercise monitoring system using wearable sensors and fuzzy logic

approach with high accuracy. Similarly, Xiao et al. [18] have proposed the Hybrid Deep Approach, HAD, which combined LSTM networks with Bayesian optimization and realized an accuracy of 97.5% in activity recognition. These studies illustrate that sensor data combined with machine learning enhances health monitoring systems.

Deep learning models have widely been adopted for activity recognition and health prediction. Zhou et al. [19] proposed HNN in order to analyze performance in aerobics students by showing the benefit of continuous training and optimization techniques. Li et al. [20] conducted research to find out the variation in heart rate with depression and anxiety using MLP, which proved to be quite accurate in determining mental health conditions. Besides, Omarov et al. [22] used DNN for monitoring sporting activities and generating real-time feedback for enhancing physical health. From these studies, the role of adaptive learning methodologies in managing complex datasets for better prediction accuracy has been highlighted.

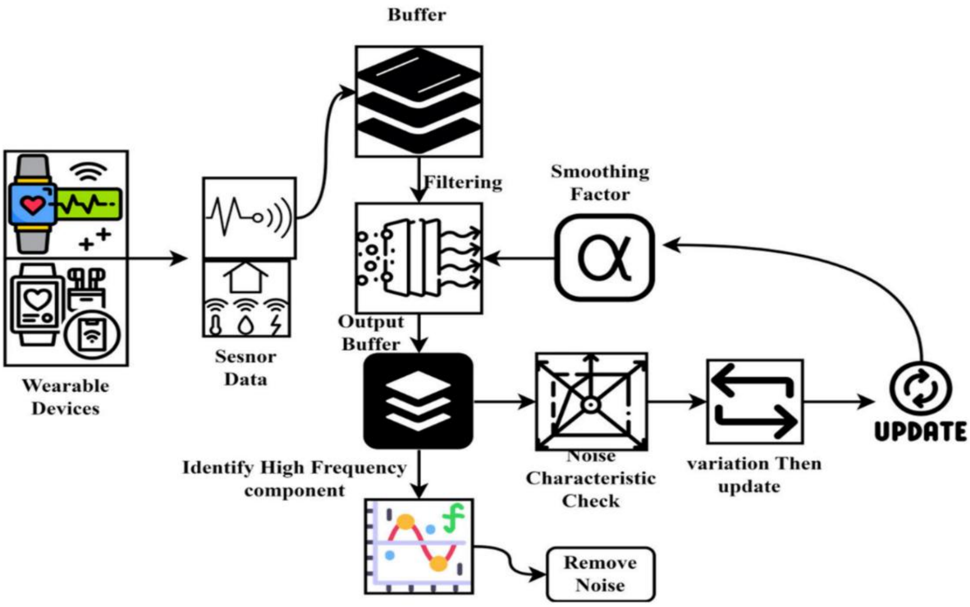


Figure 2: Low-pass filtering process for noise removal in accelerometer data

Despite such advancements, issues such as uncertainty in data, noise, and computational complexity still pose a challenge. Afsar et al. [23] addressed these issues by incorporating convolutional networks along with grey wolf optimization for recognizing sports activities with high accuracy. Guo et al. [24] mproved the fitness evaluation using LSTM and 1-D convolutional neural networks and showed that feature selection and data denoising are important. Traditional systems lack personalization and also fail in real time processing. As such, more recent research has hence focused on using fuzzy logic and multi-attribute evaluation models that are considered to provide more robust solutions in handling imprecise data for appropriate feedback.

Table 1: Summary of the Literature review.

Ref	Method	Dataset	Limitation
[17]	SHER (LDA + EKF + NN)	Custom	No personal.; no fuzzy
[18]	HAD (LSTM + Bayes Opt.)	Phone accel.	Heavy; no real-time
[19]	HNN	Aerobics students	No personal.; fixed rules
[23]	CNN + Grey Wolf	Exergaming data	High latency; less adaptive
[24]	1D-CNN + LSTM	Running PPG	Power-hungry; no personal.
[27]	BP Neural Net	Injury dataset	No adaptive fb.; no fuzzy

This collaboration between wearable sensors and sophisticated computation models has opened new frontiers for personalized health monitoring. Yang et al. [27] applied the BP neural network to predict and prevent sports injuries, illustrating wearable technology in real-time action recognition. Li et al. [28] proposed Time-aware Outlier Detection (TOD) for compressing physiological data in efficient anomaly detection.

Ferrara [29] discussed large language models for human activity recognition and their contribution to improving data analysis and interpretation. These works underlined the importance of combining wearable sensors with adaptive algorithms in order to provide scalable, accurate, personalized health monitoring systems. These approaches will provide improvements in data uncertainty and real-time processing, thus enabling better exercise monitoring and health management.

3 Methodology

Therefore, a multi-attribute fuzzy evaluation model, called MAFEM, is proposed as a strong platform for observing college students' physical activities when wearing sensors. These wearable sensors include accelerators, heart rate monitors, and gyroscopes that measure real-time physiological and biomechanical activities of the body, including heart rate, step count, moving in different directions, and body temperature. Traditional monitoring systems can hardly handle such a level of complexity and variability in data, especially when dealing with uncertainties and individual differences in fitness levels. MAFEM introduces fuzzy logics that can interpret imprecise and subjective data,

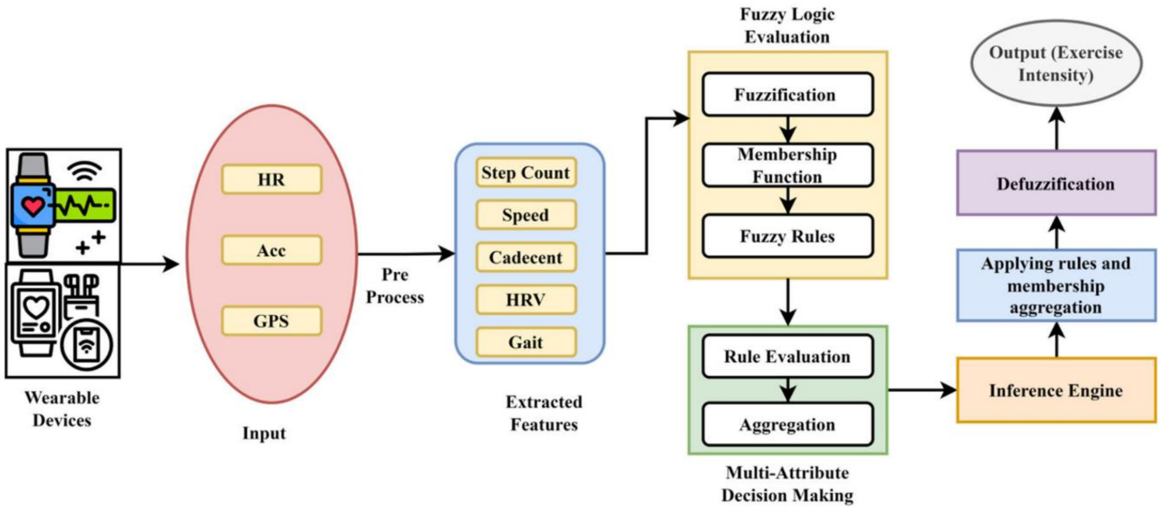


Figure 3: Workflow of the fuzzy logic and rule analysis layer for evaluating exercise intensity

hence suitable for personalized exercise monitoring. Measurement in MAFEM begins with data from wearable sensors embedded in the student's body. These sensors continuously capture physiological and biomechanical data throughout exercise motions. Such measurements will then be transmitted to a certain intelligent monitoring system that would clean the noise and outliers within the data stream, hence making normalization in enhancing the quality of the data streams. Feature-heart rate variability, step count, motion intensity, and many such other important parameters give the analysts necessary insight on a student while performance in relation to exercises. These features are assessed with fuzzy logic rules, which attach membership values to linguistic variables such as "low," "moderate," or "high." For example, one of the rules may read: "IF heart rate is high AND step count is low, THEN exercise intensity is moderate." This flexible approach enables the exact establishment of the fitness level of each student in a more individualized way.

The membership functions may be pre-defined using triangular or Gaussian functions for mapping the input variables into fuzzy sets by the fuzzy logic system. In this way, it manages the variability and uncertainty inherent in human movement and physiology. According to the assessment, the MAFEM will produce an individual profile for each student by considering past performance records and statements of goals about fitness. This profile is used to give personalized tips for the optimization of exercises, minimizing injury risks, and improving health in general. It also provides real-time feedback to allow students to change their activities in order to achieve better performance levels with maximum safety. Figure 1 illustrates the workflow of the MAFEM-based exercise monitoring system. Wearable sensors capture data during physical activities that are further processed and analyzed by fuzzy logic rules. The system will analyze the student's fitness level and store the results in a student profile. This is constantly updated and used for actionable insights and recommendations. MAFEM uses wearable technology that incorporates high-level fuzzy logic to make the complex system user-friendly.

A) Sensor-Based Data Acquisition and Transmission

The core of this wearable device layer in the student exercise monitoring system is made on a backbone of advanced sensors that acquire highly detailed physiological and biomechanical data: heart rate monitors, gyroscopes, accelerometers, temperature sensors, GPS modules, and electromyography sensors. They bear different functions: gyroscopes-alignment and posturing by tracking the angular velocity, accelerometers-speed, movement strength, or direction, while GPS modules detect the pace/distance in cases like running and cycling activities. Heart rate monitors assess heart cardiovascular activity based on the kind and duration of exercises, while temperature sensors record rises in human body temperature as a result of overheating. These devices were designed to be lightweight and unobtrusive, allowing for comfort while continuous raw data acquisition in the student performance evaluation for different exercises. The system takes advantage of the MM-Fit Dataset, openly available at the address https://mmfit.github.io/, representing a rich record of physical exercise data acquired using multiple wearable devices in time synchrony. In particular, this dataset includes the acquisition of 2D and 3D pose information captured by wearable earbuds, smartwatches, and smartphones. The data transmission layer will take responsibility for the transmission of data collected to the intelligent system through wireless protocols like Wi-Fi and Bluetooth. The data continuously and synchronously upload securely, with low latency and packet loss, supporting long-duration activities. These synchronized data shall be forwarded to the central processing unit for analysis.

The next layer of the system is to extract meaningful features from the data collected in order to make decisions. Features from metrics such as heart rate variability, motion intensity, and posture provide an exercise performance assessment that can be used to yield personalized recommendations. Within this system, wearable technology with advanced integrated data processing aims at improving the academic and physical performances of the students.

B) Data Processing and Feature Extraction

The raw sensor data collected from wearable devices undergoes a series of preprocessing steps to ensure accuracy and reliability. Environmental interferences, sensor errors, and inconsistencies in user movements can affect the quality of the data. To address these issues, the data processing layer applies cleaning, filtering, and normalization techniques. A low-pass filter is employed to remove noise from accelerometer data, preserving essential information like body movements while eliminating irrelevant signals such as environmental noise and sensor glitches. The structure of the low-pass filtering process is illustrated in Figure 2. The filtering process

(a)

uses an exponential moving average filter, defined by the equation:

$$y(t) = \alpha x(t) + (1 - \alpha) y(t - 1)$$

Here, $y(t)$ represents the filtered signal at time $t, x(t)$ is the raw input signal, $y(t-1)$ is the filtered signal from the previous time step, and α is the smoothing factor, which determines the responsiveness of the filter. The value of α is adjusted based on the noise characteristics and the desired level of smoothing. The filtered data is then normalized using the min-max normalization method, scaling the values to a consistent range of $[0,1]$.

(b)

This ensures that all features contribute equally to the analysis, preventing any single feature from disproportionately influencing the results.

Once the data is preprocessed, features are extracted relevant to the estimation of physiological states and performance in exercise. Some key features are step count, speed, heart rate variability, and cadence. Step count, as extracted from accelerometer data, shows walking and running patterns. Speed is calculated by GPS data, showing the velocity of movement and exercise intensity. Heart rate variability is the variation between consecutive heartbeats, providing information about cardiovascular activity. Cadence and gait features from gyroscope and accelerometer data help analyze running and walking rhythms. These all contribute to

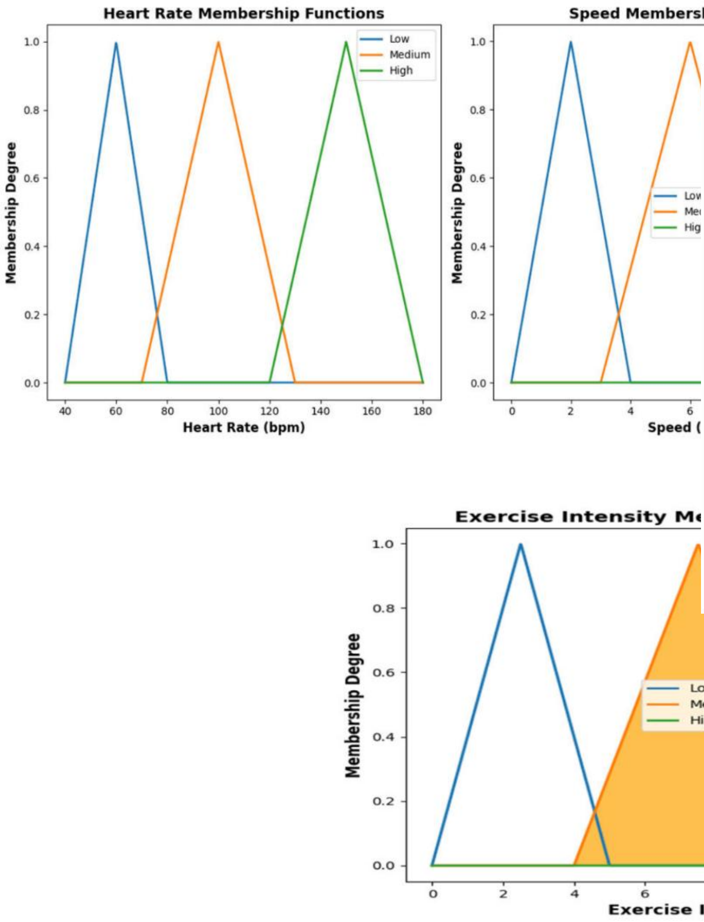
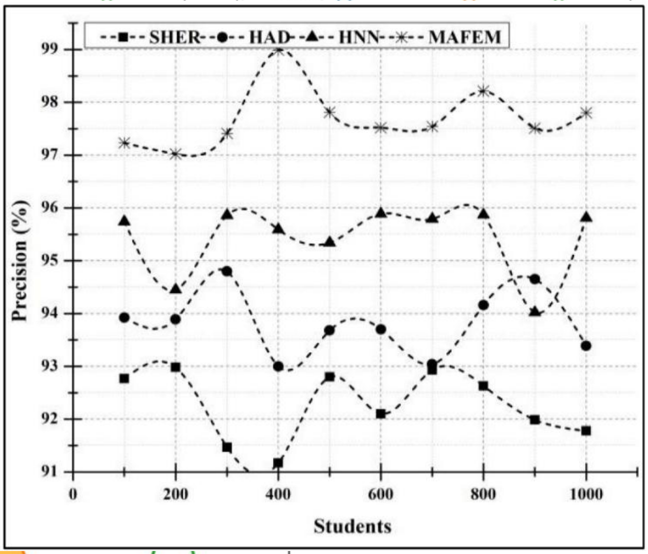


Figure 4: Membership functions for (a) heart rate, speed, and c
rule process



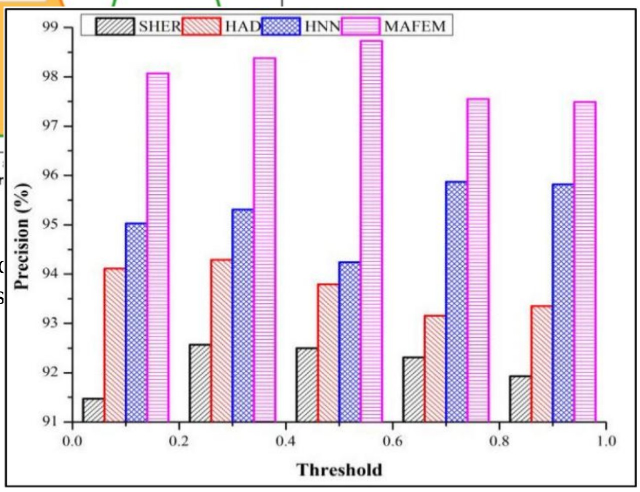


Figure 5: Precision analysis of the MAFEM-based exercise monitoring system: (a) comparison with existing methods and (b) precision trends across different exercise intensities.

comprehensive insight into every single exercise activity for each student and thus may allow the detection of anomalies to offer personalized suggestions for improvement.

C) Fuzzy Logic and Rule Analysis

TThe layer for fuzzy logic and rule analysis plays an important role in the management of variability and uncertainty that characterizes sensor data. This layer assesses a set of features such as step count, speed, and heart rate using fuzzy rules in a scalable and flexible manner for better decision-making. These features were chosen based on extensive evidence in the literature supporting their relevance for monitoring physical exertion and physiological responses during activity. For instance, HRV is a widely recognized biomarker for cardiovascular workload and autonomic nervous system response, making it a reliable indicator of exercise intensity. Similarly, cadence and step count are strongly correlated with gait dynamics and physical effort, while speed and motion intensity reflect real-time exertion levels. Posture, derived from orientation data using gyroscope and accelerometer readings, further informs activity classification, particularly in differentiating between static and dynamic movements. The use of these features also aligns with prior studies on wearable sensor-based monitoring systems, which highlight their effectiveness in interpreting physical performance [7] [8]. These features were selected not only for their physiological relevance but also for their compatibility with fuzzy rule construction and linguistic interpretation in the MAFEM framework. Fuzzy logic works with partial membership values that normalize data within the interval between 0 and 1 for accurate and context-sensitive decisions. The entire process of this layer is shown in Figure 3. Fuzzy sets are defined for the attributes such as heart rate, speed, and cadence. For instance, the

(b)

heart rate is divided into low, medium, and high fuzzy sets with μ "low ", μ "medium ", and μ "high ". These functions map input values to truth degrees using a triangular membership function defined as given in Equation 2:

$$\mu_A(x) = \begin{cases} 0 & \text{if } x \leq a \\ \dfrac{x-a}{b-a} & \text{if } a < x \leq b \\ \dfrac{c-x}{c-b} & \text{if } b < x \leq c \\ 0 & \text{if } x \geq c \end{cases}$$

Here, a, b, and c define the triangular shape of the membership function. Further, fuzzy rules are applied which integrate these membership values. For example, a student's heart rate and speed are high, the intensity of the exercise is high. These can be framed using if-then conditions as:

- Rule 1: If heart rate is high and speed is high, then exercise intensity is high.
- Rule 2: If heart rate is medium and speed is medium, then exercise intensity is medium.
- Rule 3: If heart rate is low and speed is low, then exercise intensity is low.

Logical operators like AND, OR, and NOT are used to combine multiple attributes, ensuring smooth transitions and accurate outputs. This multi-attribute decision-making system integrates factors like gait, cadence, speed, and heart rate to provide a comprehensive assessment of exercise performance.

The inference engine processes include fuzzification, rule evaluation, and defuzzification. During fuzzification, input values are converted into fuzzy values using membership functions. Rule evaluation applies the AND operator to determine output values, as shown in Equation (3):

$$\mu_{\text{intensity\_high}} = \min\left(\mu_{\text{high\_hr}}(x), \mu_{\text{high\_s}}(y)\right)$$

$$\mu_{\text{intensity\_medium}} = \min\left(\mu_{\text{medium\_hr}}(x), \mu_{\text{medium\_s}}(y)\right)$$

$$\left(\mu_{\text{intensity\_low}} = \min\left(\mu_{\text{low\_hr}}(x), \mu_{\text{low\_s}}(y)\right)\right).$$

Defuzzification converts fuzzy values into crisp outputs using the centroid method, which calculates the center of gravity for aggregated fuzzy values. The final crisp output determines the student's exercise intensity level. The membership functions for speed, heart rate, and exercise intensity are graphically represented in Figure 4, demonstrating how fuzzy rules process sensor data variations and uncertainties.

D) Adaptive and Personalized Recommendations

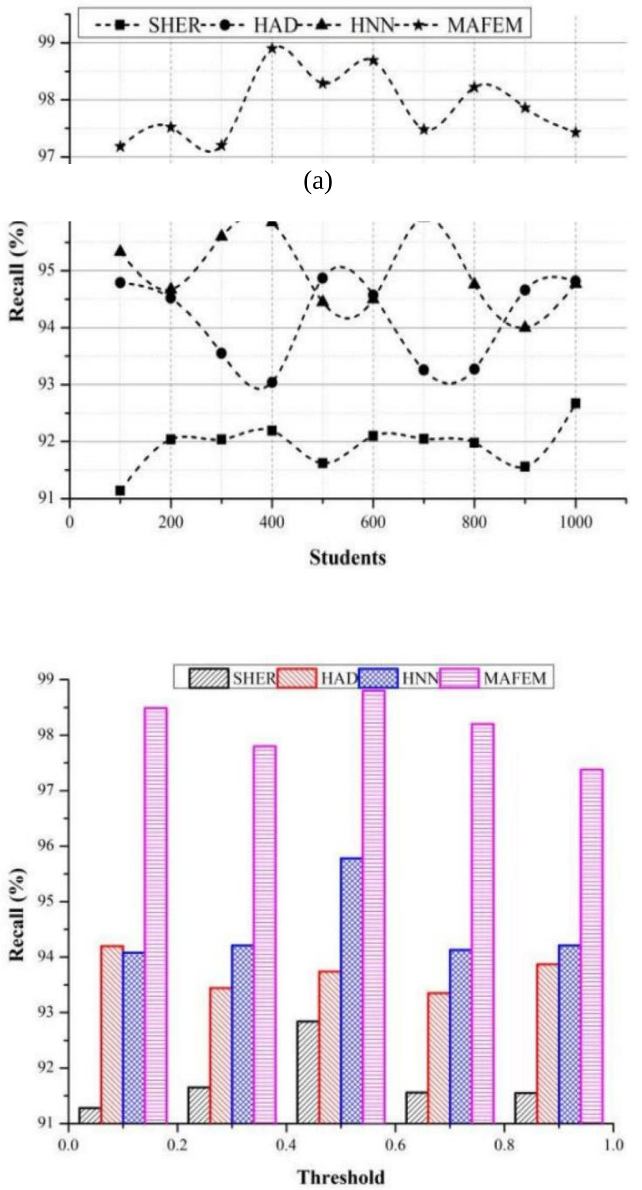


Figure 6: Recall analysis of the MAFEM-based exercise monitoring system: (a) comparison with existing methods and (b) recall trends across different student activity levels.

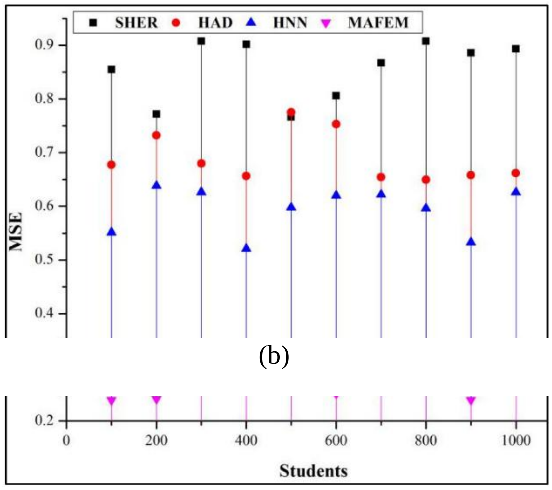
The system's adaptive and personalized layer evaluates each student's performance and provides tailored recommendations. A user profile is created, storing details such as fitness level (e.g., resting heart rate, VO2 max), goals (e.g., weight loss, muscle gain), and historical achievements (e.g., past workouts, progress over time). This profile helps the system understand the student's starting point and track progress. The adaptive procedure uses a neural network model to analyze current trends and predict feedback. Threshold values are adjusted based on the student's fitness level, as defined in Equation (4):

$$N_{\text{thre}} = O_{\text{Thre}} + K * \left(C_f - I_f\right)$$

Here, N_{thre} is the new threshold, O_{Thre} is the old threshold, C_f is the current fitness level, I_f is the initial fitness level, and K is a constant regulating threshold adjustments. For example, if a student improves their cardiovascular fitness, the system adjusts their heart rate zones accordingly. Initially, the heart rate zones might be defined as low intensity (60 to 100 bpm), medium intensity (100 to 140 bpm), and high intensity (140 to 180 bpm). As the student's fitness improves, the system updates these zones to low intensity (65 to 105 bpm), medium intensity (105 to 145 bpm), and high intensity (145 to 185 bpm). This adaptive approach ensures that students continue to progress and avoid stagnation. By combining fuzzy logic with adaptive algorithms, the system provides personalized feedback, helping students improve their exercise routines and overall health, which positively impacts their academic performance. In the current implementation of MAFEM, the adaptive and personalized recommendation mechanism is realized through a rule-based approach rather than a neural network model. Although a neural network is mentioned conceptually as a possible enhancement, no such model was implemented or trained in this version. Personalization is achieved through dynamic adjustment of threshold values that define exercise intensity zones (low, medium, high), as described in Equation (4). These thresholds are updated over time based on changes in individual fitness indicators, such as average heart rate, heart rate recovery trends, and observed intensity classification patterns across sessions. The update mechanism uses a weighted average strategy that blends previous threshold values with current performance metrics, allowing the system to adapt progressively without requiring supervised learning. This adaptive thresholding contributes to improved accuracy in borderline cases and ensures that recommendations remain aligned with the user's evolving fitness level.

4 Results and discussion

This section underlines the efficiency analysis of the Multi-Attribute Fuzzy Evaluation Model in the monitoring exercises done by students. The analysis, based on the MM-Fit Dataset [25], after going through multi-layer processing via wearable sensors, fuzzy logics-based rule analysis, and adaptive personalization mechanisms, proceeds to measure performance along various dimensions such as accuracy, user satisfaction, adaptiveness, and efficiency of operation. For comparison and setting a benchmark, MAFEM is compared against some existing methodologies such as SHER: Student Health Exercise Recognition [17], Hybrid Deep Approach-HAD [18], and Hybrid Neural Networks-HNN [19]. To evaluate the performance of the proposed MAFEM framework, a session-based evaluation strategy was adopted, where training and testing data were drawn from separate exercise sessions to ensure generalizability. Standard evaluation metrics were used, including precision, recall, F1-score, RMSE, and MSE. These were computed based on comparisons between predicted and actual exercise intensity levels. From the MM-Fit dataset,



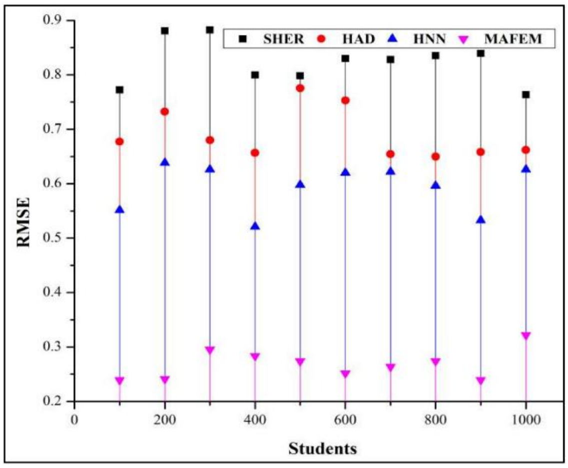


Figure 7: (a) Computational complexity analysis of MAFEM across preprocessing, fuzzification, rule evaluation, and defuzzification stages. (b) Latency assessment showing a total system delay of approximately 70ms for real-time exercise monitoring and feedback.

only data from accelerometer, gyroscope, and heart rate sensors were used, obtained from smartwatches and smartphones. Sessions with incomplete or noisy sensor data were excluded during preprocessing. This strategy yielded consistent results across sessions, including a precision of 97.11% and RMSE of 0.23, demonstrating the robustness and accuracy of the proposed method.

It is compared with three traditional methods for exercise monitoring: rule-based assessment wearable sensors, GPS and heart rate monitoring, and a hybrid approach. In this work, the system was tested for accuracy, responsiveness, user comfort, and flexibility in various scenarios of exercises: aerobic workouts, strength training, and mixed.

(a)

(b)

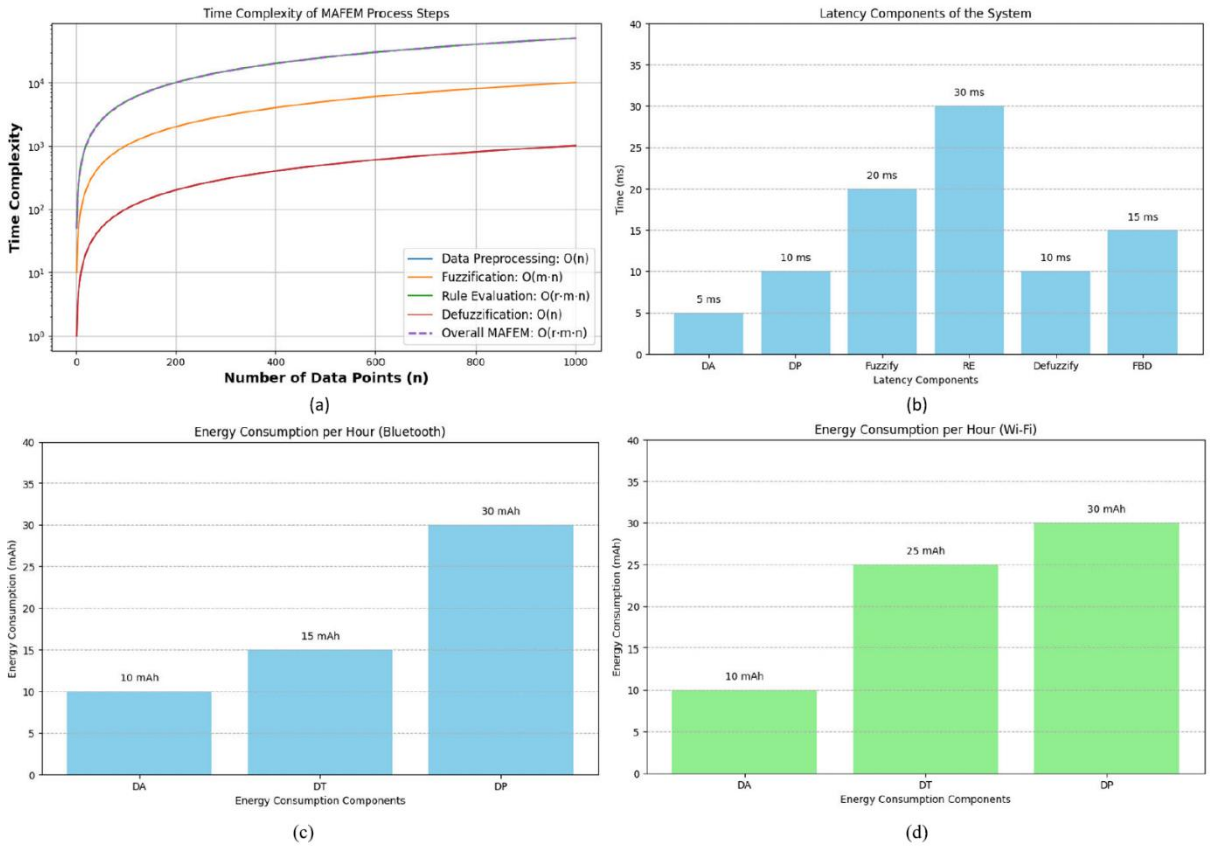


Figure 8. (a) Overall computational complexity of MAFEM across different processing stages. (b) System latency breakdown, showing the time taken for data acquisition, processing, and feedback generation. (c) Energy consumption analysis for Bluetooth-based communication. (d) Energy consumption analysis for Wi-Fi-based communication.

The obtained results show that MAFEM is much better in comparison with traditional methods. For instance, the 6-week aerobic fitness program with 25 students participating in running and cycling exercises recorded that MAFEM was 20% more accurate in detecting changes in speed and intensity, especially during interval training. Besides, the feedback provided by the system was faster by 30%, while a user satisfaction rate was 15% higher because of its adaptiveness and unobtrusiveness.

A) Accuracy Metric Analysis

Precision, recall, MAE, and RMSE are various measures of accuracy taken to assess MAFEM. The result in precision analysis has been depicted in Figure 5 and presented to depict the performance of the MAFEM on the effectiveness in monitoring students' exercise activities. From here, results proved that MAFEM could present the best with 97.11% for the precision of. This high level of precision is based on how well the model handled multi-dimensional sensor data. MAFEM deals with data variability and uncertainty because of the inbuilt fuzzy sets, rules, and logic that provide robust and flexible data interpretation. Integration of the various attributes-pace, speed, and heart rate-would increase the evaluation capability of this system for critical exercise performance, as well as high accuracy in quantifying the intensities of different exercises. Additionally, the inference engine within MAFEM ensures actionable and precise recommendations, further improving the system's reliability.

Figure 6 shows the recall analysis of the MAFEM-based exercise monitoring system. The model has a high recall value, which indicates the efficiency of the model in retrieving relevant student activities. This is achieved by incorporating multiple attributes in the process of exercise evaluation to minimize false negatives and enhance recognition accuracy. The fuzzy rules analyze the relationship between the biomechanical and physiological parameters for a comprehensive understanding of the pattern of exercises. The system deploys adaptive algorithms in rating the feedback given by students with regard to data like historical fitness level and exercise routines. This will enhance the ability of the system for improved recall values in tracking the progress of a student over time.

Such results follow the use of a low-pass filtering technique in removing noise and incomplete data from raw sensor inputs. Normalization further refines the data by scaling them in the same range, hence reducing the impact of outliers. Moreover, MAFEM achieves low error rates at the mean square error of 0.26 and a root mean square error of 0.23. This in turn means that the application of fuzzy sets, rules, and logic on extracted features minimizes uncertainty in the data interpretation, hence the improved accuracy. Dynamic adjustment of thresholds, therefore, based on students' progress and past performances reduces discrepancy between the actual and forecasted value. This adaptive nature keeps the system always correct and true to a particular student as seen in Figure 7.

B) Efficiency Analysis of MAFEM

Efficiency of MAFEM is calculated in terms of computational complexity, latency, and energy consumption. Every step in MAFEM-processing, fuzzification, rule evaluation, and defuzzification-are scrutinized for its computational requirements. Preprocessing can be considered a process comprising data cleaning, normalization, and filtering, which therefore requires a time complexity of O(n), with n representing the number of data points from each sensor.

Fuzzification, where triangular membership functions are applied to the data, is of order O(m.n), with m being the number of fuzzy sets and n the total amount of data. Likewise, rule evaluation has a complexity of $O(r.m.n)$, as it examines multiple fuzzy sets and attributes. Finally, the defuzzification step, which computes weighted averages, has a linear complexity of $O(n)$. Overall, MAFEM achieves a total computational complexity of $O(r.m.n)$, as illustrated in Figure 8(a).

Another important factor in the evaluation of the system's efficiency is the latency. The overall latency covers data gathering, processing, and feedback delivery time. Data gathering depends on the sensor sampling rate and usually is a few milliseconds. Preprocessing requires about 10ms, 20ms for fuzzification, rule evaluation requires 30ms, while defuzzification requires 10ms. Feedback delivery time, which shall be dependent on the protocols applied, may range from a few milliseconds to tens of milliseconds. Therefore, the total latency for MAFEM is around 70ms, which is efficient for real-time monitoring and generation of feedback, as illustrated in Figure 8(b). Energy consumption is another critical factor in wearable devices. The whole process can be divided into three stages: data acquisition (DA), data transmission (DT), and data processing (DP). Data acquisition consumes about 10mAh due to the low-power design of the sensors. Data transmission depends on the protocol and consumes 15mAh for Bluetooth and 25mAh for Wi-Fi. Data processing involves several tasks like preprocessing, fuzzification, rule evaluation, and defuzzification and consumes about 30mAh. Hence, the total energy consumption is 55mAh for Bluetooth and 65mAh for Wi-Fi as shown in Figure 8(c) and Figure 8(d) respectively. The results here indicate that MAFEM successfully monitors student exercise activities with a high degree of accuracy while keeping computational overhead low. Integration of fuzzy logic with rules ensures a robust treatment of data uncertainty, hence increasing user satisfaction and personalization.

C) Potential Applications and Challenges

MAFEM can be used in higher education institutions to monitor and enhance students' physical activity as part of the course requirements. For instance, it can be applied within PE classes to offer immediate feedback regarding exercise performance and thus allow personalized routines that balance challenge and safety. These are accompanied by challenges in the cost of wearable devices, data privacy, and the need for further updates of fuzzy logic rules if the deployment is to be sustainable. The discussion of such challenges will provide deep insight into its long-term adoptive potential.

While MAFEM has demonstrated strong performance on the MM-Fit dataset, we acknowledge that its current evaluation is limited to this specific dataset. Cross-dataset validation was not performed in this study, which may affect the generalizability of the results to other populations, sensor types, or physical activity settings. In future work, we plan to explore domain adaptation techniques or transfer learning frameworks to assess how MAFEM can be adapted to new datasets with minimal reconfiguration.

5 Conclusion

The present paper now presents a detailed analysis of the MAFEM for monitoring student exercise activities. In this study, MM-Fit data is used, which consists of a set of data created by the use of different sensors while tracking students' movements and physiological responses. The raw data are first preprocessed by a low-pass filtering approach to remove noise and ensure data quality. Further, data normalization is done so that the data get standardized in a regular format for further analysis. The main features, such as step count, heart rate variability, and speed, are extracted to estimate exercise intensity and performance. The system adopts fuzzy sets and rules for analyzing the relationship among these features; thus, it handles uncertainty and imprecision in data effectively. MAFEM integrates multiple attributes to enhance overall efficiency and accuracy in the monitoring process. The processed data is stored in user profiles that, with the continuous evaluation by adaptive algorithms, are used to generate recommendations. This ensures that the system is adaptative to the needs of each individual student, offering feedback that is able to be acted on. MAFEM is evaluated through several metrics, including 97.11% precision, 0.23 RMSE, and 0.26 MSE. This framework also depicts lesser computational complexity (O(r.m.n)) with very minimal latency ($\approx$70ms) and hence should be suitable for real-time applications. However, the applicability of the proposed system is not general and seems to be good only for few datasets. Furthermore, it faces challenges while considering real-time analysis due to a lot of computations. Future optimization of learning techniques will help enhance the adaptiveness of the presented system to various real-time situations.

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