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Comparative Analysis of Hybrid Intelligent Algorithms for Microsleep Detection and Prevention

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Abstract

Microsleep is a critical factor contributing to traffic accidents, posing significant risks to road safety. Research by the AAA Foundation for Traffic Safety found that 328,000 sleep-related driving accidents happen annually in the United States, underscoring the widespread and dangerous nature of drowsy driving. These incidents often occur without warning, making them especially hazardous and difficult to prevent through conventional means alone. This research aims to improve the accuracy of microsleep detection by developing a hybrid intelligent algorithms. It compares three intelligent algorithms: Fuzzy Logic (FL), representing scheme A; Fuzzy Logic combined with Artificial Neural Networks (FL-ANN), representing scheme B; and a combination of Fuzzy Logic, ANN, and Decision Trees (FL-ANN-DT), representing scheme C. These methods were evaluated using performance metrics such as MSE, MAE, RMSE, R^2, and response time. The results indicate that Scheme C (FL-ANN-DT) significantly outperforms the other approaches, achieving an MSE of 5.3617e-32, MAE of 4.3823e-17, R^2 of 1.0, and an RMSE close to zero, demonstrating near-perfect accuracy. Compared to previous models, this hybrid approach enhances prediction precision while maintaining real-time feasibility. The findings highlight the potential of FL-ANN-DT as an advanced microsleep detection system, contributing to improved road safety and real-time monitoring applications. This system can serve as a proactive safety layer in driver assistance technologies, reducing the risk of fatigue-related accidents and potentially saving lives.

Keywords : *ANN, Decision Tree, Fuzzy Logic, Intelligent Algorithms, Microsleep.*

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1. INTRODUCTION

Microsleep is a significant issue for road safety and a contributing element to the high number of traffic accidents happening worldwide. The World Health Organization (WHO) estimates that 1.19 million people die in traffic accidents annually [1]. One of the causes of accidents is being drowsy, worn out, ill, or unconscious [2]. Research by the AAA Foundation for Traffic Safety found that 328,000 sleep-related driving accidents happen annually in the United States [3]. A 2019 sociological study with 2,000 individuals about the experience of tired driving supports these statistical findings. According to the report, 27.3% of respondents drove when sleepy [4].

Operationally, microsleeps were defined as flat/incoherent tracking of 0.5–15 s (almost entirely flat during at least part of the event), complete or partial phasic eye closure (except for blinks), and clear behavioral indicators of drowsiness/sleepiness. If the duration of the event exceeds 15 s, it is classified as a sleep episode [5], where a person unconsciously enters a state of unawareness and does not respond to sensory stimuli. It has occurred because monotonous activities such as staring at a blank screen or driving a car may cause microsleep [6]. In a recent study by Fatmawati et al. (2022), which is also appropriate to a study by Waldeck MR and Lambert MI, microsleep occurs when there is a decrease of 8 beats per minute (BPM) [7].

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Tracking and alerting people before microsleep is necessary to prevent it in hazardous situations. Various methods and techniques can detect and prevent microsleep. The use of intelligent algorithms has become one of the solutions [8]. Intelligent algorithms are computing techniques replicating human cognitive processes, including reasoning, engagement, deep learning, adaptation, and sensory perception [9].

Various studies have implemented intelligent algorithms to detect and prevent microsleep. The study conducted by S. H. Zaleha et al. (2021) reviewed the integration of the Internet of Things (IoT) and artificial intelligence (AI) in microsleep detection systems [10]. Furthermore, research by Ani Dijah Rahajoe et al. (2023) implemented a real-time drowsiness detection system using facial features such as Mouth Aspect Ratio (MAR) and Eye Aspect Ratio (EAR). Their study compared Decision Tree and Random Forest algorithms, showing that Random Forest outperformed Decision Tree with an average accuracy of 65% and a peak performance of 82% when K-fold = 2 [11]. In addition [6], Another study conducted by Dubey et al. (2023) proposed a method to prevent accidents caused by microsleep in innovative vehicles through the integration of image processing and artificial intelligence, enabling visual identification of drowsiness signs [12]. Furthermore, a study by Sinha et al. (2023) applied a CNN-based method for driver drowsiness detection using physiological sensors, achieving a testing accuracy of 84.27% [13]. Although many studies have developed microsleep detection methods, there are still challenges in improving the system's accuracy, reliability, and responsiveness. Previous studies have shown varying accuracy but are still not optimal for practical implementation. However, no study has evaluated a hybrid model such as FL-ANN-DT for microsleep detection with detailed error metrics. The models aim to improve the performance of microsleep detection more accurately and responsively. Unlike previous studies, this research introduces heart rate (BPM) as the primary input for detection, which provides a physiological basis for identifying microsleep more effectively and has not been extensively explored in earlier works.

Despite advances in microsleep detection and prevention, real-time implementation remains challenging due to the trade-off between accuracy and response time. Existing systems rely on computationally intensive methods, which result in delays in detecting microsleep episodes. In addition, many factors, including variations in individual physiological responses, environmental conditions, and sensor limitations, can affect detection reliability. Addressing these challenges requires approaches that improve prediction accuracy and ensure fast and stable responses for real-world applications to implementation for microsleep detection and prevention. Therefore, optimized hybrid algorithms that balance computational efficiency and detection precision are essential for improving microsleep prevention systems.

This study conduct a comparative analysis of these three intelligent algorithms to determine the most effective approach for improving the accuracy and reliability of microsleep detection systems. Three intelligent algorithms consisting of Fuzzy Logic (FL), Fuzzy Logic combined with Artificial Neural Networks (FL-ANN), and a combination of Fuzzy Logic, ANN, and Decision Trees (FL-ANN-DT) will be evaluated. The comparison will focus on Mean Squared Error (MSE), Mean Absolute Error (MAE), R^2 (Coefficient of Determination), Root Mean Squared Error (RMSE), and response time metrics. Based on these metrics, the best-performing model will be identified. This comparative analysis is essential to address the research gap in existing microsleep detection approaches and provide an optimized, accurate, and computationally efficient solution for real-time implementation, enhancing safety in critical applications.

2. METHOD

This research aims to evaluate and compare the performance of three Intelligence Alghorithms-based methods for microsleep detection and prevention. Each method is systematically implemented

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and analyzed to determine its accuracy, adaptability, and reliability in real-world scenarios. This research highlights the strengths and limitations of each approach and provides insights into optimizing microsleep detection systems. The methodology workflow is illustrated in Figure 1, showcasing the sequential implementation of these approaches for comparative analysis.

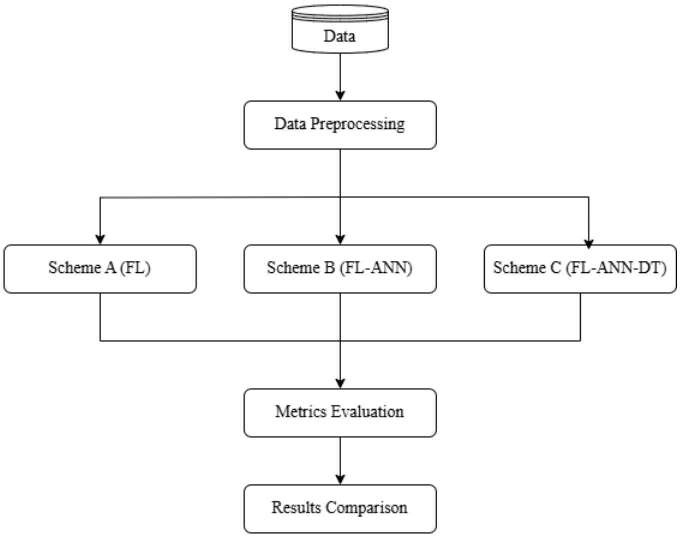

Figure 1. Workflow Model

As shown in Figure 1, the Workflow Model System consists of the following stages:

- Data Input:

The research phase began with an extensive data collection process from the Harvard-MIT Health Science and Technology Division, sourced from Kaggle. These data points primarily capture Beats Per Minute (BPM), a key physiological signal for detecting early signs of microsleep. This dataset will be the primary input for testing and validating the proposed method, ensuring its reliability and effectiveness in real-world applications [14]. Furthermore, min-max normalization was applied to scale BPM values into a 0–1 range, ensuring numerical stability and consistent performance for models such as Artificial Neural Networks (ANN) and Decision Trees (DT), which are sensitive to feature scale variations. To support the fuzzy logic component of the model, the minimum and maximum BPM values from the normalized dataset were also used to define fuzzy membership functions.

- Intelligent Algorithms Testing:

The intelligent algorithms testing were implemented using Python version 3.11, leveraging Scikit-learn library for Fuzzy Logic, ANN, and Decision Tree construction and evaluation. Intelligent algorithms testing will be carried out using three schemes as follows:

1) Scheme A: The first method involves Fuzzy Logic (FL) as a non-linear optimization method to manage uncertainty in decision-making. FL is highly efficient in representing complex, imprecise, and uncertain systems, making it well-suited for applications that demand adaptive control. This method is particularly advantageous because Fuzzy Logic is the only algorithm capable of executing commands solely based on input data—in this case, BPM (beats per minute)—without requiring an explicit mathematical model.
2) Scheme B: The second method integrates Artificial Neural Networks with Fuzzy Logic (FL-ANN) to enhance its capabilities, creating a hybrid approach. ANN eliminates the need for precise mathematical modeling and leverages its learning ability to improve system performance.
3) Scheme C: In the third method, a Decision Tree is added to the hybrid system to further refine the classification and decision-making process. Combining the strengths of Fuzzy Logic, ANN, and

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Decision Tree methods (FL-ANN-DT), the proposed framework seeks to identify the most effective solution for detecting microsleep events.

- Metrics Evaluation:

  Each scheme is tested and evaluated based on several metrics, including:

1) Mean Squared Error (MSE) is used to penalize larger errors more heavily, making it effective for highlighting significant deviations between predicted and actual BPM values lower MSE values indicate improved alignment. A smaller value of MSE reflecting better algorithm performance because the predictions align more with the actual values [15]
2) Mean Absolute Error (MAE) metric that measures the average absolute error between predicted and actual values, where smaller values indicate higher accuracy as predictions are closer to the actual data [16]
3) R^2 (Coefficient of Determination) metric that measures how well a model explains the variability of actual data about its predictions, with values close to 1 indicating a highly accurate model; the nearly perfect predictive ability suggests that the system can accurately identify BPM patterns indicative of microsleep [17]
4) Root Mean Squared Error (RMSE) as the square root of MSE, retains the error units and offers an intuitive sense of the model's average prediction deviation, where smaller values denote better performance. RMSE measures the square root of the average squared differences between predicted and actual values, with lower values indicating a more accurate model [18]
5) Time Response refers to how the output of a system reacts over time when subjected to a specific input or disturbance. It is crucial to evaluate the system's performance in transient and steady-state conditions.

This metric evaluation was used to test the performance of the algorithm model in predicting patterns by the findings of K. Zou et al., which indicated that vibrations with a frequency of 12–50 Hz could increase the level of alertness [19]. Then the research results of Zhang et al. strengthened these findings by stating that low-frequency vibrations had a more negative impact than high-frequency vibrations because they accelerated the appearance of drowsiness and significantly slowed down reaction time [20].

- Result Comparison and Best Method Selection:

The final step is to compare the results of the three methods based on the calculated metrics. This comparison comprehensively evaluates each method's accuracy, reliability, and adaptability in detecting microsleep. The most optimal method for microsleep detection is identified by analyzing these performance indicators, ensuring a balance between precision, computational efficiency, and real-time applicability. The selected method will be the foundation for further system enhancements and practical implementation in real-world scenarios.

3. DESIGN OF THE SYSTEMS

3.1. Fuzzy Logic (FL)

A symbolic logical way of thinking, the Fuzzy Logic (FL) establishes a grey area between the ideal values of zero and one, where a logical assertion of nonzero is nevertheless viable [21]. Fuzzy logic control methods depend highly on the rules or rule bases to be applied. Therefore, creating a rule base is very important, so data is needed to ensure the rule base is accurate [18]. Fuzzy logic controllers can handle incomplete or imprecise data, making them ideal for systems that are difficult to model or operate under varying conditions, such as in this study, where only BPM input is available. They are also effective in scenarios involving multiple inputs and outputs, such as complex machines that require

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precise adjustments for optimal performance. The controller makes decisions based on pre-defined rules for the inputs received [23]. In this case, the pre-defined rules are controls for any decrease in BPM.

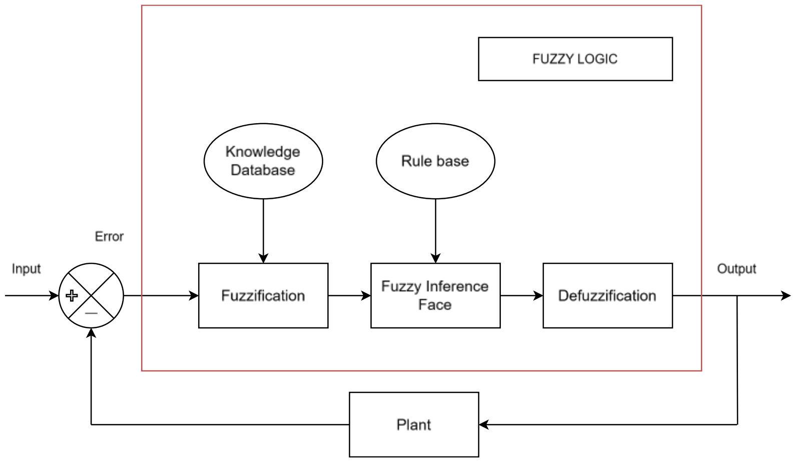
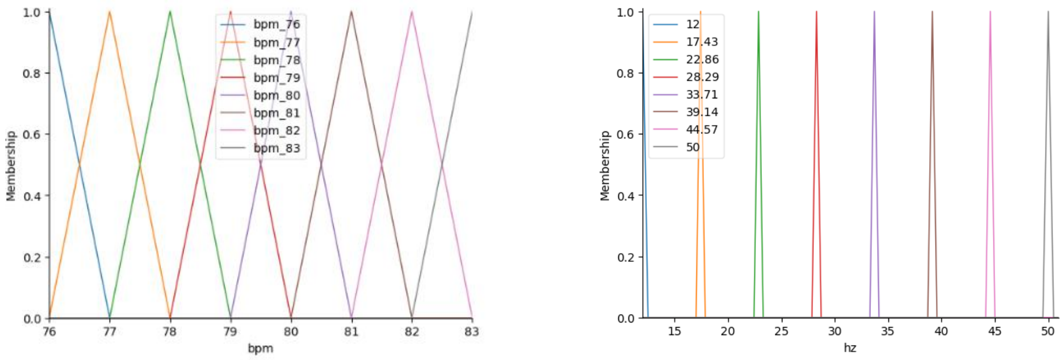


Figure 2. Fuzzy Interference System

The fuzzy interference system consists of 4 steps, as shown in Figures 2. It comprises: (1) Fuzzification of input variables, (2) Rule Evaluation, (3) Aggregation of Rule Outputs, and (4) Defuzzification. The rule-based system explains how to respond to incoming signals and reflects information from the outside world [24]. Specifically, the controller design suggests Mamdani-type rules as they provide a natural framework for incorporating expert knowledge; rules comprise a succession of basic IF THEN statements [25].

Table 1. Fuzzy Logic Rule Base for The System

BPM (Input)	**Frequency (Output)**
76	50
77	44,57
78	39,14
79	33,71
80	28,29
81	22,86
82	17,43
83	12



(a) (b)

Figure 3. Membership Function
(a) BPM (b) Frequency

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The basic fuzzy logic rule that maps the BPM (Beats Per Minute) value as input to frequency (Hz) as output is obtained by entering the data contained in table 1. The results of the BPM to frequency mapping are shown in Figure 3, which illustrates the membership function.

3.2. Artificial Neural Network (ANN)

Artificial neural networks are among the most effective machine learning models for recognizing patterns in data. Therefore, in this study, ANN is utilized to enhance the performance of fuzzy logic when dealing with unseen data [26]. The structure of ANN, used in this work is shown in figure 4.

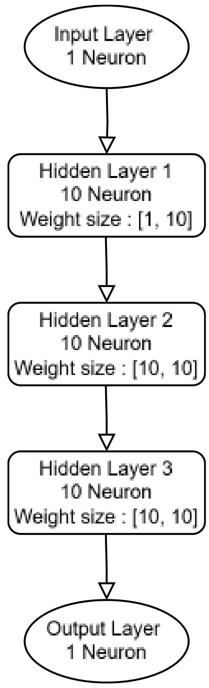

Figure 4. ANN Structure

ANN work by mimicking the structure of the human brain, where interconnected neurons process information through weighted connections. The input layer gathers raw data, which is then analyzed by one or more hidden layers that utilize activation functions to identify significant features and recognize intricate patterns. The output layer generates predictions, while the network is refined through backpropagation and gradient descent to reduce errors. ANN serves as a relationship model between input and output data [27], making it ideal for predicting motor speeds based on BPM values. Its ability to learn patterns from data, handle uncertainty, and integrate with fuzzy logic improves accuracy and interpretability [28]. Each parameter in this model, including the input layer, hidden layer, and output layer, is determined based on the configurations listed in Table 2.

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Table 2. ANN Parameters for The System

Parameters	Value
Input Layer	1 Node
Hidden Layers	3 Layer, 10 Nodes
Activation Function	ReLu
Learning Rate	0.001
Optimizer	Adam
Loss Function	Mean Squared Error

The table contains the parameters used in the ANN for the developed system. This ANN has one node in the input layer, which means there is only one input feature in the system. The hidden layer has three layers, each consisting of 10 nodes. The activation function used is ReLU (Rectified Linear Unit), which is a rule because it can overcome the vanishing gradient problem and accelerate convergence in deep learning networks. The learning rate used is 0.001, which controls how much the weights are better in each training iteration. The optimizer applied is Adam (Adaptive Moment Estimation), an optimization algorithm combining RMSProp and Momentum's advantages to improve training efficiency. Meanwhile, the loss function used is Mean Squared Error (MSE), which is suitable for regression tasks because it measures how far the ANN prediction is from the actual value.

3.3. Decision Tree (DT)

Decision Trees (DT) improve ANN output by capturing decision patterns and correcting the mismatch of motor speed values with the rules set in the fuzzy system. A decision tree is a widely used tool for both classification and prediction [29]. With a simple and computationally efficient structure, the DT can identify decision boundaries and necessary adjustments, thereby increasing the accuracy of motor speed prediction.

The Decision plays a role in refining the mapping between the ANN-predicted motor speeds and the corresponding fuzzy motor speed levels because of its ability to capture decision boundaries and handle non-linear corrections effectively. It provides a simple, interpretable structure that identifies patterns or adjustments in the ANN's output, ensuring more accurate alignment with the desired fuzzy logic (FL) outputs. Previous studies indicate that decision trees are the most computationally efficient method, making them ideal for producing fast and interpretable results [30]. Table 3 shows the parameters used in the DT for the system under test. The model has one input and output, with the target being a continuous value. The Random state is set to 42 for consistent results, using the Squared Error criterion for separation evaluation, and is limited to 33 leaf nodes.

Table 3. Decision Tree Parameters for The System

Parameters	Value
Input	1
Target	Continuous Value
Random State	42
Criterion	Squared Error
Leaf Nodes	33
Output	1

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4. RESULT AND DISCUSSION

This study implements various intelligent algorithms that will be used to detect and prevent microsleep by improving the accuracy, reliability, and responsiveness of the system. This study was conducted on a benchmark dataset; real-world testing is needed to validate model robustness under sensor noise and variable conditions. Scheme A employs Fuzzy Logic (FL) as a non-linear optimizer, consisting of membership functions, rule-based inference, and defuzzification. It efficiently manages uncertainties but requires expert tuning. Scheme B integrates Artificial Neural Networks (ANN) with FL (FL-ANN). It combined an ANN model, fuzzy inference, and adaptive tuning to improve performance without precise mathematical modeling. Meanwhile, scheme C extends the previous method by adding a Decision Tree (DT) into the FL-ANN framework (FL-ANN-DT), which includes decision nodes, classification branches, and final decision leaf nodes for better-structured learning. By leveraging FL for uncertainty handling, ANN for adaptive learning, and DT for structured decision-making, this study identifies the most effective method for microsleep detection. Figure 5 - Figure 8 are the test results of each metric used in this study.

The results obtained show that scheme A has good performance with an MSE value of 0.0004631, as shown in Figure 5,which presents the MSE comparison. Indicating high prediction accuracy. Scheme B produces an MSE of 0.0087618, which is higher than scheme A, possibly due to the need for further tuning of the ANN parameters. Meanwhile, the scheme C approach produces the best results with an MSE close to zero (5.3617e-32), indicating a nearly perfect prediction without any indication of overfitting. In a different study conducted by Adam et al., who also conducted an MSE test the MSE value obtained was 0.069 and was considered very good; [31]. Therefore, when compared to that study, these results indicate that scheme C is the most accurate choice. In general, the MSE value is considered good if it is getting closer to 0.

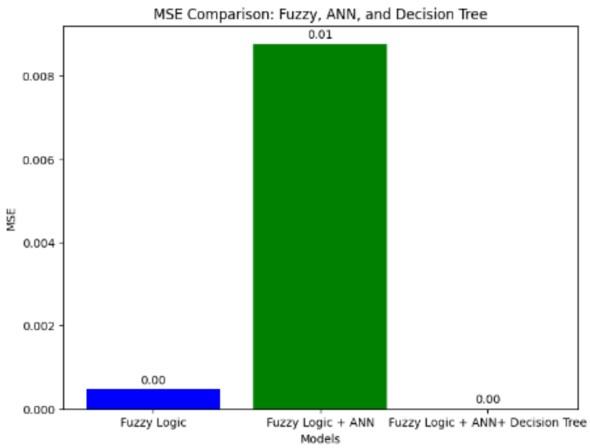

Figure 5. MSE Comparison

For MAE comparison, the result of scheme A achieves good accuracy with an MAE of 0.0028, as shown in Figure 6, which presents the MAE comparison. It indicates a prediction quite close to the actual value. A higher MAE of 0.0166 is provided in scheme B which means the ANN model needs improvement to improve its accuracy. The study conducted by Adam et al. produced an MAE value of 0.004 and was considered very good [31]. Meanwhile, the results show that scheme C is the best choice because it produces the best results with an MAE close to zero (4.3823e-17), in addition to showing very accurate predictions with minimal errors. Thus, Scheme C is the most effective method in terms of prediction accuracy.

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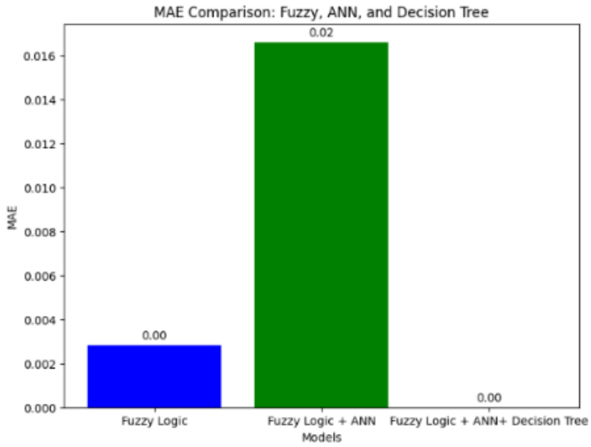

Figure 6. MAE Comparison

The R^2 metric results are shown in Figure 7, which presents the R^2 comparison. Scheme A achieved an R^2 value of 0.9999766, indicating that the model explains almost all data variability effectively. Scheme B produces an R^2 of 0.9995575, slightly lower, but still shows excellent ability to explain the data. Meanwhile, scheme C gives the best results with a perfect R^2 of 1.0, indicating that the model is able to explain 100% of data variability and produce very accurate predictions. For comparison, research conducted by Resti et al. obtained an R^2 value of 0.99, which has been considered very good [32]. Therefore, the results of scheme C are also included in the very good category because they achieve an R^2 value of 1.0.

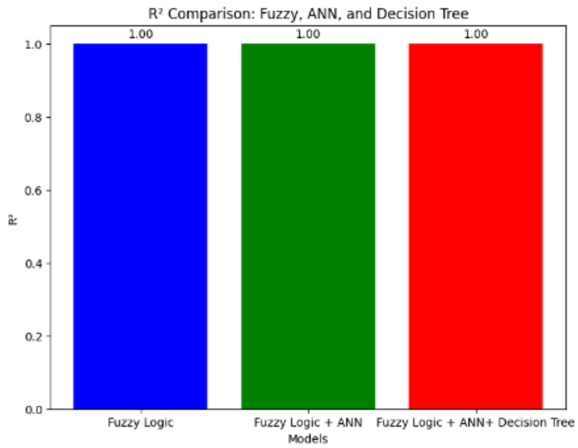

Figure 7. R^2 Comparison

The RMSE evaluation results are shown in Figure 8, which presents the RMSE comparison. Scheme A has an RMSE value of 0.0215, indicating a relatively low prediction error. Scheme B has a higher RMSE of 0.0936, indicating a slight increase in prediction errors rate compared to scheme A. Meanwhile, scheme C gives the best results with an RMSE close to zero (2.3155e-16), indicating that this model has a very minimal error rate and high prediction accuracy. In research conducted by Fuadi A et al., the RMSE value obtained was 0.37 and was considered good [33]. Therefore, the RMSE value in this study can also be categorized as good, the accuracy of all tends to be close to 0.

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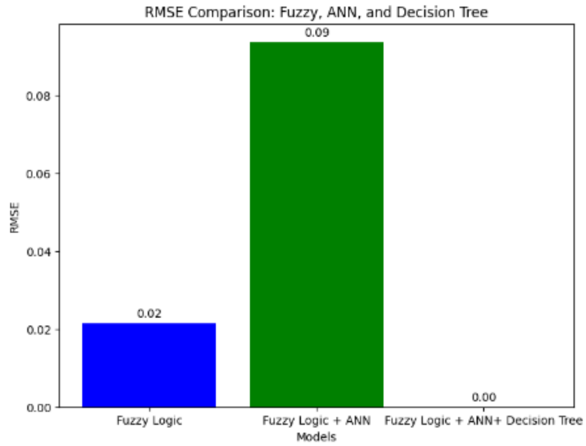

Figure 8. RMSE Comparison

Figure 9 shows that scheme A provides a motor response of 39.10 Hz with a stabilization time of 2.29 seconds. Meanwhile, the combination in scheme B yields a slightly lower motor response of 39.03 Hz and a stabilization time of 2.28 seconds, indicating a minor improvement in stabilization but a slight decrease in response. Scheme C produces similar results to scheme B, with a motor response of 39.03 Hz and a stabilization time of 2.28 seconds. The combination methods offer slight improvements in response time stability, making them suitable for more complex applications requiring enhanced precision.

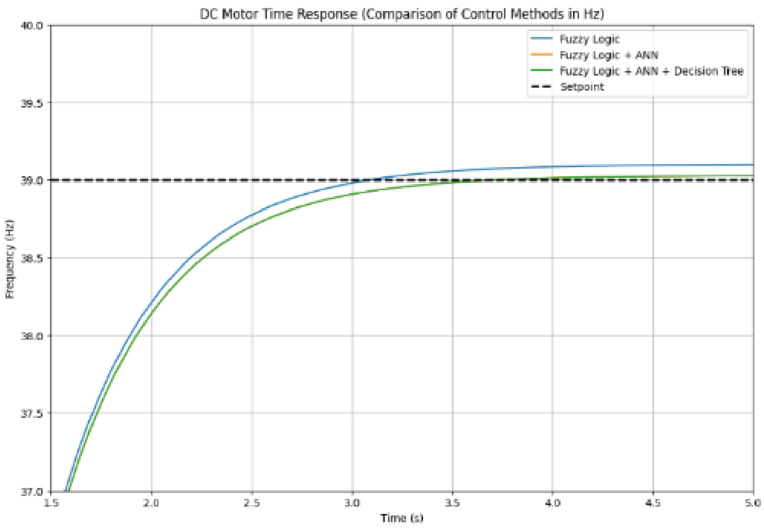

Figure 9. Time Response Comparison

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Table 4. Results of Three Schemes

Metric	Scheme A (FL)	Scheme B (FL-ANN)	Scheme C (FL-ANN-DT)
MSE	0.0004631	0.0087618	**5.3617e-32**
MAE	0.0028	0.0166	**4.3823e-17**
R^2	0.9999766	0.9995575	**1.0**
RMSE	0.0215	0.0936	**2.3155e-16**
Motor Response (Hz)	39.10	39.03	**39.03**
Stabilization Time (s)	2.29	2.28	**2.28**

Table 4 shows the evaluation results of three different schemes in microsleep detection and prevention, namely Scheme A (FL), which uses pure fuzzy logic; Scheme B (FL-ANN), which combines fuzzy logic with artificial neural network (ANN); and Scheme C (FL-ANN-DT) which combines fuzzy logic, ANN, and decision tree (DT). The table shows that Scheme C (FL-ANN-DT) gives the best results, with the smallest MSE, MAE, and RMSE values and a perfect R^2 value (1.0), indicating that this model produces the most accurate microsleep predictions. Regarding error metrics, Scheme C has a much lower error rate than the other schemes. In contrast, Scheme A has a lower error than Scheme B, indicating that ANN alone without a decision tree does not constantly improve accuracy. In addition, the R^2 value = 1.0 in Scheme C indicates a perfect match between the model and the actual data, while Schemes A and B have slightly lower R^2 values.

Regarding system response, all three schemes show stable performance, with a motor response of around 39.03–39.10 Hz and a stabilization time of around 2.28–2.29 seconds, so the accuracy improvement in Scheme C does not sacrifice the system response speed. In conclusion, Scheme C is the most accurate algorithm for microsleep detection and prevention because it can accurately predict microsleep events without changing the system's stability. The fuzzy logic component handles uncertainty and vague input values effectively, the ANN captures complex, nonlinear relationships in the BPM data through adaptive learning, and the Decision Tree improves the model's interpretability and decision-making by refining classification boundaries. This synergy allows Scheme C to produce more accurate, stable, and context-aware predictions, making it particularly suitable for real-time, safety-critical applications like microsleep detection. Therefore, combining fuzzy logic, ANN, and decision trees is the best approach to improve the accuracy of microsleep detection and further research to actively mine the algorithm parameters and test its implementation in actual conditions.

5. CONCLUSION

This study evaluated three intelligent algorithm techniques for microsleep detection by analyzing their prediction accuracy and response stability. The three intelligent algorithms have successfully compared MSE, MAE, R^2, and RMSE to measure response stability and prediction accuracy. The results show that scheme C produces the most accurate prediction with the MSE of 4.3823e-17 and MAE 4.3823e-17, a perfect R^2 value of 1.0, and a very small RMSE of 2.3155e-16. This scheme has a stabilization period of 2.28 seconds, with a motor response that remains stable at 39.03 Hz. Although fuzzy logic works independently, combining it with ANN and decision trees increases accuracy and resilience. Based on these results, scheme C can be actively used as an algorithm to detect and prevent

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microsleep, as evidenced by the system's increased accuracy, reliability, and responsiveness. The findings highlight the strength of hybrid models in complex, safety-critical tasks like microsleep detection, supporting the development of accurate and responsive driver monitoring systems to help prevent drowsiness-related accidents and enhance road safety. Future research should optimize the intelligent algorithm parameters to improve real-time microsleep detection and explore FL-ANN-DT integration with real-time vehicle sensors using edge AI frameworks.

REFERENCES

[1] "Road traffic injuries." Accessed: Jan. 24, 2025. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/road-traffic-injuries

[2] "Drowsy Driving Statistics and Facts 2024 | Bankrate." Accessed: Jan. 24, 2025. [Online]. Available: https://www.bankrate.com/insurance/car/drowsy-driving-statistics/

[3] "Fatigued Driving - National Safety Council." Accessed: Jan. 24, 2025. [Online]. Available: https://www.nsc.org/road/safety-topics/fatigued-driver

[4] "Drowsy Driving Statistics in 2025 | The Zebra." Accessed: Jan. 31, 2025. [Online]. Available: https://www.thezebra.com/resources/research/drowsy-driving-statistics/#yearly

[5] M. H. Zaky, R. Shoorangiz, G. R. Poudel, L. Yang, C. R. H. Innes, and R. D. Jones, "Increased cerebral activity during microsleeps reflects an unconscious drive to re-establish consciousness," *International Journal of Psychophysiology*, vol. 189, pp. 57–65, Jul. 2023, doi: 10.1016/J.IJPSYCHO.2023.05.349.

[6] B. N. Kasodu, A. Y. Zakiyyah, Z. E. Rasjid, and I. H. Parmonangan, "CNN-based Drowsiness Detection with Alarm System to Prevent Microsleep," *Proceeding - 6th International Conference on Information Technology, Information Systems and Electrical Engineering: Applying Data Sciences and Artificial Intelligence Technologies for Environmental Sustainability, ICITISEE 2022*, pp. 200–204, 2022, doi: 10.1109/ICITISEE57756.2022.10057692.

[7] L. Fatmawati, A. Subakti Ariyanto, R. Kalila Firdausi, and D. Rakis Agustina, "MiDA (Microsleep Detection Base on Arduino)," 2022. [Online]. Available: www.ijisrt.com

[8] Y. Zhang, F. Liu, J. Zheng, L. Tang, and X. Han, "Research on Algorithm Multi-Dimensional Testing and Evaluation for NLP Intelligent Algorithms," *2024 IEEE 2nd International Conference on Sensors, Electronics and Computer Engineering, ICSECE 2024*, pp. 504–509, 2024, doi: 10.1109/ICSECE61636.2024.10729386.

[9] S. Secinaro, D. Calandra, A. Secinaro, V. Muthurangu, and P. Biancone, "The role of artificial intelligence in healthcare: a structured literature review," *BMC Med Inform Decis Mak*, vol. 21, no. 1, pp. 1–23, Dec. 2021, doi: 10.1186/S12911-021-01488-9/FIGURES/12.

[10] S. H. Zaleha *et al.*, "Microsleep Accident Prevention for SMART Vehicle via Image Processing Integrated with Artificial Intelligent," in *Journal of Physics: Conference Series*, IOP Publishing Ltd, Dec. 2021. doi: 10.1088/1742-6596/2129/1/012082.

[11] A. Dijah Rahajoe, M. Rafli, A. Subekti, and M. Suriansyah, "REAL-TIME DROWSY FACE DETECTION FOR ONLINE LEARNING BASED ON RANDOM FOREST AND DECISION TREE ALGORITHMS," *Jurnal Teknik Informatika (Jutif)*, vol. 4, no. 6, pp. 1549–1554, Dec. 2023, doi: 10.52436/1.JUTIF.2023.4.6.1554.

[12] S. Dubey, V. Samadhia, S. Chauhan, N. Deshmukh, and D. C. Sati, "Micro-Sleep Accident Prevention by SMART Vehicle Using AI and Image Processing," *2023 3rd Asian Conference on Innovation in Technology, ASIANCON 2023*, 2023, doi: 10.1109/ASIANCON58793.2023.10270583.

Vol. 6, No. 3, Juni 2025, Page. 1241-1254
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.3.3540

[13] J. Sinha, P. Mangla, S. Purwar, Naman, and T. Akilan, "Driver Drowsiness Detection using Deep Learning; Approach towards Automating Object Recognition," *Proceedings - IEEE 2023 5th International Conference on Advances in Computing, Communication Control and Networking, ICAC3N 2023*, pp. 641–646, 2023, doi: 10.1109/ICAC3N60023.2023.10541587.

[14] "Heart rate time series / MIT-BIH Database." Accessed: Jan. 10, 2025. [Online]. Available: https://www.kaggle.com/datasets/ahmadsaeed1007/heart-rate-time-series-mitbih-database

[15] S. Shahani and K. K. Singh, "The Performance Analysis of Mean Square Error and Bit Error Rate for Wireless Communication Using a Modified Firefly Algorithm with NN Equalizer," *2023 IEEE 4th Annual Flagship India Council International Subsections Conference: Computational Intelligence and Learning Systems, INDISCON 2023*, 2023, doi: 10.1109/INDISCON58499.2023.10270806.

[16] M. Panwar, A. Sharma, O. P. Mahela, and B. Khan, "K-means Clustering Powered Context Aware Food Recommender System," *International Conference on Integrated Intelligence and Communication Systems, ICIICS 2023*, 2023, doi: 10.1109/ICIICS59993.2023.10421677.

[17] K. Karthika, P. Balasubramanie, K. Dharshini, P. Shanmugapriya, and T. E. Ramya, "Harnessing Artificial Neural Network Model to Anticipate Housing Market Rates," *2024 15th International Conference on Computing Communication and Networking Technologies, ICCCNT 2024*, 2024, doi: 10.1109/ICCCNT61001.2024.10723986.

[18] K. Rajesh and M. S. Saravanan, "Prediction of Customer Spending Score for the Shopping Mall using Gaussian Mixture Model comparing with Linear Spline Regression Algorithm to reduce Root Mean Square Error," *Proceedings - 2022 6th International Conference on Intelligent Computing and Control Systems, ICICCS 2022*, pp. 335–341, 2022, doi: 10.1109/ICICCS53718.2022.9788162.

[19] K. Zou, M. Fard, J. L. Davy, and S. R. Robinson, "Application of modulated vibration to restore driver alertness," *Transportation Engineering*, vol. 16, Jun. 2024, doi: 10.1016/j.treng.2024.100249.

[20] N. Zhang, M. Fard, J. Xu, J. L. Davy, and S. R. Robinson, "Road safety: The influence of vibration frequency on driver drowsiness, reaction time, and driving performance," *Appl Ergon*, vol. 114, Jan. 2024, doi: 10.1016/j.apergo.2023.104148.

[21] A. Zaineb, M. Vijayasanthi, and P. N. Mandadi, "Fuzzy Logic Controller Based Charging and Discharging Control for Battery in EV Applications," *International Journal of Electrical and Electronics Research*, vol. 12, no. 1, pp. 1–7, Jan. 2024, doi: 10.37391/IJEER.120101.

[22] G. A. Rahardi, W. Muldayani, M. D. A. Wijaya, D. Setiabudi, and H. M. Firdausi, "Early Warning System Design for Flood Disasters Using the IoT-Based Fuzzy Logic Control Method," *ICEECIT 2022 - Proceedings: 2022 International Conference on Electrical Engineering, Computer and Information Technology*, pp. 131–135, 2022, doi: 10.1109/ICEECIT55908.2022.10030237.

[23] S. Sahoo, N. K. Jena, A. Anurag, A. K. Naik, B. K. Sahu, and P. C. Sahu, "Frequency Regulation of Microgrid using Fuzzy-logic based controllers," *2023 International Conference in Advances in Power, Signal, and Information Technology, APSIT 2023*, pp. 120–123, 2023, doi: 10.1109/APSIT58554.2023.10201752.

[24] H. Eluri and M. Gopichand Naik, "Energy Management System and Enhancement of Power Quality with Grid Integrated Micro-Grid using Fuzzy Logic Controller," *International Journal of Electrical and Electronics Research*, vol. 10, no. 2, pp. 256–263, Apr. 2022, doi: 10.37391/IJEER.100234.

[25] O. Daood, M. Najeeb, and I. Ibrahim Ali, "An Efficient Load Frequency Control for Multiple Power Systems Using Fuzzy Logic-Proportional Integral Derivative Controller," *International*

Vol. 6, No. 3, Juni 2025, Page. 1241-1254
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.3.3540

Journal of Electrical and Electronics Research, vol. 12, no. 2, pp. 654–661, Jun. 2024, doi: 10.37391/IJEER.120243.

[26] I. K. Sinha, K. P. Singh, and S. Verma, "DP-ANN: A new Differential Private Artificial Neural Network with Application on Health data (Workshop Paper)," *Proceedings - 2020 IEEE 6th International Conference on Multimedia Big Data, BigMM 2020*, pp. 351–355, Sep. 2020, doi: 10.1109/BIGMM50055.2020.00061.

[27] D. V. Rayudu and J. F. Roseline, "Accurate Weather Forecasting for Rainfall Prediction using Artificial Neural Network Compared with Deep Learning Neural Network," *Proceedings of the International Conference on Artificial Intelligence and Knowledge Discovery in Concurrent Engineering, ICECONF 2023*, 2023, doi: 10.1109/ICECONF57129.2023.10084252.

[28] G. Ambati, A. Ganga Dinesh Kumar, T. Raghu, B. V. Seshukumari, R. R. Duvvuru, and C. Rami Reddy, "Power Quality Improvement of PV fed Grid Connected System using ANN Controlled Shunt Active Power Filter," *International Journal of Electrical and Electronics Research*, vol. 12, no. 4, pp. 1287–1292, Nov. 2024, doi: 10.37391/IJEER.120421.

[29] S. M. Taghavinejad, M. Taghavinejad, L. Shahmiri, M. Zavvar, and M. H. Zavvar, "Intrusion Detection in IoT-Based Smart Grid Using Hybrid Decision Tree," *2020 6th International Conference on Web Research, ICWR 2020*, pp. 152–156, Apr. 2020, doi: 10.1109/ICWR49608.2020.9122320.

[30] A. D. Riyanto, A. M. Wahid, and A. A. Pratiwi, "ANALYSIS OF FACTORS DETERMINING STUDENT SATISFACTION USING DECISION TREE, RANDOM FOREST, SVM, AND NEURAL NETWORKS: A COMPARATIVE STUDY," *Jurnal Teknik Informatika (Jutif)*, vol. 5, no. 4, pp. 187–196, Jul. 2024, doi: 10.52436/1.JUTIF.2024.5.4.2188.

[31] K. B. Adam, D. K. Silalahi, B. S. Aprillia, and H. A. Adhari, "Support Vector Regression Method for Predicting Off-Grid Photovoltaic Output Power in the Short Term," *Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi)*, vol. 6, no. 4, pp. 548–554, Aug. 2022, doi: 10.29207/RESTI.V6I4.4134.

[32] J. Resti, A. Setiawan, E. Utami, and D. Ariatmanto, "Cattle Weight Estimation Using Linear Regression and Random Forest Regressor," *Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi)*, vol. 8, no. 1, pp. 72–79, Feb. 2024, doi: 10.29207/RESTI.V8I1.5494.

[33] A. Z. Fuadi, I. N. Haq, and E. Leksono, "Support Vector Machine to Predict Electricity Consumption in the Energy Management Laboratory," *Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi)*, vol. 5, no. 3, pp. 466–473, Jun. 2021, doi: 10.29207/RESTI.V5I3.2947.