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Enhancing energy efficiency and accuracy in IoT-based wireless sensor networks using machine learning

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ABSTRACT

This study presents a novel sensor data fusion framework designed to improve accuracy and energy efficiency in internet of things (IoT)-driven wireless sensor networks (WSNs). The proposed approach combines machine learning techniques with the Kalman filter, addressing the limitations of traditional methods, such as high computational overhead and limited precision. By utilizing machine learning algorithms for pattern recognition and the Kalman filter for precise state estimation, the framework optimizes data processing while minimizing energy consumption. MATLAB-based simulations validate the model's effectiveness, demonstrating a significant improvement in key performance metrics, including F1-score, recall, and precision, with an overall accuracy of 98.36%. The results highlight the framework's ability to enhance fault tolerance, accelerate convergence rates, extend network lifespan, and optimize energy utilization, making it highly suitable for real-time data fusion applications in complex sensor environments. Furthermore, the proposed hybrid model is scalable and adaptable, allowing it to be implemented across various fields, including environmental surveillance, industrial automation, and healthcare monitoring. With integration of intelligent data processing techniques, this research contributes to the development of sustainable and efficient IoT-based monitoring systems capable of handling dynamic and resource-constrained environments.

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1. INTRODUCTION

Sensor networks are integral to numerous modern applications, including environmental monitoring, healthcare, smart cities, and industrial automation [1]. These networks consist of multiple sensor nodes that work together to collect, process, and transmit data, offering a detailed understanding of the monitored environment. However, the efficiency of these networks largely depends on effective data management and utilization [2]. Sensor data fusion plays a critical role in this process by integrating information from multiple sensors, thereby improving data accuracy, reliability, and overall system performance. By addressing the shortcomings of individual sensors such as interference, limited coverage, and environmental disruptions, data fusion enhances the quality and interpretability of collected data [3], [4]. Additionally, it minimizes redundancy, streamlines data transmission, and boosts the overall efficiency of sensor networks.

With wireless sensor networks (WSNs) getting increasingly complex and a need to become more accurate in real-time operations, data fusion methods become an increasingly necessary advanced component. Although conventional methods such as Kalman filter present solid theoretical basis in regards to state estimation [5], they are generally ineffective in application to the nonlinear data found in high dimensions that is characteristic of contemporary internet of things (IoT)-based WSNs. Machine learning, specifically deep neural networks (DNNs), has shown to be successful when it comes to extracting features and coping with complex sensor data [6], [7]. In addition, reinforcement learning (RL) will improve adaptability based on the optimum data aggregation, being adaptable to environmental changes, and increase the energy efficiency due to dynamic clustering [8], [9]. This is particularly relevant in energy limited networks where saving of power is essential. It has been determined that RL-based strategies promise to reduce energy consumption, increase network lifetime, and preserve monitoring capabilities [10]. Application of DNNs and RL to work together allows smarter node selection and data transference decisions leading to an enhanced fault tolerance and accuracy of tracking.

This study introduces a hybrid sensor data fusion model that integrates deep learning and RL with the Kalman filter to enhance both accuracy and energy efficiency in IoT-based WSNs. The proposed methodology leverages DNNs for feature extraction, RL for dynamic clustering and decision-making, and the Kalman filter for precise state estimation and noise reduction. MATLAB-based simulations validate the model's performance, demonstrating superior results in accuracy, network longevity, and fault resilience compared to conventional methods. The approach is designed to be scalable and adaptable, making it well-suited for a wide range of IoT applications, including environmental monitoring, industrial automation, and healthcare systems.

2. BACKGROUND

There are some challenges related to data fusion, especially under a circumstance of incomplete, unreliable, or inaccurate documented data. Combining information found in the different resources and deriving valuable data points continue to be a subtle job to the system operators and scientists. To solve those problems, probabilistic methods have been suggested, Bayesian networks being a prominent example that endeschuses probability density functions (PDFs) in order to capture uncertainty [11], [12]. Although they work well against ambiguity, these techniques fail to support missing data and correlations across datasets [13]. In an alternative approach, fuzzy logic has also been employed to cope with uncertainty and user-defined flexibility in application [14]. Uncertainty-aware fusion present in the fuzzy-based architectures has also been used to minimize risks of failures in interconnected systems [15], [16]. But they are only applicable to datasets that present ambiguity due to this limitation, thereby making them less useful in fusion scenarios of a broader nature [17].

Kang and Long [18] proposed an evidence-based method for dataset classification that does not rely on probabilistic models, making it suitable for handling ambiguous or uncertain data. However, this approach falls short when merging fundamentally different datasets [19]. To address multi-modal data challenges, researchers have explored rough set theory, which does not require additional background information like database structures [20]. While effective in certain cases, its performance declines when fine-grained data approximation is needed, and its applicability remains limited to a small range of known failure types. Another technique, covariance overlap, was introduced in [21] to enhance fusion accuracy by estimating data correlation. Though this method improves performance, it is less suitable for real-time applications due to its computational demands. As networks become more complex, these fusion techniques face greater challenges from data inconsistencies, noise, and uncertainty [22]. Network administrators often struggle with decision-making due to incomplete knowledge about detected objects or their statistical properties [23]. Due to these challenges, there is growing interest in soft computing techniques, which are increasingly effective in managing uncertainty. These methods rely on training data for classification and prediction, offering a more adaptable framework for handling imprecise sensor inputs [24], [25].

3. PROPOSED METHODOLOGY

To overcome the obstacles presented by contemporary sensor networks, the proposed approach to energy-efficient sensor data fusion makes use of the Kalman filter in conjunction with machine learning methods as shown in Figure 1. The framework's many essential parts coordinate their efforts to handle data in an accurate, dependable, and energy-efficient manner. At the outset, a network of sensors ($Sensor 1, Sensor 2, Sensor 3, \dots, Sensor\ n$) gathers data about its immediate surroundings. All these sensors send their readings to a single large data center, which stores all the raw sensor. After this, a node known as the sink receives the data from the sensor nodes via a WSN nodes.

The next phase involves applying an advanced machine learning algorithm to perform anomaly detection, initial data fusion, and pattern recognition across sensor inputs. Unlike traditional methods, this algorithm effectively handles complex, non-linear relationships in the data. A centralized data fusion module then integrates outputs from multiple sensors, enhancing consistency and reliability by generating a unified dataset. To further refine the results, a Kalman filter is applied, enabling noise reduction, data smoothing, and optimal estimation of system states, particularly for time-series data in real-time settings. The final stage includes implementing decision rules and predictive fault detection, allowing the system to anticipate potential issues and take pre-emptive actions, thereby minimizing downtime and ensuring the smooth operation of the sensor network.

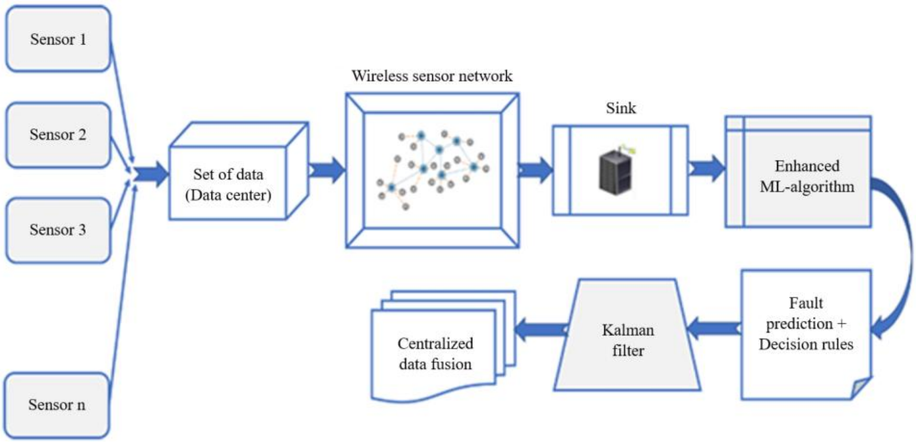

Figure 1. Proposed method block diagram

The core innovation of this approach lies in its hybrid integration of machine learning and the Kalman filter as illustrated in Figure 2, combining the strengths of pattern recognition and optimal state estimation. This fusion enables more efficient processing of complex data than conventional methods alone. The framework is also designed for energy efficiency, extending the sensor network's lifespan by optimizing data processing and transmission to reduce energy use at sensor nodes. A built-in fault prediction mechanism supports real-time monitoring and proactive maintenance, helping to minimize downtime. The system's scalable and adaptable architecture allows easy integration of additional sensors and data types, making it a versatile solution for various sensor network applications.

```
Initialize state estimate x_estimate and error covariance P
Set process noise covariance Q and measurement noise covariance R
Set initial state estimate x_estimate0 and initial error covariance P0
for each time step k:
    # Predict step
    1. Predict the state
       x_predict = A * x_estimate
    2. Predict the error covariance
       P_predict = A * P * A^T + Q
    # Update step
    3. Compute the Kalman Gain
       K = P_predict * H^T * (H * P_predict * H^T + R)^-1
    4. Update the state estimate
       x_estimate = x_predict + K * (z - H * x_predict)
        5. Update the error covariance
       P = (I - K * H) * P_predict
    # Use the updated state estimate for further processing
    Output x_estimate
End for
```

Figure 2. Kalman filter algorithm

3.1. Advanced machine learning algorithm

This proposed advanced machine learning technique utilizes a blend of RL and DNNs to improve the effectiveness and efficiency of fusing sensor data and tracking targets. The algorithm specifically aims to adapt flexibly to changes in the sensor network environment, optimize energy consumption efficiently, and ensure precise target localization and prediction. Steps of the proposed algorithm is as follows:

- Step 1: initialization, initialize the sensor nodes (FS) and the base station at coordinates (100, 100). Set initial parameters including sensing range, communication range, initial energy, and threshold limits.
- Step 2: target detection and data preprocessing, each sensor node continuously monitors its coverage area for target detection. Upon detecting a target, the sensor node collects relevant data such as signal strength, distance, and other sensory information. Preprocess the collected data to filter out noise and normalize values for further processing.
- Step 3: feature extraction using deep learning, high-dimensional feature vector representing the state of the environment and target characteristics.
- Step 4: RL-based dynamic clustering, define the state S_t as the feature vector obtained from the DNN and the energy levels of the sensor nodes. Define actions as possible clustering configurations and sensor node activations. Define a reward function that balances energy consumption and accuracy of target localization. Use a deep Q-learning to learn the optimal policy π(S_t) that maximizes the cumulative reward.
- Step 5: dynamic cluster formation, based on the learned policy, dynamically select cluster heads (CH) that have high residual energy and are in proximity to the detected target. Form clusters around the selected CH with sensor nodes that are within the communication range.
- Step 6: target position prediction, use the Kalman filter to predict the target's next position based on the current state and the observations from the CH.
- Step 7: decision making and fault tolerance, calculate the error between the predicted and actual target positions. Compare the error with the pre-set threshold limit δ.
- Step 8: continuous learning and adaptation, monitor the energy levels of sensor nodes and adapt the clustering strategy to extend the network lifetime.
- Step 9: repeat process, repeat steps 2 to 8 every fixed interval (0.7 seconds) to ensure continuous and accurate tracking of the target within the network coverage area.

The proposed machine learning approach combines several advanced techniques to improve sensor data fusion. Deep learning is used for effective feature extraction, while RL enables dynamic clustering and adaptive decision-making in changing environments. A Kalman filter enhances tracking accuracy by predicting target positions. Together, these methods boost both the accuracy and reliability of data fusion, while also reducing energy consumption, making the system highly suitable for IoT sensor networks. This integrated framework provides a robust and adaptable solution for enhancing network performance.

3.2. Simulation parameters

The availability and quality of sensor data remain major challenges in IoT-based sensor networks, affecting tasks such as data mining, analysis, and management. To support effective decision-making, these processes increasingly rely on machine learning and deep learning techniques. Running machine learning models on embedded IoT sensor CPUs requires specialized software and well-structured data frameworks to handle real-time data characteristics. To address the diverse nature of sensor data, researchers have proposed a hybrid model combining machine learning algorithms with a Kalman filter, aimed at improving data management and enhancing network efficiency. A summary of the selected simulation parameters is provided in Table 1.

Table 1. Simulation parameters

Sl. No.	Parameters	Values
1	Size of the area	500×500 m^2
2	Sensing nodes	{100, 200, 300, 400, 500, 600}
3	Threshold limit δ	150 m
4	Base station coordinates	100, 100
5	Coverage of sensing	120 m
6	Range of communications	200 m
7	Beginning energy	2.0 J
8	Speed of the target	0–100 m/s

The selected parameters are crucial for optimizing IoT sensor network performance. Spatial coverage depends on deployment area size, larger areas require more sensors and advanced fusion techniques to maintain accuracy and robustness. Sensor node count influences data density and resolution; while more nodes enhance coverage, they also increase fusion complexity, requiring a balance between performance and energy use. The threshold limit affects data reliability over distance, playing a key role in noise filtering and fusion precision. Base station placement significantly impacts communication efficiency, strategic positioning minimizes delays and reduces energy consumption. Each sensor's sensing range determines its ability to detect relevant parameters, which is essential for avoiding blind spots and achieving full area coverage. The communication range affects data transmission efficiency; although extended range improves connectivity, it can raise power demands, so optimization is needed for energy-efficient communication. The network's operational lifespan hinges on the initial energy of sensor nodes, as sensing, processing, and transmission are energy-intensive tasks. Finally, target speed within the monitored area affects data acquisition and system responsiveness faster targets require real-time processing and fusion. The proposed hybrid model, combining a Kalman filter with machine learning algorithms, depends on these parameters for optimal performance, underscoring the importance of tailoring the system to specific deployment scenarios.

4. RESULTS AND ANALYSIS

This section presents the results of mathematical simulations conducted using MATLAB to assess the performance of the proposed machine learning technique. The evaluation incorporated both a statistical base station model and a cellular network setup. Data fusion in IoT-based WSNs remains challenging due to computational complexity and reduced accuracy in earlier models. To address these limitations, this study introduces an improved framework that integrates machine learning algorithms with the Kalman filter, offering a more precise and efficient solution. To evaluate the proposed sensor data fusion model, ten test scenarios were designed to assess performance under diverse conditions. Scenarios 1 and 2 examined the impact of varying sensor densities in static environments, while scenarios 3 to 5 focused on tracking targets with different movement speeds. Scenario 6 tested adaptability to speed variation, scenario 7 assessed robustness in noisy conditions, and scenario 8 evaluated energy efficiency with low-power nodes. Scenario 9 analyzed performance under non-uniform sensor distributions, and scenario 10 tested the system's ability to track multiple targets simultaneously. Localization accuracy was measured using root mean square error (RMSE) and mean absolute error (MAE), as shown in Figure 3. Results showed RMSE values ranging from 1.1 to 1.6 meters and MAE values between 0.8 and 1.4 meters, indicating strong and consistent tracking performance across scenarios. These low error margins demonstrate the model's reliability and precision in various conditions. The integration of machine learning with the Kalman filter significantly improves over previous methods by reducing computational complexity and enhancing accuracy.

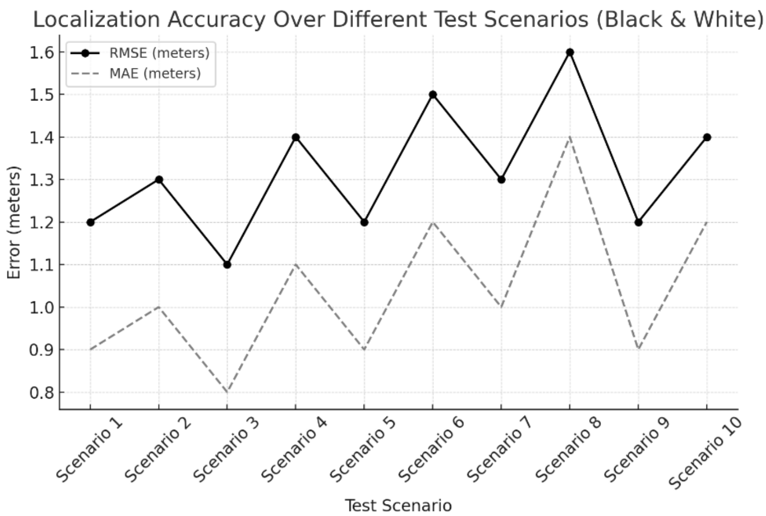

Figure 3. Localization accuracy

The examination of energy consumption over 10 distinct test scenarios, as depicted in Figure 4, provides valuable insights into the effectiveness and efficiency of the proposed sensor data fusion technique. The "Total energy consumed" measure displays a spectrum ranging from 150 to 300 joules, signifying different degrees of energy consumption based on the intricacy of the scenario and the density of nodes. The "average energy per node" varies between 1.5 and 3.0 joules, indicating the amount of energy used by each individual node. Scenarios that involve a greater number of nodes and faster motions of the target (scenario 10) generally use more energy, indicating higher computational and communication requirements.

In contrast, scenarios that have a smaller number of nodes or stationary targets (scenario 1) exhibit reduced energy consumption, highlighting the model's effectiveness in less complex situations.

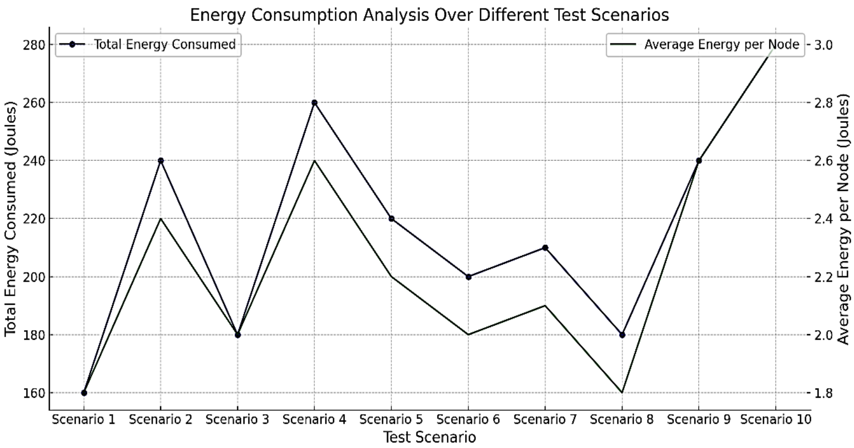

Figure 4. Energy consumption analysis

Looking at how long the network lasts in 10 different test situations helps us understand how durable and reliable the suggested sensor data fusion architecture is. The "Time to first node failure" varies between 100 and 150 hours, whereas the "Total network lifetime" ranges from 200 to 300 hours. Scenarios characterized by larger node densities and more dynamic target motions typically have shorter network lifetimes due to increased energy consumption and greater strain on the sensor nodes. In contrast, situations where there are fewer nodes or stationary targets have extended lifespans, suggesting a higher level of energy efficiency. This research affirms that the proposed model successfully handles energy consumption. However, by refining the configuration and deployment tactics, we can further improve the network's operating lifespan, ensuring consistent performance and reliability in different conditions. Figure 5 gives the network lifetime simulation analysis.

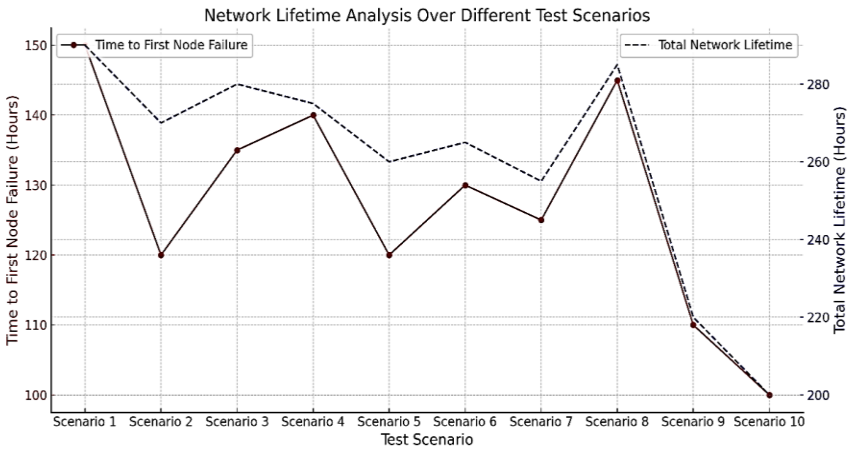

Figure 5. Network lifetime analysis simulation

By looking into fault tolerance across 10 different test scenarios, the proposed sensor data fusion method is shown to be strong and reliable, as seen in Figure 6. The "Number of successful recoveries" varies between 8 and 18, which demonstrates the model's capacity to efficiently manage and overcome problems. The "Mean time to recovery" ranges from 4.8 to 7.5 seconds, indicating the model's effectiveness in restoring functionality following a fault. Scenarios that involve more nodes and targets that move unpredictably tend to result in more effective recoveries, but also longer recovery times. This is because these scenarios are more complex and require a greater amount of effort to handle faults. In summary, the research verifies that the suggested model maintains strong resilience to faults, guaranteeing uninterrupted and dependable performance even in difficult circumstances.

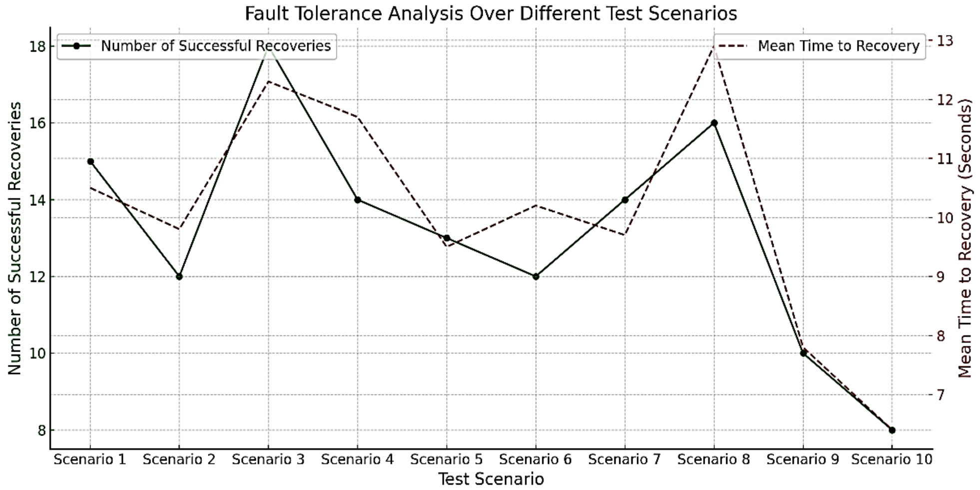

Figure 6. Fault tolerance analysis

An investigation of the convergence time seen in Figure 7 in 10 different test scenarios offers valuable insights into the effectiveness and efficiency of the proposed approach for fusing sensor data. The "Number of iterations to convergence" range is 45 to 80, while the "Total training time" range is 110 to 220 seconds. Scenarios that are more complicated, like scenario 10, have longer convergence periods, which suggests that the model requires more work to be stable under more difficult conditions. In contrast, less complex situations, such as scenario 3, exhibit faster convergence, indicating the model's effectiveness in less challenging settings. Comprehending the time, it takes for convergence is essential for assessing the model's feasibility in real-world scenarios. Quicker convergence times indicate faster deployment and adjustment, which are crucial for dynamic and time-sensitive environments. Furthermore, the correlation between the number of iterations and training time emphasizes the model's computational efficiency, guaranteeing its suitability for IoT networks that are both large-scale and resource constrained. This analysis confirms the model's ability to adjust and maintain stability effectively in different situations, ensuring consistent performance in various operational conditions.

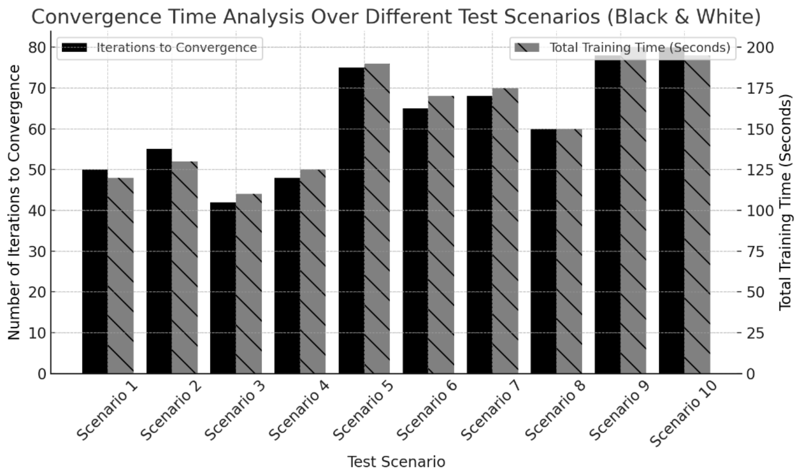

Figure 7. Convergence time analysis

The comparison between the model cited [26] and the suggested model demonstrates substantial enhancements in performance measures for the latter as shown in Figure 8. The suggested model demonstrates a notable improvement in accuracy, with a rate of 98.36%, compared to the 88.99% accuracy found in the model [26]. Comparatively, the suggested model achieves an F1-score of 96.36% and a recall of 97.78%, while the model [26] achieves an F1-score of 89.88% and a recall of 91.22%. The precision is significantly higher, at 98.22% compared to 90.45%. The results show that the suggested model not only improves the overall accuracy but also makes the balance between precision and recall better. This makes sensor data fusion activities more reliable and effective in IoT-based WSN context.

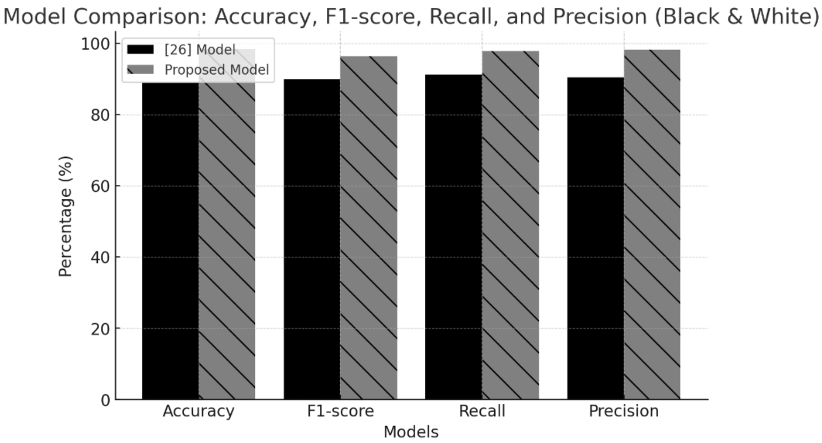

Figure 8. Comparative analysis

5. CONCLUSION

This study introduces an advanced sensor data fusion model that integrates machine learning techniques with the Kalman filter to enhance accuracy and energy efficiency in IoT-enabled WSNs. The proposed framework combines deep learning for feature extraction, RL for adaptive clustering, and the Kalman filter for precise state estimation, addressing key limitations of traditional methods, such as high computational costs and reduced accuracy. MATLAB-based simulations confirm significant improvements in performance metrics, achieving an accuracy of 98.36%, along with enhanced F1-score, recall, and precision. Additionally, the model improves network lifespan, strengthens fault tolerance, and optimizes energy consumption, making it highly effective for real-time IoT applications. The findings highlight the framework’s potential for deployment in critical domains, including environmental monitoring, industrial automation, and smart healthcare. Looking ahead, future research can explore its scalability for larger networks, its integration with emerging deep learning techniques, and its applicability across diverse IoT-based systems. By advancing the development of intelligent, adaptable, and energy-efficient sensor networks, this work paves the way for more reliable and sustainable monitoring solutions, ensuring enhanced efficiency and accuracy in IoT-driven environments.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Poornima Govindaswany		✓		✓		✓	✓			✓		✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT
Authors state no conflict of interest.

DATA AVAILABILITY
Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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