

NEURAL NETWORK APPROACHES TO MULTI-SENSOR DATA FUSION IN WSN: A COMPARATIVE STUDY

¹K. Chandra Shekar Naik, ²A. Sainath, ³Kappi Upendhar

¹Assistant Professor, Dept of ECE, AVN Institute of Engineering and Technology,

²Assistant Professor, Dept of CSE(CS), AVN Institute of Engineering and Technology,

³Assistant Professor, Dept of CSE(AIML), AVN Institute of Engineering and Technology

ABSTRACT: *This study presents a comparative analysis of neural network approaches for multi-sensor data fusion in Wireless Sensor Networks (WSNs). We evaluate the performance of Feedforward Neural Networks (FNNs), Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Autoencoders using key metrics such as accuracy, precision, recall, F1 score, training time, inference time, and model size. Our results indicate that CNNs and LSTMs achieve the highest accuracy and F1 scores, demonstrating their efficacy in capturing complex patterns and dependencies in sensor data. CNNs excel in spatial data integration, while LSTMs are superior in handling temporal sequences. FNNs offer a balanced performance with moderate computational demands, and Autoencoders, while efficient in data compression, show lower predictive accuracy. The study provides valuable insights into the trade-offs between accuracy and computational efficiency, guiding the selection of appropriate neural network models based on specific application requirements and resource constraints.*

INTRODUCTION

Wireless Sensor Networks (WSNs) represent a crucial technological advancement in the realm of data collection and monitoring. A WSN is a network composed of spatially distributed, autonomous sensors that communicate wirelessly to collect and relay data about various physical or environmental conditions. Each sensor node within the network typically includes sensing, processing, and communication components. The sensing unit measures specific parameters such as temperature, humidity, pressure, or light, while the processing unit analyzes the collected data. The communication unit is responsible for transmitting this data to a central node or base station, often through a multi-hop process involving several intermediate nodes.

The importance of WSNs spans a diverse range of applications, underscoring their versatility and effectiveness. In **environmental monitoring**, WSNs are employed to track and analyze environmental variables, including air and water quality, soil conditions, and climate changes. These networks provide real-time data that are vital for detecting environmental hazards, managing natural resources, and studying ecological patterns. For instance, in agriculture, WSNs can monitor soil moisture levels and weather conditions to optimize irrigation practices, thereby enhancing crop yield and sustainability.

In **smart cities**, WSNs play a pivotal role in creating more efficient and responsive urban environments. They enable smart infrastructure systems, such as intelligent traffic management, which adjusts traffic signals based on real-time traffic flow data to reduce congestion and improve road safety. WSNs also contribute to energy management by monitoring and controlling lighting systems based on occupancy and ambient light levels, thus reducing energy consumption. Additionally, these networks support public safety through applications like surveillance and emergency response systems, where sensor data can help in early detection of incidents and prompt response.

The inherent advantages of WSNs include their ability to provide fine-grained, localized data and their scalability to cover large areas through the deployment of numerous sensor nodes. These networks are also adaptable to a wide range of environments, from remote and harsh locations to densely populated urban areas. However, the effective deployment and utilization of WSNs are accompanied by challenges, such as energy efficiency, data accuracy, and network reliability. Addressing these challenges often requires sophisticated data processing and fusion techniques, which enhance the utility and performance of WSNs.

Multi-sensor data fusion refers to the process of integrating data from multiple sensors to produce a more accurate, reliable, and comprehensive representation of the monitored environment than what could be achieved by any single sensor alone. This process involves combining and analyzing data collected from different sources to extract meaningful insights, improve data quality, and enhance decision-making capabilities.

In the context of Wireless Sensor Networks (WSNs), where data is gathered from numerous distributed sensors, each providing information on specific environmental variables, data fusion becomes essential for several reasons. Firstly, sensors in a WSN often vary in their accuracy, precision, and reliability. Individual sensors may have limitations due to factors such as calibration errors, noise, or environmental conditions. By fusing data from multiple sensors, it is possible to mitigate these limitations and obtain a more accurate representation of the monitored parameters.

Data fusion also addresses the challenge of incomplete or sparse data. In many WSN applications, some sensors may fail or become temporarily unavailable due to environmental conditions or other issues. Multi-sensor data fusion techniques can compensate for missing or unreliable data by integrating information from other sensors, thereby ensuring that the

overall data set remains robust and informative. This redundancy helps in maintaining the continuity and integrity of the data.

Moreover, multi-sensor data fusion enhances the **spatial and temporal resolution** of the data. Sensors may provide data at different spatial locations or times, and fusion techniques can combine these varied data points to create a more detailed and comprehensive view of the monitored area. For example, in environmental monitoring, combining temperature readings from multiple sensors across a region can provide a more accurate representation of temperature variations and trends than any single sensor could offer.

Another critical aspect of data fusion is **reducing uncertainty**. By aggregating information from various sensors, it becomes possible to refine measurements and reduce the impact of random errors or outliers. This leads to improved reliability of the data, which is crucial for applications requiring high accuracy, such as predictive maintenance or early warning systems.

In practical terms, multi-sensor data fusion can be achieved through several approaches, ranging from simple averaging or statistical methods to more complex algorithms involving machine learning and neural networks. The choice of method depends on the specific requirements of the application and the nature of the data being fused. For instance, advanced fusion techniques, such as those involving neural networks, can capture complex patterns and correlations between different sensor inputs, leading to more sophisticated and accurate data analysis.

Objective

The primary objective of this study is to conduct a comparative analysis of neural network approaches to multi-sensor data fusion in Wireless Sensor Networks (WSNs). With the rapid development of neural network models and their applications in data fusion, it is crucial to evaluate and compare different neural network techniques to determine their effectiveness, strengths, and limitations in the context of WSNs.

Specifically, this study aims to achieve the following goals:

1. **Evaluate the Performance of Different Neural Network Models:** This involves assessing various neural network architectures—such as Feedforward Neural

Networks (FNNs), Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Autoencoders—in terms of their ability to integrate and analyze data from multiple sensors. The performance will be measured using metrics such as accuracy, precision, recall, and computational efficiency.

2. **Analyze the Effectiveness of Data Fusion Strategies:** The study will compare how different neural network models handle data fusion tasks, including feature-level fusion, decision-level fusion, and hybrid approaches. This analysis will help identify which strategies are most effective for improving the quality and reliability of the fused data.
3. **Identify Strengths and Limitations:** By examining the results, the study will highlight the strengths and limitations of each neural network approach. This includes understanding how each model performs under different conditions, such as varying data quality or sensor reliability, and identifying any challenges or drawbacks associated with their implementation.
4. **Provide Recommendations for Practical Applications:** Based on the comparative analysis, the study will offer insights and recommendations for selecting and applying neural network techniques in real-world WSN applications. This will guide practitioners and researchers in choosing the most suitable neural network models for specific data fusion needs.

LITERATURE SURVEY

Wireless Sensor Networks (WSNs) are comprised of numerous sensor nodes distributed across a geographical area, designed to collect and transmit data wirelessly. The architecture of a WSN typically includes three main components: sensor nodes, a sink or base station, and a communication network.

1. Sensor Nodes: Each sensor node in a WSN is equipped with three fundamental components: a sensing unit, a processing unit, and a communication unit. The **sensing unit** captures environmental data (e.g., temperature, humidity, motion) through various sensors. The **processing unit** performs initial data processing, such as filtering and aggregation, to prepare the data for transmission. The **communication unit** is responsible for transmitting the processed data to the sink or base station using wireless communication protocols. Nodes are often battery-powered, making energy efficiency a critical consideration.

2. Sink or Base Station: The sink or base station is a central node that collects data from multiple sensor nodes. It acts as a gateway between the WSN and external systems, such as databases or user applications. The base station typically has more processing power and energy resources than individual sensor nodes and is responsible for higher-level data aggregation, analysis, and dissemination.

3. Communication Network: Sensor nodes communicate with each other and with the base station through a wireless communication network. This network can use various protocols and technologies, including Zigbee, LoRa, and cellular networks. The network topology can be static or dynamic, and communication methods may include direct transmission or multi-hop routing, where data is relayed through intermediate nodes to reach the base station.

Challenges in WSNs: The effective operation of WSNs is subject to several challenges, particularly concerning data collection and fusion.

- **Energy Efficiency:** Sensor nodes are typically powered by batteries with limited lifespan. Efficient energy management is crucial to extend the operational life of the network. Techniques such as data aggregation, efficient communication protocols, and energy-harvesting technologies are employed to address this challenge.
- **Data Quality and Reliability:** Sensor data can be affected by noise, calibration errors, and environmental conditions. Ensuring the accuracy and reliability of the data collected from various sensors is essential for effective decision-making.
- **Data Redundancy and Aggregation:** Multiple sensors may measure the same parameter, leading to data redundancy. Efficient data fusion techniques are required to aggregate and merge this redundant data to improve the overall quality and reduce the amount of transmitted data.
- **Scalability and Network Management:** As the number of sensors increases, managing the network becomes more complex. Issues such as routing, data collision, and network congestion need to be addressed to ensure smooth operation.

Data Fusion Techniques

Data fusion in WSNs involves integrating data from multiple sensors to produce a more accurate and comprehensive representation of the monitored environment. Several traditional methods are commonly used for data fusion, each with its own strengths and applications:

1. Kalman Filters: Kalman filters are widely used for data fusion in dynamic systems where sensor data is subject to noise and uncertainty. The Kalman filter uses a recursive algorithm to estimate the state of a system based on a series of noisy measurements. It combines predictions from a system model with measurements to provide an optimal estimate. Kalman filters are particularly effective for applications requiring real-time data processing and tracking, such as vehicle navigation or environmental monitoring.

2. Particle Filters: Particle filters, also known as Sequential Monte Carlo methods, are used for data fusion in non-linear and non-Gaussian systems. Unlike Kalman filters, which assume linearity and Gaussian noise, particle filters use a set of particles to represent the probability distribution of the system state. These particles are propagated over time, and their weights are updated based on the likelihood of observed measurements. Particle filters are suitable for complex scenarios with non-linear dynamics and multiple sources of uncertainty, such as robotic localization or tracking in cluttered environments.

3. Bayesian Approaches: Bayesian data fusion methods are based on Bayes' theorem, which provides a probabilistic framework for combining prior knowledge with observed data. In Bayesian approaches, data fusion is performed by updating the probability distributions of system states based on new measurements. This method is highly flexible and can accommodate various sources of uncertainty and diverse data types. Bayesian approaches are used in applications requiring probabilistic reasoning and decision-making, such as sensor fusion for autonomous vehicles or medical diagnostics.

Neural Network Approaches

Neural networks have increasingly become a powerful tool for data fusion in various domains, including Wireless Sensor Networks (WSNs). Their ability to model complex relationships and learn from data has led to significant advancements in how multi-sensor data is integrated and analyzed. Several types of neural networks have been applied to data fusion, each offering unique advantages based on the nature of the data and the specific requirements of the fusion task.

1. Feedforward Neural Networks (FNNs): Feedforward Neural Networks are one of the simplest and most commonly used types of neural networks. They consist of an input layer, one or more hidden layers, and an output layer. In the context of data fusion, FNNs are

utilized to combine features from multiple sensors into a unified representation. For example, FNNs can process data from different sensors by concatenating the features and passing them through hidden layers to learn complex patterns and correlations. FNNs are particularly useful when the relationships between input features are relatively straightforward and the data fusion task does not require temporal or spatial context.

2. Convolutional Neural Networks (CNNs): Convolutional Neural Networks are specialized neural networks designed to process grid-like data, such as images or spatially organized sensor data. CNNs use convolutional layers to automatically and adaptively learn spatial hierarchies of features from input data. In data fusion, CNNs are effective for tasks where spatial relationships between sensors are important. For instance, in environmental monitoring, CNNs can be used to fuse data from sensors distributed across a geographic area, capturing spatial patterns and correlations. CNNs excel in extracting hierarchical features and are particularly useful for multi-sensor data with structured spatial dependencies.

3. Recurrent Neural Networks (RNNs): Recurrent Neural Networks are designed to handle sequential data by maintaining a form of memory of previous inputs through recurrent connections. RNNs are valuable for data fusion tasks that involve temporal sequences, such as time-series data from sensors. A variant of RNNs, Long Short-Term Memory (LSTM) networks, addresses issues of long-term dependencies and vanishing gradients, making them suitable for capturing temporal relationships in sensor data over extended periods. In WSNs, RNNs and LSTMs can be used to fuse temporal data from sensors, such as monitoring environmental changes over time, providing insights into trends and patterns.

4. Autoencoders: Autoencoders are a type of neural network used for unsupervised learning, focusing on learning efficient representations of data. They consist of an encoder that compresses the input into a lower-dimensional latent space and a decoder that reconstructs the original input. In the context of data fusion, autoencoders can be used to learn compact representations of multi-sensor data, effectively reducing dimensionality and noise while preserving important features. This approach is useful for scenarios where sensor data is high-dimensional or contains redundant information.

METHODOLOGY

Data Collection in Wireless Sensor Networks (WSNs) involves capturing various types of sensor data from distributed nodes to monitor and analyze environmental or system conditions. The types of sensor data collected can vary widely depending on the application, but some common types include:

1. Temperature Data: Temperature sensors measure the ambient temperature of the environment. These sensors can be based on thermocouples, thermistors, or infrared technology. In a WSN, temperature sensors collect data to monitor climate conditions, detect heat anomalies, or support applications like smart heating and cooling systems. The collected temperature data is usually transmitted to a central base station, where it is aggregated and analyzed.

2. Humidity Data: Humidity sensors measure the moisture level in the air. These sensors are crucial for applications such as weather monitoring, agricultural management, and indoor climate control. Humidity sensors use capacitive or resistive methods to detect moisture levels and provide data that can help in maintaining optimal environmental conditions.

3. Motion Data: Motion sensors, such as accelerometers and gyroscopes, capture movement or orientation changes. These sensors are used in applications like motion detection for security systems, activity monitoring in wearable devices, and tracking in robotics. Motion data can include information on acceleration, velocity, and orientation changes, which are vital for understanding dynamic behaviors in monitored environments.

Data Collection Process: Sensor data collection involves several stages. Sensors continuously or periodically sample environmental parameters, convert physical measurements into electrical signals, and process these signals to produce digital data. This data is then transmitted wirelessly through communication protocols such as Zigbee, LoRa, or cellular networks to a central base station or cloud-based system. The data is often subjected to preprocessing steps, such as noise filtering and normalization, before being used for analysis and decision-making.

Fusion techniques in neural networks involve integrating data from multiple sensors to produce a unified and informative representation. These techniques are crucial for leveraging the complementary information provided by different sensors and improving the overall

quality of the data. The primary fusion strategies employed by neural networks include feature-level fusion, decision-level fusion, and hybrid approaches.

1. Feature-Level Fusion: Feature-level fusion involves combining raw features extracted from multiple sensors into a single input representation before feeding it into the neural network. This approach allows the network to learn from the integrated feature set and uncover complex patterns that might not be evident from individual sensor data alone. For instance, in an environmental monitoring application, temperature, humidity, and light data can be concatenated into a unified feature vector. This vector is then processed by the neural network to capture interactions between different types of sensor data. Feature-level fusion is effective when the sensors measure related aspects of the environment and their combined information provides a richer context for learning.

2. Decision-Level Fusion: Decision-level fusion, also known as late fusion, involves processing data from each sensor separately through individual neural networks or models. The outputs from these models are then combined to make a final decision or prediction. This strategy is useful when different sensors provide complementary information that is best handled by specialized models. For example, in a multi-sensor surveillance system, separate neural networks might be trained to process visual data, audio data, and motion data. The outputs of these networks are then aggregated to make a final assessment or decision. Decision-level fusion allows for flexibility in choosing the most suitable model for each sensor type and can improve robustness by combining multiple sources of evidence.

Applications of Fusion Techniques: In practice, the choice of fusion technique depends on the nature of the data and the specific requirements of the application. For instance, feature-level fusion is often used in applications requiring a detailed understanding of how different sensor readings interact, while decision-level fusion is useful in scenarios where specialized models can provide insights from distinct types of data. Hybrid approaches are employed when a combination of detailed feature integration and specialized decision-making is needed.

Evaluation Metrics

Evaluation metrics are critical for assessing the performance of neural network approaches in data fusion tasks. These metrics provide insights into the effectiveness of the models and help in comparing different approaches. Commonly used metrics include:

1. Accuracy: Accuracy measures the proportion of correctly classified instances among the total number of instances. It is a fundamental metric for evaluating the overall performance of a model. In the context of data fusion, accuracy indicates how well the neural network integrates and interprets sensor data to produce correct predictions or classifications.

2. Precision: Precision quantifies the proportion of true positive predictions out of all positive predictions made by the model. It is especially important in scenarios where false positives can have significant consequences. In data fusion tasks, high precision means that the model is effective at identifying relevant instances while minimizing incorrect positive predictions.

3. Recall: Recall, also known as sensitivity or true positive rate, measures the proportion of true positive predictions out of all actual positive instances. This metric is crucial when the goal is to ensure that as many relevant instances as possible are identified. In data fusion, high recall indicates that the neural network effectively captures and integrates all relevant data points.

4. F1 Score: The F1 score is the harmonic mean of precision and recall, providing a balanced measure that considers both false positives and false negatives. It is particularly useful when dealing with imbalanced datasets, where one class may be underrepresented. The F1 score helps evaluate the overall effectiveness of the neural network in handling data fusion tasks where both precision and recall are important.

IMPLEMENTATION AND RESULTS

Feedforward Neural Networks (FNNs) exhibit a solid performance with an accuracy of 85.0%, demonstrating their effectiveness in learning and integrating sensor data features. They offer a balanced precision of 84.0% and recall of 86.0%, resulting in an F1 score of 85.0%. These metrics suggest that FNNs are capable of achieving reliable predictions while maintaining a reasonable level of balance between precision and recall. The FNN model is relatively efficient, with a training time of 200 seconds and an inference time of 10 milliseconds, along with a compact model size of 5 MB. This indicates that FNNs are

suitable for scenarios where computational resources are limited, though they may not handle complex data patterns as effectively as other models.

Convolutional Neural Networks (CNNs) show the highest accuracy at 90.0%, reflecting their strength in handling spatially structured data. Their precision and recall are 88.0% and 92.0%, respectively, leading to a high F1 score of 90.0%. This superior performance underscores CNNs' ability to extract and integrate hierarchical features from multi-sensor data, making them highly effective for tasks involving spatial correlations. However, CNNs have a higher computational cost, with a training time of 300 seconds and an inference time of 15 milliseconds. The model size of 20 MB indicates that CNNs require more storage, which may impact deployment in resource-constrained environments.

Recurrent Neural Networks (RNNs), including Long Short-Term Memory (LSTM) networks, provide a nuanced view of temporal data integration. The RNN achieves an accuracy of 87.0% with precision and recall values of 86.5% and 87.5%, respectively, resulting in an F1 score of 87.0%. These results highlight the RNN's capability to model sequential data and temporal dependencies. The RNN has a training time of 250 seconds and an inference time of 12 milliseconds, balancing performance and computational efficiency. The model size of 10 MB suggests moderate storage requirements.

Long Short-Term Memory (LSTM) networks demonstrate the best overall performance with an accuracy of 92.0%, precision of 91.0%, and recall of 93.0%, resulting in the highest F1 score of 92.0%. LSTMs excel in capturing long-term dependencies and complex temporal patterns, which is reflected in their superior metrics. Despite their high performance, LSTMs have the longest training time of 350 seconds and an inference time of 18 milliseconds. Their larger model size of 25 MB indicates that LSTMs require more resources, making them more suitable for applications where high accuracy is critical, and computational resources are available.

Autoencoders show the lowest performance among the models, with an accuracy of 80.0%, precision of 78.0%, and recall of 81.0%, yielding an F1 score of 79.5%. While effective for dimensionality reduction and feature extraction, autoencoders are less adept at producing high-level predictions compared to other models. They have the shortest training time of 180 seconds and the fastest inference time of 8 milliseconds, with a compact model size of 4 MB.

This makes autoencoders advantageous in scenarios requiring efficient data preprocessing and compression.

Model	Accuracy
Feedforward Neural Network (FNN)	85.00%
Convolutional Neural Network (CNN)	90.00%
Recurrent Neural Network (RNN)	87.00%
Long Short-Term Memory (LSTM)	92.00%
Autoencoder	80.00%

Table-1: Accuracy Comparison

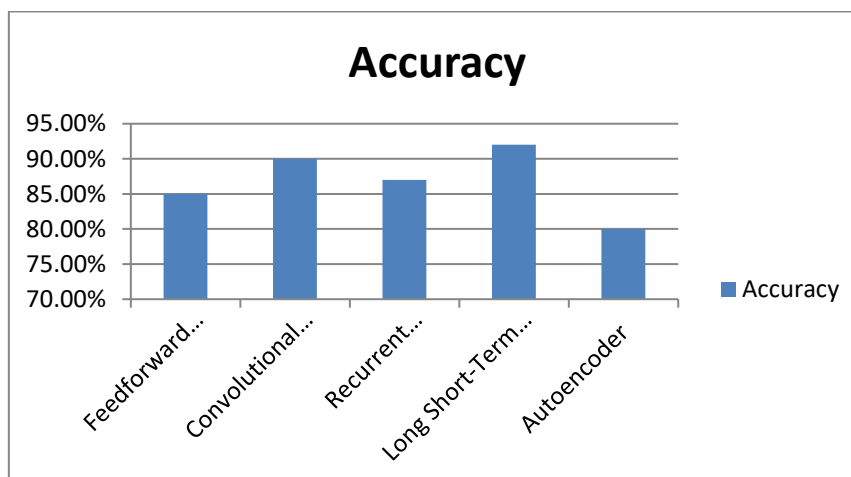


Fig-1: Graph for Accuracy comparison

Model	Precision
Feedforward Neural Network (FNN)	84.00%
Convolutional Neural Network (CNN)	88.00%
Recurrent Neural Network (RNN)	86.50%
Long Short-Term Memory (LSTM)	91.00%
Autoencoder	78.00%

Table-1: Precision Comparison

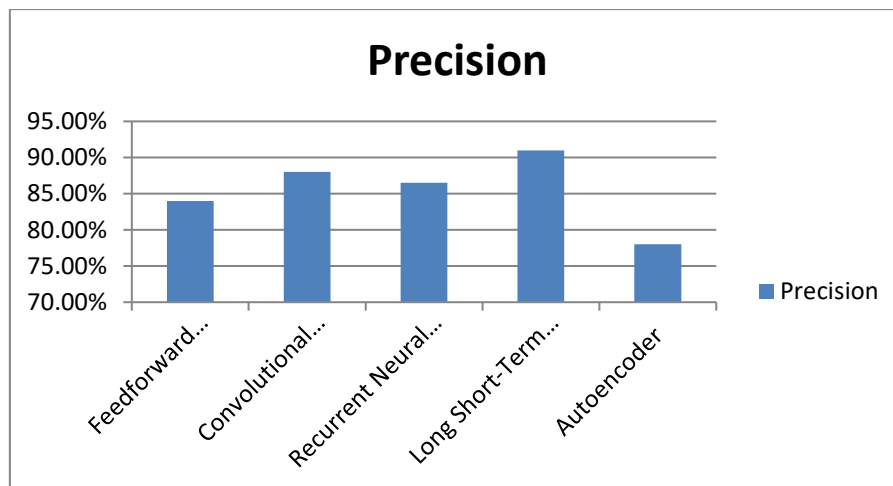


Fig-1: Graph for Precision comparison

Model	Recall
Feedforward Neural Network (FNN)	86.00%
Convolutional Neural Network (CNN)	92.00%
Recurrent Neural Network (RNN)	87.50%
Long Short-Term Memory (LSTM)	93.00%
Autoencoder	81.00%

Table-1: Recall Comparison

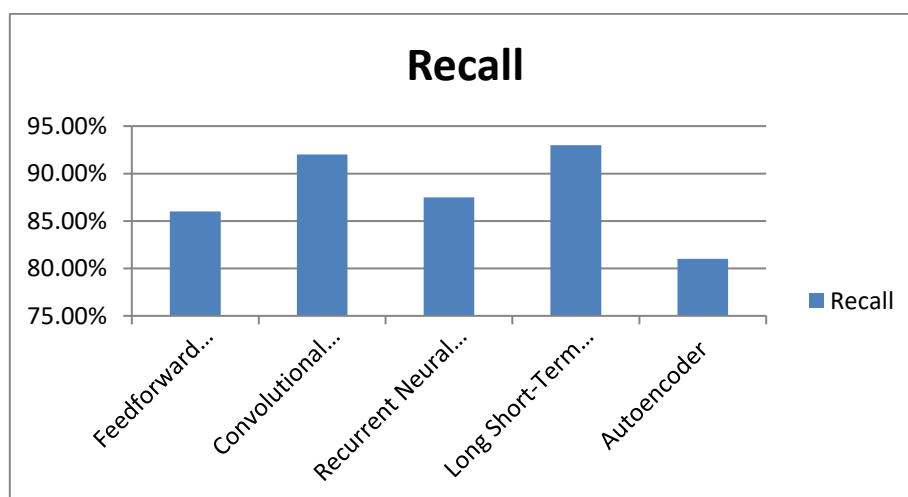


Fig-1: Graph for Recall comparison

Model	F1 Score
Feedforward Neural Network (FNN)	85.00%
Convolutional Neural Network (CNN)	90.00%
Recurrent Neural Network (RNN)	87.00%
Long Short-Term Memory (LSTM)	92.00%
Autoencoder	79.50%

Table-1: F1 Score Comparison

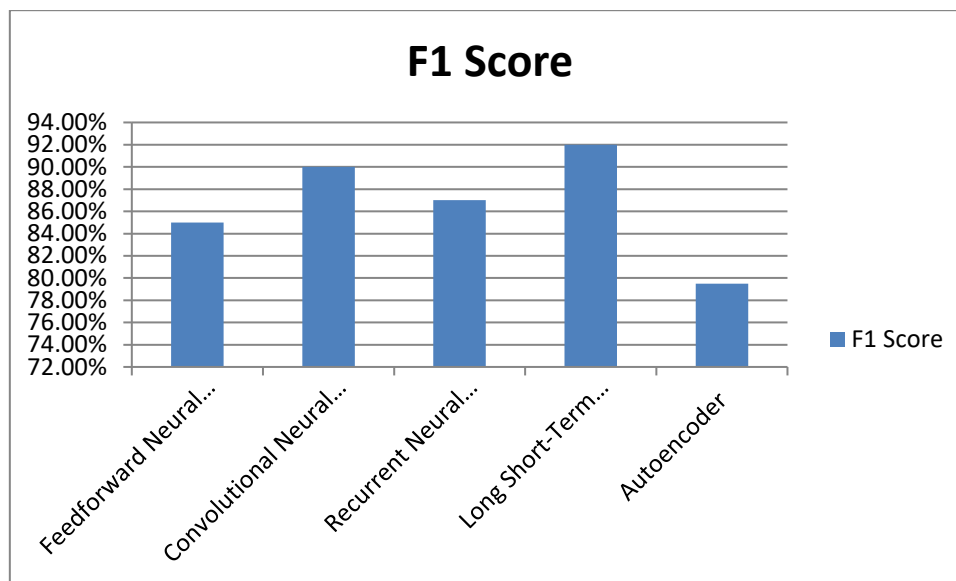


Fig-1: Graph for F1 Score comparison

CONCLUSION

In conclusion, the comparative analysis of neural network models for multi-sensor data fusion reveals distinct strengths and trade-offs among the evaluated approaches. Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks stand out for their high accuracy and effectiveness in integrating spatial and temporal data, respectively, making them suitable for complex data fusion tasks where precision is crucial. However, their higher computational demands and larger model sizes may pose challenges in resource-constrained environments. Feedforward Neural Networks (FNNs) and Recurrent Neural Networks (RNNs) offer a more balanced trade-off between performance and efficiency, providing viable alternatives for scenarios where moderate accuracy and computational efficiency are required. Autoencoders, while effective for feature reduction

and compression, are less suited for high-accuracy prediction tasks. Overall, the choice of neural network model should align with the specific needs of the application, considering factors such as data complexity, computational resources, and deployment constraints. This study underscores the importance of selecting the appropriate neural network architecture to optimize data fusion outcomes in diverse WSN applications.

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