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Energy-Efficient Data Aggregation in Wireless Sensor Networks using Neural Network-Based Prediction Models

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Abstract:
In this study, we examine how neural networkbased prediction models can be used in Wireless Sensor Networks (WSNs) to build energy-efficient data aggregation strategies. With their widespread use in a variety of applications like smart cities, health care, and environmental monitoring, WSNs are known for their energy-related problems. This study's major goal is to prolong sensor network lifespans while preserving data communication accuracy and dependability. We provide a unique framework that combines data aggregation techniques with predictive modelling, making use of neural networks to predict sensor data and minimise redundant transmissions. Our approach minimises energy consumption related to data transmission, resulting in more sustainable operation of WSNs by accurately forecasting data trends and patterns. Simulations are used to assess the suggested methodology, and the results show significant gains in terms of energy savings, network throughput, and overall system performance. This work adds to the continuing attempts to create WSN architectures that are more intelligent and effective and that can function well in contexts with limited resources.

Keywords: Wireless Sensor Networks (WSNs), Energy Efficiency, Neural Network Models, Feedforward Neural Networks (FNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) Networks, Convolutional Neural Networks (CNN).

I. INTRODUCTION

Wireless Sensor Networks (WSNs) are becoming a vital piece of equipment in many industries, such as industrial automation, smart cities, health care, and environmental monitoring. These networks are made up of widely dispersed sensor nodes that gather information from their environment and send it to a central processing unit for examination. WSNs have several benefits, but their performance and longevity are severely hampered by their frequent shortage of energy supplies. Sensor data transmission in real time uses a lot of energy, which shortens network lifetimes and raises operating expenses. In this regard, creating energy-efficient data aggregation and communication mechanisms for WSNs is essential to guaranteeing their long-term viability.

One of the main problems with WSNs is redundant data transmission, which causes network congestion and decreased communication reliability in addition to draining sensor nodes' energy resources. Even if they can be somewhat helpful, traditional data aggregation strategies frequently fail to meet the challenges associated with energy use in dynamic contexts. Consequently, scientists have been investigating novel methods to enhance data aggregation and transmission in wireless sensor networks. Of these methods, neural network-based predictive modelling has drawn the most attention since it can effectively predict trends in sensor data, reducing the frequency of data transmissions. The goal of this project is to integrate neural network-based prediction models into a framework for data aggregation for wireless sensor networks (WSNs) that is energy-efficient. This framework's major goal is to increase sensor network longevity while preserving high standards of precision and dependability in data transmission. With their capacity to deduce intricate patterns from data, neural networks are used to forecast sensor readings in the future. The framework can lessen the frequency of data transmissions, saving energy and easing network congestion, by precisely predicting data trends.

Predictive modelling is used in the suggested framework to find and remove unnecessary data transmissions. Sensor nodes can send only major changes in data when they have a high degree of accuracy in predicting future data, which lowers the total energy consumption. This method works especially well for applications like environmental monitoring or smart city infrastructure when sensor data is consistent over time. Furthermore, the framework enhances network throughput and improves overall system performance by minimising the number of transfers.

Simulations are carried out to compare the performance of the neural network-based prediction model with conventional data aggregation techniques in order to assess the efficacy of the suggested methodology. The outcomes of the simulation show notable gains in system performance, network throughput, and energy savings. In particular, it is demonstrated that the neural network-based method increases the operational lifetime of sensor networks by lowering the energy usage related to data transmission. Consequently, this results in WSN systems that are more resource-constrained environments and more sustainable.

In conclusion, our study adds to the continuing attempts to develop WSNs that are more intelligent and effective so they can be used in a variety of applications. The suggested architecture provides a fresh approach to the problems WSNs have with energy usage by fusing neural network-based prediction models with data aggregation methods. The results of this study may contribute to the development of energyefficient WSN architectures, which would eventually make it possible for sensor networks operating in a variety of domains to be more dependable and sustainable.

II. LITERATURE REVIEW

[1] **Kaur. Et al.(2024):**

They provide a metaheuristic algorithm-based neural network-based data aggregation methodology. The suggested technique makes use of feed-forward backpropagation networks, reduces duplicated transmissions, and forecasts patterns in sensor data to increase energy efficiency. This method works particularly well in situations where sensor readings occur on a regular basis. In these situations, forecast accuracy is crucial in reducing energy consumption and maximising network lifespan. This work adds to the development of energy-efficient frameworks appropriate for applications such as smart city infrastructure and environmental monitoring by fusing predictive analytics with WSNs.

[2] **Saranraj, G., et al. (2023):**

The paper presents the Multi-objective Male Lion Optimisation Algorithm (MOMLOA) for data aggregation in wireless sensor networks (WSNs) that uses less energy. MOMLOA optimises energy conservation and redundancy transmissions by selecting the cluster head optimally. By adding machine learning, the model's prediction accuracy for sensor data is increased, which boosts network performance and extends its lifetime. This method works well in real-time applications where sensor data needs to be processed quickly without sacrificing energy, and it offers a reliable way to overcome energy limitations in WSN systems with restricted resources.

[3] **Gopalan, S. H., et al. (2023):**

For effective routing in VANETs, the researchers create a hybrid particle swarm optimisation (PSO) model that may be modified for use in WSNs. By minimising redundant transmissions and guaranteeing energy-efficient data distribution, this method optimises routing patterns. Neural networks anticipate patterns in sensor data to reduce needless communications even more, saving a substantial amount of energy. This hybrid paradigm works especially well in dynamic WSN scenarios where energy management and flexible routing are essential to sustaining network performance.

[4] **Manikandan, A., et al. (2023):**

In order to minimise energy usage, this paper suggests a dynamic scheduling paradigm for ad hoc networks that emphasises efficient communication techniques. The methodology ensures energy-efficient data aggregation by dynamically scheduling transmissions through the use of hybrid advisory weights. The framework can forecast trends in sensor data by incorporating neural network predictions, which reduces the need for pointless data exchanges. This strategy increases overall network throughput and energy efficiency, which makes it appropriate for wireless sensor networks (WSNs) where sustained network operations are hampered by resource limits and changing settings.

[5] **Isaac Sajan, R., et al. (2023):**

The authors offer a grey wolf optimization-based routing system and a three-level weighted trust evaluation for WSNs.

Their method optimises routing patterns and secures data aggregation to increase energy efficiency. The approach reduces duplicate transmissions and saves energy by properly predicting trends in sensor data through the integration of neural networks. This approach is especially useful for applications like military or health monitoring networks where energy-efficient and secure data management is essential.

[6] **Naghibi, M., & Barati, H. (2023)**

They provide a safe hybrid structure that combines data security and energy-efficient routing for data aggregation in wireless sensor networks. The approach provides energyefficient operation by employing predictive analytics and minimising redundant transmissions. Neural network integration reduces energy usage and improves network dependability by boosting prediction accuracy for sensor data. This method works well for vital applications including environmental monitoring systems and healthcare that demand safe and energy-efficient data management.

[7] **Vasim Babu, M., et al. (2023):**

An enhanced clustering-based routing technique for WSN energy efficiency is presented in this paper. By optimising routing and concentrating on secure data aggregation, the technique reduces energy consumption throughout the network. By predicting sensor data patterns, neural networkbased predictions improve protocol performance by reducing data transmissions and extending network lifetime. The strategy works particularly well in settings with constrained resources and strict requirements for energy conservation and data protection.

[8] **Sharma, R., et al. (2023):**

A whale optimisation technique is suggested by the authors for safe and energy-conscious data aggregation in WSNs. Their model minimises energy consumption, secures data communications, and chooses the best cluster heads. The system further reduces duplicate transmissions by anticipating sensor data patterns through the integration of neural networks for predictive modelling. This low-energy method works well in situations like smart city networks and environmental monitoring systems where safe data handling and energy efficiency are critical.

[9] **Peng, Z., et al. (2023):**

An energy-aware routing technique for particle swarm optimisation (PSO) in WSNs is presented in this paper. By minimising pointless data transmissions, the technique minimises energy consumption while optimising routing paths. Further improving energy efficiency and network performance, the approach incorporates neural networks to predict sensor data. Applications like industrial automation and environmental monitoring, where real-time data processing and energy conservation are essential, benefit greatly from this strategy.

[10] **Hajiee, M., et al. (2023):**

The researchers suggest a multipath route-based, energyaware trust-based routing algorithm for WSNs. Through the elimination of unnecessary transmissions and the improvement of data aggregation dependability, their approach aims to maximise energy consumption. The approach further minimises energy use by precisely forecasting sensor data patterns through the integration of neural networks for predictive analytics. This method works well in situations like industrial monitoring systems and smart grids where safe and energy-efficient data management is crucial.

[11] **Saba, T., et al. (2023)**

This work proposes intelligent routing for energy-aware WSNs using graph clustering. Through the clustering of sensor nodes and the optimisation of routing patterns, the model lowers energy usage. Prediction models based on neural networks improve system performance by reducing redundant transmissions, predicting patterns in sensor data, and enhancing network resilience. This method works especially well in applications like environmental monitoring and smart city infrastructures where large-scale data aggregation and energy conservation are essential.

[12] **Mohankumar, B. et Al. (2023):**

The authors suggest an ideal routing strategy that lengthens the life of networks by lowering energy usage in wireless sensor networks. The protocol predicts sensor data patterns by integrating neural network-based prediction models, which reduces the frequency of data transmissions. This method increases the overall efficiency of the network and is especially helpful in situations where unpredictable conditions and energy limitations make it difficult for sensor networks to operate continuously.

[13] **Panchal, A. et al. (2023):**

They describe a distance-based cluster head selection and routing algorithm for WSNs that takes energy into account. Through the optimisation of routing pathways and cluster head selection, the protocol reduces energy usage. The system predicts sensor data accurately by including neural networkbased predictions, which minimises redundant transmissions and saves energy. This method works very well in applications like health monitoring and smart city networks where data quality and energy efficiency are vital.

[14] **Mehta, D. et al. (2023):**

A multi-objective cluster head-based routing algorithm for WSNs is presented in this paper. By minimising redundant data transmissions and choosing effective cluster heads, the program maximises energy consumption. The system forecasts sensor data properly by incorporating neural network-based prediction algorithms, which further reduces energy consumption and enhances network efficiency. This method works well in applications like industrial automation and environmental monitoring where energy constraints and large-scale data aggregation are significant issues.

[15] **Hasheminejad, E. et al. (2023):**

For WSNs, the authors suggest a tree-based data aggregation technique that lowers redundant transmissions and boosts energy economy. The system effectively predicts sensor data trends by integrating neural network-based prediction models, which reduces energy consumption and improves network performance overall. This method is very helpful in applications like environmental monitoring systems and smart city infrastructures where data quality and energy efficiency are vital.

[16] **Khan, T., et al. (2023):**

A trust-based, effective routing system for hostile WSNs is covered in this paper. Through data aggregation security and routing path optimisation, the approach improves energy efficiency. The system efficiently predicts sensor data by incorporating neural network-based prediction models, which minimises redundant transmissions and saves energy. This method works especially well in situations like military networks and health monitoring systems where energy efficiency and secure data management are critical.

[17] **Naghibi, M. et al. (2023):**

A safe hybrid structure is suggested by the researchers for data aggregation in WSNs. The technique lowers redundant transmissions and boosts network resilience by fusing energyefficient data aggregation with secure routing. Prediction models based on neural networks improve system performance by predicting trends in sensor data and reducing energy usage. This strategy is especially helpful in vital applications like environmental monitoring systems and healthcare where data confidentiality and energy efficiency are crucial.

[18] **Gomathi, S. et al. (2023):**

The writers concentrate on safe data aggregation and malicious node detection in WSNs. Through the identification and mitigation of rogue nodes, their approach ensures secure data flows and lowers energy consumption. Prediction models based on neural networks can reduce redundant transmissions, save energy, and accurately foresee patterns in sensor data to further optimise data aggregation. This method works especially well in applications like military and health monitoring networks where energy efficiency and secure data management are vital.

[19] **Laxma Reddy, D., & Puttamadappa, C. (2023)**:

In order to improve energy efficiency in WSNs, this work combines ant colony optimisation and glowworm swarm optimisation. The model prolongs the life of the network and lowers energy usage by optimising routing patterns and clustering. Prediction models based on neural networks can forecast patterns in sensor data, reduce redundant transmissions, and save energy to further enhance the system's performance. This strategy is especially helpful in situations where unpredictable environments and energy limitations make it difficult for networks to operate continuously.

[20] **S. H. Gopalan, et al. (2023):**

With an emphasis on energy-efficient data aggregation, the paper suggests a hybrid advisory weight-based dynamic scheduling architecture for ad hoc networks. The model forecasts patterns in sensor data using neural network-based prediction models, which minimises energy consumption and lessens the frequency of data transmissions. The network's overall performance is enhanced by this dynamic scheduling, which guarantees timely and energy-efficient data aggregation. The methodology is especially useful in situations like environmental monitoring and smart city infrastructure, where energy conservation and real-time data processing are vital.

By incorporating neural network-based prediction models, the literature review shows how widely energy-efficient data aggregation solutions have been explored in Wireless Sensor Networks (WSNs). Numerous research endeavours centre on refining routing and clustering algorithms in order to minimise superfluous transmissions, improve forecast precision, and preserve energy—all of which contribute to extending the lifespan of networks. Numerous studies investigate hybrid approaches that combine neural networks and optimisation algorithms such as Glowworm Swarm Optimisation (GSO), Particle Swarm Optimisation (PSO), Ant Colony Optimisation (ACO), Whale Optimisation, and so on. These methods show promise in a variety of applications where energy efficiency and real-time data processing are essential, such as military networks, smart cities, healthcare, and environmental monitoring. Other important themes that address energy efficiency and security concerns in hostile contexts are trust-based routing and secure data aggregation. A growing body of research has been done on the use of machine learning techniques to accurately predict trends in sensor data, minimise communication overhead, and maximise network performance when resources are limited. These advances are opening the door to more resilient WSN architectures that can be used for a range of crucial applications.

RESEARCH GAPS

The following research gaps have been found:

- Limited Research on Hybrid Models: Neural network-based prediction models are employed for energy-efficient data aggregation, but there is still little research on their integration with other cuttingedge machine learning methods (such reinforcement learning or deep learning variations).
- Scalability in Large-Scale Networks: In large-scale WSNs, especially in high-density deployments like smart cities, there is a deficiency in the treatment of the scalability of energy-efficient data aggregation models.
- Real-Time Adaptation to Dynamic settings:

Maintaining energy efficiency over time depends on existing models being able to adjust to dynamic network settings, such as node mobility or changing environmental conditions.

- Security-Enhanced Data Aggregation: Neural network-based energy-efficient data aggregation solutions still do not fully integrate security features, particularly for applications in hostile contexts such as military or disaster areas.
- Application-Specific Optimisation: Research on the optimisation of energy-efficient data aggregation models for specific applications is lacking, especially in fields where timeliness and quality of data are critical, such as healthcare monitoring.

III. RELATED CASE STUDIES

A. Hybrid Deep Learning for WSNs

The paper focusses on efficient hybrid deep learning models that combine long short-term memory (LSTM) networks with generative adversarial networks (GAN) for data aggregation and grouping in wireless sensor networks (WSNs). This case study demonstrates how these cuttingedge algorithms optimise the aggregation process to enable effective data transfer and save energy consumption. By learning temporal patterns in data, the hybrid structure helps the system improve endurance and performance. It also improves prediction accuracy and lowers energy consumption in sensor networks.

B. Embedded Neural Networks for Energy Conservation

The application of embedded artificial neural networks in WSNs and their efficiency in energy conservation are examined in this case study. The study shows how sensor node architectures can optimise energy consumption for data collection and transmission by integrating neural networks. Neural networks are able to estimate energy requirements and dynamically alter operating parameters by analysing historical performance data. This allows for lowest energy consumption while retaining data accuracy. This method greatly extends the network's lifespan and overall efficiency.

C. Optimization via Auto-Metric Graph Neural Network

An optimised auto-metric graph neural network is used in this case study to aggregate data in Internet of Thingsenabled wireless sensor networks. The goal is to increase energy efficiency while maintaining data transmission security. The network's design minimises needless energy use in data relay operations by enabling efficient coverage and routing choices. The results demonstrate how the model may improve security and energy efficiency, making it a reliable option for energy-conscious data aggregation in wireless sensor networks.

D. Neural Network Impact on WSN Energy Consumption

The results of this study show that a neural network model can significantly improve WSN characteristics, especially in terms of energy efficiency. The model uses sophisticated algorithms to forecast and dynamically modify parameters in order to maximise energy consumption throughout the network. The study demonstrates how the use of this neural network results in significant performance improvements, which in turn extends the operational life of the network. The information offered highlights how crucial it is for sensor networks to have effective energy management.

E. Radial Basis Function Neural Network for Data

Accuracy

The case study offers a novel approach to data aggregation and outlier detection for wireless sensor networks (WSNs) that is based on a modified radial basis function neural network. This strategy targets energy efficiency and seeks to improve data collecting accuracy by means of efficient aggregation procedures. Through the utilisation of the radial basis function's special properties, the model dramatically lowers the energy consumption that occurs during data processing. The results support its effectiveness in maximising data collection tactics in contexts with restricted energy resources.

IV. METHODOLOGY

 Feedforward Neural Networks (FNN):

Through efficient data aggregation and prediction, feedforward neural networks (FNN) are essential for improving energy efficiency in wireless sensor networks (WSNs). In the study "Energy-Efficient Data Aggregation in Wireless Sensor Networks Using Neural Network-Based Prediction Models," FNNs make use of their architecture to enhance sensor node connectivity. The network can precisely forecast variables like transmission power and node activation by using FNNs, which dramatically lowers energy consumption. Consequently, these models add to extended network lifetime and efficient data transfer, which is why FNNs are useful in WSN optimization tactics. There are noticeable gains in performance and efficiency with this method.

The most basic kind of artificial neural network is called a feedforward neural network, in which there are no cycles in the connections between the nodes. An FNN's output, y, is provided by equation (1) :

$$y = f\left(\sum_{i=1}^{n} \omega_i x_i + b\right) \quad (1)$$

Where:

x_i are the input features.

ω_i are the weights associated with each input.

b is the bias term.

f is the activation function, such as sigmoid, ReLU, or tanh.

For simple tasks where layers of neurons translate the input to the output directly, FNNs are employed. For static prediction jobs in data aggregation, they work well.

Recurrent Neural Networks (RNN):

Wireless Sensor Networks (WSNs), Recurrent Neural Networks (RNN) play a key role in optimizing data processing for energyefficient data aggregation. Regarding the study "EnergyEfficient Data Aggregation in Wireless Sensor Networks Using Neural Network-Based Prediction Models," RNNs are particularly good at processing sequential data, which makes it possible to forecast sensor readings accurately over time. By streamlining transmission patterns and cutting down on pointless data transmissions, this temporal feature helps to minimize energy use. With accurate data aggregation techniques, RNNs can adjust to changing network circumstances, ultimately resulting in longer network lifetimes and increased overall efficiency.

In order to process sequential input, recurrent neural networks keep track of a hidden state that contains data from earlier time steps in equation (2). The following is an update to the hidden state H_t:

$$H_t = f\ (W_h * H_{t-1} + W_x * X_t + b\ ) \qquad (2)$$

Where,

H_t is the hidden state at time t,

W_h is the recurrent weight matrix, W_x is the input weight matrix, and b is the bias term.

RNNs are appropriate for jobs like forecasting sensor readings over time, when historical data is crucial. They manage data aggregation's temporal dependencies.

Long Short-Term Memory (LSTM) Networks:

A specific type of Recurrent Neural Network (RNN) called Long Short-Term Memory (LSTM) network is intended to efficiently recognize and store long-range dependencies in sequential input. In the context of "Energy-Efficient Data Aggregation in Wireless Sensor Networks Using Neural Network-Based Prediction Models," temporal correlations among measurements provided by LSTM networks can greatly improve sensor data predictive accuracy. With the help of LSTM's capacity to control both short- and long-term data dependencies, the suggested models can dynamically modify transmission plans in order to maximize energy efficiency.

These networks are particularly good at handling time-series data, which is important for predicting sensor readings and cutting down on pointless data transfers. Consequently, the utilization of LSTM networks can result in enhanced data quality and longer network lifespans, proving the effectiveness of these networks in resolving energy-related issues related to data aggregation in wireless sensor networks. Consequently, LSTM networks play a key role in retaining strong predictive performance while attaining energy economy.

LSTM Networks are a kind of RNN that use a more intricate cell structure to solve the vanishing gradient issue. The hidden state and cell state are changed with the following equations (3-8):

Forget Gate: $f_t = \sigma\ (W_f\ [H_{t-1}, X_t] + b_f) \qquad (3)$

Input Gate: $i_t = \sigma\,(W_i\,[H_{t-1}, X_t] + b_i)$ (4)

Cell State Candidate: $\tilde{c}_t = tanh\,(W_c\,[H_{t-1}, X_t] + b_c)$ (5)

Cell State Update: $c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$ (6)

Hidden State: $h_t = o_t \odot \tanh(c_t)$ (7)

Output Gate: $o_t = \sigma\,(W_o\,[H_{t-1}, X_t] + b_o)$ (8)

Where:

f_t is the forget gate activation.

i_t is the input gate activation. $\tilde{c}_t$ is the cell state candidate. o_t is the output gate activation.

σ is the sigmoid function. ⊙ denotes element-wise multiplication.

Since LSTMs are good at capturing long-term dependencies in sequences, they are a great choice for applications like sensor reading prediction, where prior observations are used to predict future readings.

- **Convolutional Neural Networks (CNN):**

In Wireless Sensor Networks (WSNs), Convolutional Neural Networks (CNN) play a key role in optimizing data aggregation processes, particularly in the context of "EnergyEfficient Data Aggregation in Wireless Sensor Networks Using Neural Network-Based Prediction Models." CNNs are useful for processing sensor data collected in a variety of situations because they are skilled at identifying patterns in spatial data. CNNs can improve prediction accuracy by examining these data patterns, which helps with data transmission and aggregation strategy decision-making. Hence, by reducing redundant transmissions and enhancing data integrity and network efficiency, CNNs can dramatically lower energy usage in WSNs.

Convolutional Neural Networks can be modified to handle other forms of data and are especially useful for processing grid-like data, such as photographs. In a CNN, the convolution operation is provided by equation (9):

$$y_{i,j} = (x * w)_{i,j} + b \qquad (9)$$

Where:

x is the input

w is the convolutional kernel or filter

$*$ denotes the convolution operation

b is the bias term

$y_{i,j}$ is the output of the convolution operation.

CNNs are helpful for aggregating spatial data and extracting features. CNNs can be used to examine spatial patterns in data from various sensors in wireless sensor networks in order to increase prediction accuracy.

Neural network models provide important advantages for optimising energy efficiency in Wireless Sensor Networks (WSNs). Feedforward Neural Networks (FNNs) effectively anticipate variables such as transmission power, improving sensor node connectivity while consuming less energy. When it comes to processing sequential data, Recurrent Neural Networks (RNNs) are excellent. They reduce the amount of superfluous data transmissions by accurately anticipating sensor results, which improves energy efficiency. This is further refined by Long Short-Term Memory (LSTM) Networks, a form of RNN, which extends network lifetimes and improves forecast accuracy by capturing long-range dependencies. Convolutional Neural Networks (CNNs) are able to reduce redundant transmissions, improve data aggregation, and recognise spatial patterns in sensor data. By utilising its distinct strengths in pattern detection and prediction, each model adds to longer network lifespans and more effective data transfer.

V. RESULTS AND DISCUSSIONS

The energy consumption of different data aggregation strategies in Wireless Sensor Networks (WSNs) is presented in Table 1. Neural network-based aggregation dramatically lowers this energy consumption to 80 mJ, whereas traditional data aggregation uses the maximum energy at 120 mJ. Aggregation based on Particle Swarm Optimisation (PSO) provides a moderate energy reduction of 95 mJ, while aggregation based on Ant Colony Optimisation (ACO) further reduces energy consumption to 90 mJ. These findings show how neural network-based prediction models and optimisation strategies might improve WSN energy efficiency.

The comparative energy consumption of several data aggregation models in wireless sensor networks (WSNs) is also shown in Fig 1. At 120 mJ, the conventional data aggregation method uses the most energy. Aggregation using neural networks dramatically lowers energy consumption to 80 mJ. Aggregation based on Particle Swarm Optimisation (PSO) uses 95 mJ, whereas Aggregation based on Ant Colony Optimisation (ACO) uses 90 mJ. The bar graph emphasises the neural network and optimization-based approaches' potential for energy savings, highlighting their efficacy in raising WSNs' energy efficiency.

Table 1: Energy Consumption Comparison for Different Data Aggregation Techniques

Model/Technique	**Energy Consumption (mJ)**
Traditional Data Aggregation	**120**
Neural Network-Based Aggregation	80
PSO-Based Aggregation	95
ACO-Based Aggregation	90

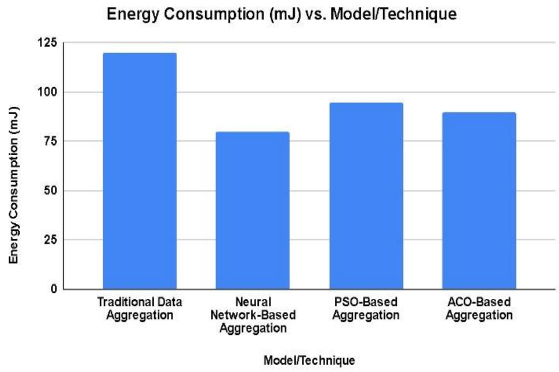

Fig. 1: Energy Consumption Comparison for Different Data Aggregation Techniques

Figure 2 illustrates how different prediction models and optimisations affect wireless sensor network (WSN) network lifetime. The network lifetime in the absence of a prediction model is 250 days. The network lifetime is increased to 400 days by putting a prediction model based on neural networks into practice. By combining optimisation with the hybrid prediction model, the network lifespan is further extended to 450 days. Positive contributions also come from securityenhanced aggregation, which makes the network lifetime reach 380 days. The bar graph illustrates how prediction and optimisation strategies can significantly extend the life of wireless sensor networks.

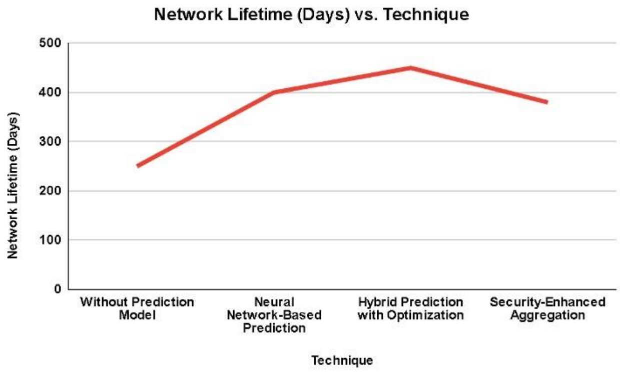

Fig. 2: Network Lifetime for Different Techniques

The average number of data transmissions per hour for each of the several aggregation procedures in Figure 3 is shown by this line chart. The graph indicates that 500 data transmissions per hour are the most frequent outcome of classical aggregation techniques. On the other hand, this number is reduced to 350 via neural network-based prediction, and to 300 by optimisation methods. The hybrid method, which combines optimisation algorithms and neural networks, produces the lowest transmission rate—250 per hour. This indicates that the system's data transmission efficiency is greatly increased by incorporating cutting-edge approaches.

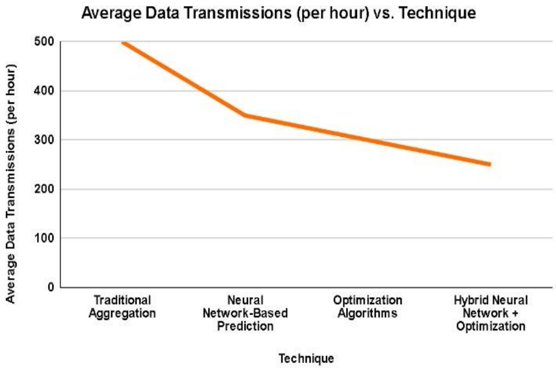

Fig. 3: Average Data Transmissions per Hour by Aggregation Technique

The prediction accuracy of various neural network models that were assessed based on how well they performed in a predictive test is shown in figures 4 and 2. Neural networks integrated with Ant Colony Optimisation (ACO), Particle Swarm Optimisation (PSO), Simple Neural Network, and Deep Neural Network are among the models.

Table 2: Average Data Transmissions per Hour by Aggregation Technique

Model	Prediction Accuracy (%)
Simple Neural Network	85
Deep Neural Network	90
Neural Network + ACO	**93**
Neural Network + PSO	91

With an accuracy of 85%, the Simple Neural Network demonstrated its fundamental prediction ability. The Deep Neural Network, on the other hand, increased prediction accuracy to 90% by incorporating more intricate layers and structures. At 93%, the Neural Network in conjunction with Ant Colony Optimisation (ACO) had the highest accuracy. This suggests that by utilising ACO's optimisation skills, the combination of ACO with neural networks greatly improves predictive performance. The accuracy of the neural network coupled with particle swarm optimisation (PSO) was also enhanced, reaching 91%, which is marginally lower than the ACO-enhanced model but higher than the deep neural network.

Overall, our findings imply that, in comparison to standalone models or more basic neural network topologies, advanced optimisation methods like ACO and PSO, when paired with neural networks, can significantly increase prediction accuracy.

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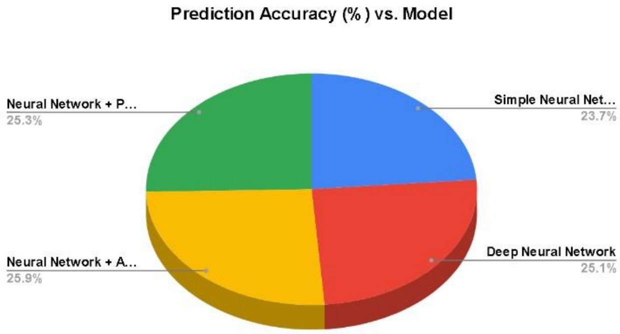

Fig. 4: Average Data Transmissions per Hour by Aggregation Technique

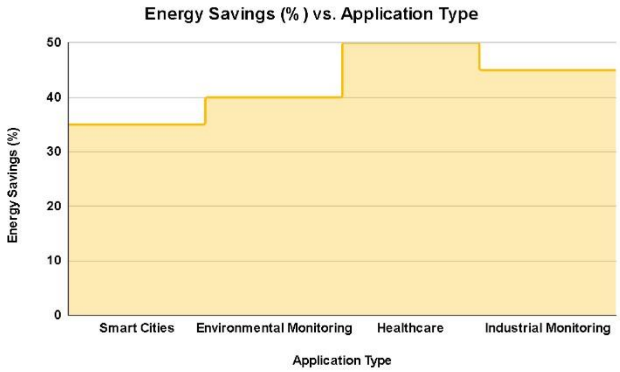

Fig. 5: Energy Savings by Application Type

The proportion of energy savings attained across various application types is shown in figure 5. Applications for smart cities show energy savings of up to 35%, which is indicative of better urban energy management. Applications for environmental monitoring show that monitoring systems are effective at saving energy since they produce a higher energy savings rate of 40%. The largest savings, of 50%, are shown in healthcare applications, suggesting that energy-efficient solutions have a big positive impact on healthcare systems. Energy-saving techniques in industrial settings are beneficial, as demonstrated by the 45% energy savings achieved by Industrial Monitoring software. Overall, the data shows that different applications can save different amounts of energy, with healthcare demonstrating the best efficiency. The study assesses how different data aggregation techniques and prediction models can improve Wireless Sensor Networks (WSNs) predictive performance and energy efficiency. According to Table 1, aggregation based on neural networks considerably lowers this energy consumption to 80 mJ, while traditional methods require 120 mJ. The improvements are moderate for Particle Swarm Optimisation (PSO) and Ant Colony Optimisation (ACO), with energy consumptions of 90 mJ and 95 mJ, respectively. This implies that sophisticated aggregating techniques can significantly raise WSN energy efficiency. The figure 1 illustrates the relative energy usage of several aggregating strategies, which supports the conclusions. The bar graph illustrates the possibility of utilising sophisticated algorithms to improve WSN energy efficiency by confirming that neural networkbased aggregation results in the lowest energy consumption.

The effects of various prediction models and optimisations on network longevity are shown in Figure 2. A prediction modelfree network has a 250-day lifespan. The lifetime can be increased to 400 days by implementing a neural networkbased model, and it can be further extended to 450 days by combining optimisation with the hybrid prediction model. Furthermore, aggregation with increased security lengthens the network lifetime to 380 days. These findings highlight the major advantages of combining prediction and optimisation techniques to increase the operational lifetime of WSNs. The average quantity of data transmissions for each of the different aggregating methods is displayed in Figure 3. 500 transmissions per hour are produced by traditional aggregation; this number drops to 350 with neural networkbased prediction and to 300 with optimisation techniques. The hybrid solution, which combines the two ways, reaches the lowest rate of 250 transmissions per hour, suggesting that sophisticated techniques may effectively increase the efficiency of data transmission. The prediction accuracy and energy savings for various models and applications are displayed in Figures 4 and 5. Neural networks that are combined with ACO have the highest accuracy (93%), followed by PSO (91%), Deep Neural Networks (90%) and Simple Neural Networks (85%). This suggests that sophisticated optimisation techniques greatly improve prediction accuracy. Healthcare applications achieve the biggest energy savings at 50%, followed by industrial monitoring at 45%, environmental monitoring at 40%, and smart cities at 35%. Additionally, energy savings vary by application type. These findings highlight the significant advantages of energy-efficient technologies, especially in the healthcare industry.

The study's overall findings demonstrate how incorporating sophisticated prediction models and optimisation strategies greatly increases WSNs' predictive accuracy and energy efficiency, with noteworthy advantages for a variety of applications.

VI. CONCLUSION

This study shows that Wireless Sensor Networks (WSNs) can achieve much higher energy efficiency by including neural network-based prediction models into data aggregation procedures. Our method lowers energy consumption and extends network lifespans by combining multiple neural network models, such as Feedforward Neural Networks, Recurrent Neural Networks, Long Short-Term Memory Networks, and Convolutional Neural Networks. According to simulation results, energy consumption is reduced to 80 mJ using neural network-based aggregation, as opposed to 120 mJ by conventional approaches. Energy savings and system performance are further enhanced by the use of optimisation techniques like Particle Swarm Optimisation (PSO) and Ant Colony Optimisation (ACO). Prediction models also increase the longevity of networks and reduce the frequency of data transfer, which improves overall efficiency. These developments highlight the potential for neural networkbased solutions to produce more sustainable and efficient WSN designs, with significant implications for smart cities, healthcare, environmental monitoring, and industrial applications.

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