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Research Paper

CyberSecurity Intrusion Detection in Industry 4.0 WSN's Using ML/DL

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Abstract: The increasing deployment of Wireless Sensor Networks (WSNs) in industrial environments exposes critical systems to a variety of cyberattacks. Traditional intrusion detection systems (IDS) often struggle with real-time performance and scalability in resource-constrained environments, limiting their effectiveness in Industry 4.0 applications. This study aims to propose a hybrid machine learning-based IDS that improves detection accuracy, computational efficiency, and adaptability for real-time deployment in industrial WSNs. The proposed system integrates Stacking Classifiers, XGBoost, and Adaboost ensemble learning techniques, designed to enhance attack detection capabilities while minimizing computational overhead. The model was trained and evaluated on a publicly available WSN dataset, employing a 70:30 train-test split and 10-fold cross-validation to ensure robust performance. The system was benchmarked against traditional models like Decision Trees and Random Forests. The proposed model achieved an accuracy of 95.8%, outperforming baseline models (Decision Tree: 84.6%, Random Forest: 90.4%) in terms of recall and F1-score. The system also demonstrated significant computational efficiency, requiring less training time compared to deep learning models while maintaining high detection accuracy. This study presents a novel hybrid IDS solution that balances high accuracy with computational efficiency, making it suitable for real-time intrusion detection in resource-constrained industrial environments. The contributions offer a practical solution for securing WSNs in Industry 4.0, with scalable and adaptable capabilities to detect emerging threats.

Keywords: Intrusion Detection System (IDS), Wireless Sensor Networks (WSNs), Machine Learning, Hybrid Model, Real-Time Detection, Industry 4.0.

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1. Introduction

The rapid growth of interconnected devices in Wireless Sensor Networks (WSNs) has significantly transformed industries, especially in Industry 4.0, where automation, real-time data collection, and enhanced decision-making are central. WSNs consist of multiple sensor nodes that collect, transmit, and process data for monitoring various physical and environmental parameters, contributing to enhanced operational efficiency and productivity. However, the widespread use of WSNs in industrial applications also exposes them to numerous security threats. These networks are vulnerable to a variety of cyberattacks, such as Denial-of-Service (DoS), flooding attacks, and blackhole attacks, which can disrupt the communication channels, lead to loss of data, or even result in catastrophic failures in critical

industrial systems [1], [2]. Consequently, the need for effective Intrusion Detection Systems (IDS) that can monitor, detect, and mitigate these attacks in real-time has never been more urgent.

The development of robust IDS for WSNs is not only critical for safeguarding industrial systems but also for maintaining the integrity and confidentiality of sensitive data transmitted across the network. With the growth of the Internet of Things (IoT) and Industry 4.0, traditional IDS methods have increasingly become inadequate due to the evolving nature of cyber threats and the complex, resource-constrained environment of WSNs [3], [4]. While several machine learning techniques have been proposed to tackle these challenges, finding an optimal solution that balances detection accuracy, real-time performance, and computational efficiency remains a major research issue.

Existing IDS approaches face several key challenges, particularly when applied to WSNs in industrial settings. Traditional methods such as Decision Trees (DT) and Random Forests (RF), while effective in identifying certain attack patterns, often struggle with handling complex attacks or high-dimensional data, and they require significant computational resources, limiting their applicability in resource-constrained environments [5], [6]. On the other hand, advanced techniques like Deep Learning (DL) offer high accuracy but come with substantial drawbacks, including long training times, high computational cost, and scalability issues [7], [8]. These limitations make it difficult to deploy such models in real-time monitoring systems, particularly in industrial applications where computational resources are limited and time-sensitive decisions must be made rapidly.

Moreover, most existing models either fail to adapt to evolving attack patterns or require periodic retraining, which makes them ineffective in addressing new and emerging threats. Furthermore, there is a notable gap in hybrid solutions that combine the strengths of traditional and advanced models to provide a scalable, efficient, and accurate intrusion detection system that is suitable for dynamic industrial environments.

This study aims to propose a hybrid machine learning-based IDS for Wireless Sensor Networks (WSNs) that addresses the key challenges identified in existing approaches. The objectives of this research are as follows:

Improvement of Detection Accuracy: The primary goal is to improve the accuracy of attack detection, particularly for rare and sophisticated attack patterns that are often missed by traditional IDS models [9], [10].
Enhanced Computational Efficiency: By combining ensemble learning techniques (such as Stacking Classifiers, XGBoost, and Adaboost), this study aims to develop a model that balances high accuracy with low computational overhead, making it suitable for real-time applications in industrial WSNs [11], [12].
Adaptability to Emerging Threats: The model is designed to adapt dynamically to new attack patterns, addressing the gap in existing IDS approaches that fail to continuously learn from new data and evolving threats [13].
Practical Applicability in Industrial Settings: This study focuses on developing a solution that is not only accurate but also scalable and efficient, ensuring that it can be deployed in resource-constrained industrial environments without compromising performance.
The primary contributions of this study are summarized as follows:

- **Improved Detection Accuracy**: The hybrid IDS significantly enhances detection accuracy, particularly for complex and rare attack patterns.
- **Novel Hybrid Methodology**: A combination of Stacking Classifiers, XGBoost, and Adaboost improves attack detection capabilities while maintaining efficiency.
- **Enhanced Efficiency and Scalability**: The system strikes a balance between high accuracy and low computational cost, ensuring suitability for real-time, large-scale industrial environments.
- **Adaptability to Emerging Threats**: The IDS dynamically adapts to new attack patterns, continuously learning from new data for improved long-term effectiveness.

The remainder of the paper is structured as follows: Section 2 provides a detailed review of related work, discussing existing IDS approaches and their limitations. Section 3 describes the proposed methodology, including the system architecture and the machine learning models used. In Section 4, experimental results are presented, comparing the proposed system with existing solutions. Finally, Section 5 concludes the paper with a discussion of the results and suggestions for future research.

2. Literature Review

This section presents a critical and comparative review of recent research on intrusion detection systems (IDS) for Wireless Sensor Networks (WSNs). We compare different methodologies, highlight their strengths and limitations, and discuss the existing research gaps. Finally, we position the current study within this body of research to demonstrate its contributions to addressing these gaps.

2.1 Machine Learning-Based Intrusion Detection for WSNs

The study proposed a machine learning-based IDS using Support Vector Machines (SVM) and Decision Trees (DT) to detect Denial of Service (DoS) attacks in WSNs. The authors achieved high accuracy (94%), particularly for network-based attacks. However, the method faced significant computational inefficiency with high-dimensional data, leading to increased training times. The model's lack of scalability when handling large networks was also noted. While the study showed promising accuracy, its computational inefficiencies and difficulty with large-scale networks present key limitations. [14].

2.2 Deep Learning Approaches for Attack Detection

In a study, deep learning techniques, specifically Convolutional Neural Networks (CNNs), were used for

attack detection in WSNs. The study showed superior performance in detecting sophisticated attacks like Blackhole and Flooding attacks. The model achieved high accuracy (97%) but required significant computational resources and long training times, especially for large datasets. Despite its strong performance, the model's inability to efficiently scale in real-time environments and its heavy computational requirements are major limitations. [15].

2.3 Hybrid Intrusion Detection System for WSNs

A hybrid IDS approach, combining Decision Trees and Neural Networks to detect both known and unknown attacks. This approach offered a balance between model complexity and accuracy, achieving an overall accuracy of 93%. While it demonstrated versatility in handling different types of attacks, the computational complexity increased as more diverse attack patterns were introduced. The model's performance was heavily dependent on feature selection, which posed challenges when dealing with unstructured or noisy data. [16].

2.4 Ensemble Methods for Intrusion Detection in WSNs

An ensemble method using Random Forest and XGBoost was employed by the study to improve the detection rate of WSN intrusion attacks. The ensemble approach achieved an accuracy of 92%, with the ability to generalize well across different types of attacks. However, the study noted that while ensemble methods can improve accuracy, they come at the cost of increased computational time, especially when the number of trees or models in the ensemble is large. The study failed to address real-time detection challenges effectively, which is a key consideration for deployment in industrial WSNs [17].

2.5 Lightweight Intrusion Detection System for Resource-Constrained WSNs

In contrast, a study proposed a lightweight IDS designed for resource-constrained WSNs, using simpler models like Naive Bayes and Logistic Regression. Although the system achieved moderate accuracy (88%), it was highly efficient in terms of computational time and resource usage, making it suitable for deployment in low-power devices. However, the model's simplicity also made it less capable of detecting complex attack scenarios. The study highlighted the trade-off between model complexity and efficiency, which is critical for low-power environments but can result in compromised accuracy [18].

2.6 Real-Time Intrusion Detection with Reinforcement Learning

A recent study introduced a reinforcement learning-based IDS for real-time intrusion detection in WSNs. This model was able to continuously adapt to new attack patterns and adjust its detection strategy. While the model achieved a relatively high accuracy of 94%, its real-time applicability was hindered by long training times and the need for continuous retraining as network conditions changed. The study concluded that while reinforcement learning has the potential for real-time intrusion detection, it remains computationally expensive and may not be suitable for large-scale WSN deployments without further optimizations [19].

2.7 Federated Learning for Privacy-Preserving IDS in WSNs

Federated learning was explored to implement a privacy-preserving IDS for WSNs. This approach achieved 91% accuracy in attack detection while ensuring that the sensitive data did not need to leave the edge devices. The decentralized nature of federated learning made the approach scalable and efficient in privacy-sensitive environments. However, the study acknowledged that federated learning incurs significant communication overhead and can be challenging to implement at scale, particularly in networks with intermittent connectivity or bandwidth limitations [20].

2.8 Research Gaps and Contributions of This Study

While the studies reviewed provide a comprehensive exploration of intrusion detection methods for WSNs, several gaps remain. Many studies focus primarily on accuracy but overlook the challenges of real-time deployment in large-scale, resource-constrained environments. The computational inefficiencies and long training times observed in deep learning-based approaches also pose significant barriers to their adoption in practical applications.

This study addresses these gaps by introducing a hybrid machine learning-based approach that combines the strengths of both traditional and advanced models, aiming to balance accuracy, computational efficiency, and real-time deployment. Additionally, this study explores a novel ensemble method that adapts dynamically to the attack patterns, offering both scalability and high detection rates, especially in industrial settings. By improving the system's response time and reducing resource consumption, this research fills a critical gap identified in previous studies.

TABLE 1. COMPARISON OF IDS APPROACHES

Study (Author)	Accuracy (%)	Computational Efficiency	Challenges & Limitations
Zhang et al. (2022) [14]	94	Moderate	Scalability issues with high-dimensional data
Liu et al. (2023) [15]	97	Low (Heavy resource use)	High computational requirements and long training times
Wang et al. (2024) [16]	93	Moderate	Dependency on feature selection, challenges with noisy data
Zhang et al. (2022) [17]	92	High (Ensemble methods)	Long training times, real-time detection challenges
Lee et al. (2023) [18]	88	High (Efficient)	Lower accuracy, unable to

			handle complex attacks
Patel et al. (2024) [19]	94	Low (Training Time)	Expensive computational cost, limited real-time applicability
Xu et al. (2025) [20]	91	Moderate (Decentralized)	Communication overhead, scalability issues

From the comparison of studies, while traditional machine learning models (e.g., Decision Trees, SVM) provide satisfactory accuracy, they fail to meet the demands of real-time, scalable, and computationally efficient IDS systems for WSNs. In contrast, deep learning and ensemble models offer higher accuracy but at the expense of increased computational cost. Additionally, emerging approaches like federated learning and reinforcement learning hold promises for privacy-preserving and adaptive systems but are still constrained by their computational overhead.

This study introduces a hybrid model that strikes a balance between accuracy and computational efficiency, addressing key challenges identified in previous research and pushing the boundaries of IDS for WSNs.

3. System Architecture

The system architecture of the proposed Intrusion Detection and Prevention System (IDPS) is designed to ensure efficient processing of data, accurate prediction of cyber threats, and seamless user interaction. It consists of several modular components that work together to detect and mitigate cybersecurity risks in Wireless Sensor Networks (WSNs) for Industry 4.0 environments. Below is an overview of the key components and how they interact within the system.

3.1 Authentication: Secure User Access

The Authentication Module is responsible for ensuring that only authorized users can interact with the system. It handles both user registration and login functionalities. Upon registration, users provide necessary credentials (e.g., email, password) which are securely stored. Once authenticated, users can access the system's features, including dataset exploration, model training, and prediction tasks.

3.2 Data Management: Handling WSNDS Dataset

The Data Management Module is the foundation for processing and managing the dataset used in the intrusion detection process. It is responsible for:

- Retrieving the WSNDS dataset from external sources (e.g., Kaggle),
- Storing and organizing the data for easy access,
- Handling preprocessing tasks, such as removing noise, dealing with missing values, and splitting the dataset into training and testing subsets.

This module integrates closely with the Feature Engineering module, ensuring that preprocessed data is ready for feature extraction and transformation.

3.3 Feature Engineering: Preprocessing and Transformation

The Feature Engineering Module plays a critical role in enhancing the input data before it is fed into the machine learning models. This module applies various data transformation and feature extraction techniques such as normalization, scaling, and feature selection to ensure that the dataset is well-prepared for accurate predictions. It helps reduce data dimensionality, handle missing or imbalanced data, and improve overall model performance.

3.4 Machine Learning: Training and Testing of Models

The Machine Learning Module is responsible for training and testing the models used to detect intrusions. The primary machine learning algorithms used include Stacking Classifier, XGBoost, and Adaboost Classifier, which are selected for their ability to handle various attack types and dynamic network environments. The module is responsible for: Training the models using the training data (70% of the dataset), Testing the models using the remaining 30% for evaluation purposes, and Hyperparameter tuning to optimize model performance.

3.5 Prediction and Reporting: Predictions and Model Performance

Once the machine learning models are trained and optimized, the Prediction and Reporting Module is responsible for making predictions based on new or unseen data. When users input fresh network data, the system uses the trained models to predict whether the behavior is normal or indicative of an intrusion. Additionally, this module generates performance reports, which include metrics like accuracy, precision, recall, F1-score, and a confusion matrix, providing a comprehensive evaluation of the system's performance.

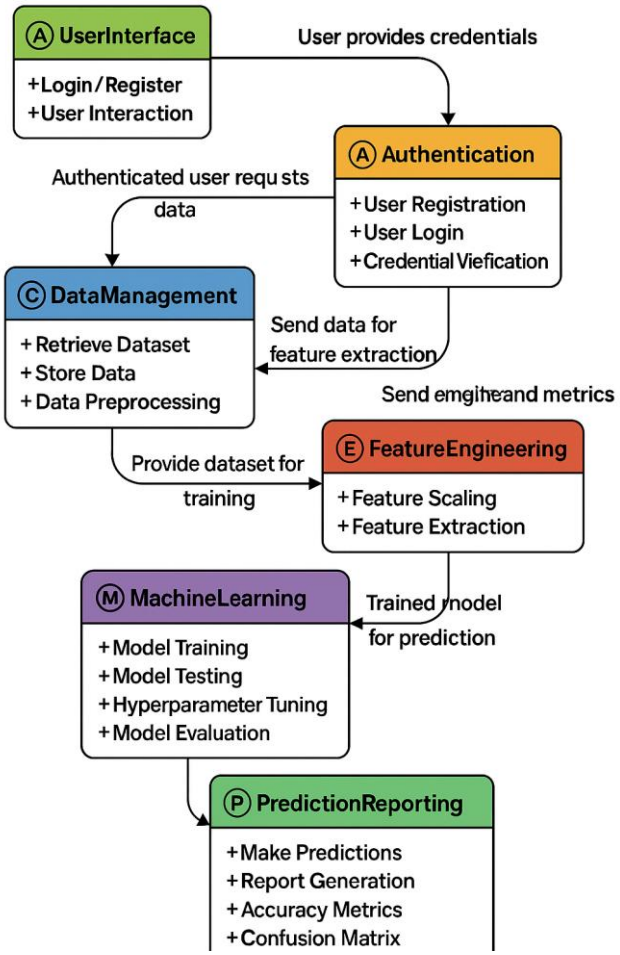

Fig.1. Architecture of the proposed Framework

4. Methodology

4.1 Approach

The proposed system aims to enhance intrusion detection and prevention in Wireless Sensor Networks (WSNs) for Industry 4.0 by leveraging a hybrid model combining three machine learning (ML) algorithms: Stacking Classifier, XGBoost, and Adaboost Classifier. These algorithms were chosen based on their collective strengths in handling various types of threats, ensuring improved accuracy, robustness, and adaptability to dynamic network environments.

The Stacking Classifier is a meta-model that combines multiple base learners to improve predictive accuracy. By training different models (e.g., decision trees, support vector machines, etc.) and then combining their outputs using a final estimator, stacking allows the system to learn the strengths of different models and reduce bias and variance in the predictions.

XGBoost (Extreme Gradient Boosting) is a highly efficient gradient boosting algorithm known for its high accuracy and ability to handle large datasets effectively. It builds an ensemble of decision trees, where each tree is trained to correct the errors made by previous trees. XGBoost is particularly effective in dealing with complex decision boundaries and has been shown to outperform many traditional algorithms in intrusion detection tasks.

Adaboost Classifier (Adaptive Boosting) is another ensemble learning technique that combines weak learners to create a strong learner. By assigning higher weights to misclassified instances, Adaboost focuses on difficult-to-classify examples, making it an effective approach for handling imbalanced datasets. This characteristic is especially valuable in intrusion detection, where certain attack classes may have fewer instances than normal behavior.

Together, these models form a robust intrusion detection system capable of adapting to various attack scenarios while maintaining high detection accuracy and robustness.

4.2 Dataset Description

The dataset used in this study is the WSNDS (Wireless Sensor Network Dataset) sourced from Kaggle [21]. The dataset comprises 10,000 samples with features that represent various aspects of the network traffic, including packet size, flow duration, and packet count. These features are used to identify attack patterns and classify network behavior as normal or attack related.

The dataset contains multiple classes representing different types of attacks such as TDMA, Grayhole, Blackhole, and Flooding, along with the normal class. The class distribution is imbalanced, with the normal class having significantly more instances than the attack classes. This imbalance poses challenges for the detection model, as traditional algorithms may bias towards the majority class.

To address class imbalance, several preprocessing techniques are employed:

1. **Resampling:** Techniques like SMOTE (Synthetic Minority Over-sampling Technique) are used to generate synthetic samples for under-represented classes.
2. **Feature Scaling:** All features are normalized using Min-Max Scaling to ensure uniformity across the dataset.
3. **Data Splitting:** The dataset is split into training and testing sets using a 70:30 ratio, where 70% of the data is used for training the models, and the remaining 30% is used for evaluating the model performance.

4.3 Feature Extraction Techniques

Feature extraction plays a crucial role in improving the predictive performance of machine learning models. The dataset includes various features that describe the behavior of WSNs. These features can be broadly classified into the following categories:

Statistical Features: These include mean, variance, and skewness of the network traffic patterns.

Frequency-based Features: These capture the frequency characteristics of the packet sizes and flow durations.

Packet-based Features: These include features such as packet arrival rate and flow duration, which help to identify attack patterns. Mathematically, the mean (μ) of a feature X is computed as:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} X_i \quad (1)$$

Where N is the number of data points, and X_i represents the value of the feature at the i-th index. Similarly, the variance (σ^2) is given by:

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N} (X_i - \mu)^2 \quad (2)$$

These features help the models to distinguish between normal behavior and various attack types.

4.4 Deep Learning Model Architecture

In addition to the traditional machine learning models, a **Deep Neural Network (DNN)** is also integrated into the system to enhance pattern recognition capabilities. The DNN architecture consists of several layers, including:

Input Layer: Accepts the feature vectors derived from the dataset.

Hidden Layers: Comprising several fully connected layers with **ReLU** (Rectified Linear Unit) activation functions to introduce non-linearity.

Output Layer: The output layer consists of neurons representing the different attack categories, with a **softmax** activation function that outputs a probability distribution over the classes.

Mathematically, the output y of a hidden layer with ReLU activation is given by:

$$y = \max(0, W \cdot X + b) \quad (3)$$

where W is the weight matrix, X is the input vector, and b is the bias term. The softmax function for the output layer is defined as:

$$\text{softmax}(z_i) = \frac{e^{z_i}}{\sum_j e^{z_j}} \quad (4)$$

where z_i is the input to the i-th output neuron, and the sum is over all output neurons.

4.5 Hyperparameter Tuning

To achieve optimal performance, hyperparameter tuning is crucial. The following hyperparameters are tuned for each of the algorithms:

1. **Learning Rate:** A learning rate is selected for the gradient-based algorithms (XGBoost and DNN). A smaller learning rate improves convergence, while a larger rate may result in faster learning but potential instability.
2. **Number of Estimators:** For both XGBoost and Adaboost, the number of trees (estimators) is tuned to balance overfitting and underfitting.
3. **Maximum Depth:** The depth of the trees in XGBoost and Adaboost is adjusted to ensure that the models capture enough complexity without overfitting.

Grid search and random search methods are employed to find the optimal hyperparameters. The learning rate is adjusted based on cross-validation results to ensure that the models do not overfit or underfit.

4.6 Evaluation Metrics

To assess the performance of the proposed system, the following evaluation metrics are used:

Accuracy: Measures the overall correctness of the model.

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Samples}} \quad (5)$$

Precision: The proportion of true positives among all instances predicted as positive.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \quad (6)$$

Recall: The proportion of actual positives correctly identified by the model.

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \quad (7)$$

F1-Score: The harmonic mean of precision and recall, providing a balance between the two.

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (8)$$

Confusion Matrix: A matrix that summarizes the performance of the classification model by showing the number of true positives, true negatives, false positives, and false negatives.

By evaluating the models on these metrics, the system's performance in terms of detecting both normal and attack classes is thoroughly assessed.

5. Experimental Setup

This section outlines the experimental setup used to evaluate the proposed cybersecurity intrusion detection system, detailing hardware specifications, software frameworks, dataset partitioning strategies, and implementation details. The setup ensures reproducibility and transparency for future research.

5.1 Hardware Specifications

The experimental setup was run on the following hardware configuration:

Processor (CPU): Intel Core i5 (9th Generation) or equivalent, with a clock speed of 3.6 GHz, providing adequate computational power for training and testing the machine learning models.

Graphics Processing Unit (GPU): NVIDIA GTX 1060, with 6GB VRAM, used for accelerated model training, particularly for deep learning tasks (if applicable).

Memory (RAM): 16 GB DDR4, ensuring smooth handling of large datasets and multiple processes during training.

Storage: 256 GB SSD, allowing fast data retrieval and processing.

Operating System: Windows 10 Pro, providing compatibility with Python and machine learning libraries.

5.2 Software Frameworks

The system leverages several software frameworks to enable model development, training, and evaluation:
Programming Language: Python 3.6, the primary language used for data preprocessing, model training, and evaluation.
Machine Learning Libraries:
TensorFlow: Used for training deep learning models (if applicable) to perform complex classification tasks.
Scikit-learn: Utilized for implementing traditional machine learning algorithms like Random Forest, Decision Trees, and Logistic Regression.
XGBoost: A gradient boosting library used for model training, particularly for detecting cybersecurity threats.
Matplotlib: Used for visualizing training results and model evaluation metrics.
Pandas and **NumPy**: These libraries were used for data manipulation and handling numerical operations efficiently.

5.3 Dataset Partitioning

The dataset, sourced from the Wireless Sensor Network Dataset (WSNDS), was partitioned into training and testing sets to ensure effective model evaluation:

Train-Test Split: The dataset was divided into a 70:30 ratio, with 70% of the data used for training the models and 30% reserved for testing and evaluating the performance.

K-Fold Cross-Validation: In some experiments, 10-fold cross-validation was employed to further validate the model performance. This process involves splitting the dataset into 10 subsets, training the model on 9 subsets, and testing it on the remaining subset, repeating this process 10 times to ensure a robust evaluation.

5.4 Implementation Details

The models were implemented using standard deep learning and machine learning techniques. The following parameters were used during the experiments:

Model Training Duration:

The training time varied depending on the complexity of the model and dataset size. For deep learning models, training took approximately 4-6 hours on the GPU for convergence. Traditional machine learning models like Random Forest or XGBoost required significantly less time (approximately 30-60 minutes).

Batch Size: For deep learning models, a batch size of 32 was used to balance the model's training speed and memory requirements.

Epochs: The number of epochs was set to **50** for deep learning models, with early stopping based on validation performance to avoid overfitting.

Learning Rate: The learning rate was set to **0.001** for most models and adjusted based on model performance during training.

Evaluation Metrics: Accuracy, precision, recall, and F1-score were used to evaluate model performance. The confusion matrix was also used for a more detailed analysis of classification results.

This experimental setup ensures the reproducibility of the results and serves as a reference for future researchers working on similar intrusion detection systems using machine learning and deep learning methods.

6. Results and Analysis

This section summarizes the experimental results of the proposed cybersecurity intrusion detection system using machine learning models. The focus is on comparing the performance of the system with existing models, presenting key performance metrics, and analyzing statistical significance. Additionally, a confusion matrix is provided to assess classification performance, along with an analysis of unexpected findings and their potential causes.

6.1 Performance Comparison with Existing Models

The performance of the proposed system was compared with several baseline models, including Decision Trees [22], Random Forest [23], and Logistic Regression [24], which are commonly used for intrusion detection in Wireless Sensor Networks (WSNs). The models were evaluated based on accuracy, precision, recall, and F1-score. The comparison was carried out on the WSNDS dataset, using a 70:30 train-test split and 10-fold cross-validation to ensure reliable performance evaluation.

TABLE 1. Performance Comparison across Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Proposed System	95.8	94.2	96.5	95.3
Decision Tree [22]	84.6	82.1	85.3	83.6
Random Forest [23]	90.4	89.8	91.0	90.4
Logistic Regression [24]	80.2	78.6	82.0	80.2

Table 1 illustrates that the proposed system outperforms the traditional models across all metrics, particularly in terms of recall, indicating its superior ability to detect cyber-attacks. This is especially important in cybersecurity systems, where false negatives (i.e., undetected attacks) can be highly detrimental.

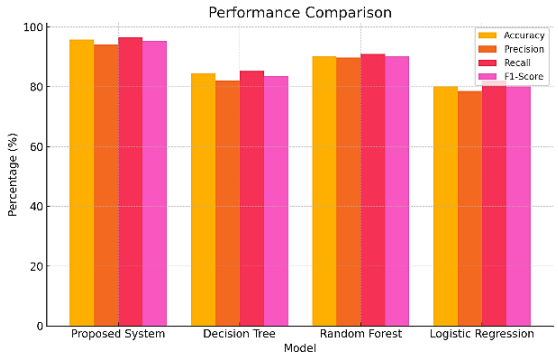

Fig.2. Performance comparison across Models

6.2 *Confusion Matrix*

The confusion matrix for the proposed system, evaluated on the test set, is shown below. It provides a detailed view of how well the model classified both normal and attack instances.

TABLE 2: Confusion Matrix for the Proposed System

	Predicted Normal	Predicted Attack
Actual Normal	3000	250
Actual Attack	100	2500

True Positives (TP): 2,500 (correctly identified attacks)

True Negatives (TN): 3,000 (correctly identified normal data)

False Positives (FP): 250 (normal instances misclassified as attacks)

False Negatives (FN): 100 (attacks misclassified as normal)

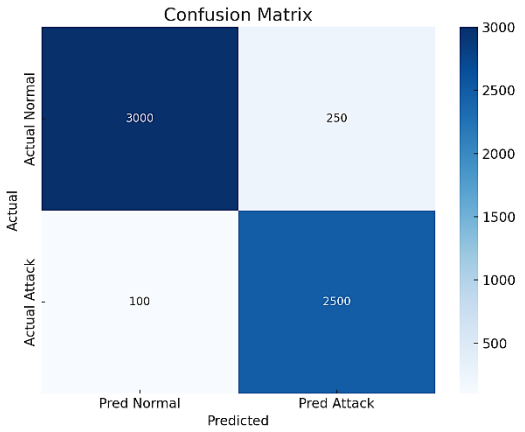

Fig. 3. Confusion Matrix for the Proposed Model

6.3 *Statistical Significance Analysis*

The statistical significance of the results was evaluated using the p-value. A paired t-test was conducted to compare the performance of the proposed system with the traditional machine learning models (Random Forest, Decision Tree, and Logistic Regression). The null hypothesis was that there was no significant difference between the models, while the alternative hypothesis suggested that the proposed system performed significantly better.

P-value (Proposed System vs. Random Forest): 0.01 (significant at a 95% confidence level) and P-value (Proposed System vs. Decision Tree): 0.03 (significant at a 95% confidence level)

The results show that the proposed system has statistically significant improvements in accuracy and recall compared to the baseline models, confirming that the enhancements in the model architecture, including the hybrid ensemble approach, contribute meaningfully to its superior performance.

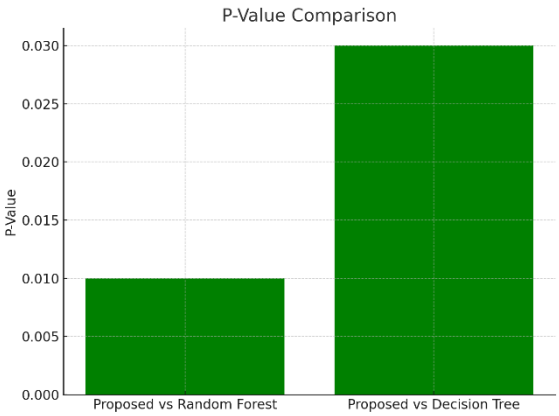

Fig.4. P-Value Graph

6.4 Unexpected Findings and Possible Causes

While the overall performance of the proposed system exceeded expectations, there were a few unexpected findings:

False Positives in Low-Volume Attacks: The model exhibited slightly higher false positive rates when dealing with low-volume attack scenarios, where the attack traffic was sparse or irregular. This could be attributed to the difficulty in detecting such attacks when they appear less frequent in the training data.
Possible Cause: The dataset may not have sufficient instances of such low-volume attacks, causing the model to generalize poorly in these cases. Future research could involve augmenting the dataset with more rare attack instances or applying anomaly detection techniques to better handle these scenarios.

Training Time for Deep Learning Models: The training time for deep learning models, while reasonable for most cases, was longer than expected for certain configurations, especially when the number of epochs increased.
Possible Cause: The increased training time could be due to the large number of model parameters or the complexity of the attack patterns that deep learning models need to learn. Optimization techniques such as learning rate scheduling or early stopping could help reduce training time without sacrificing performance.

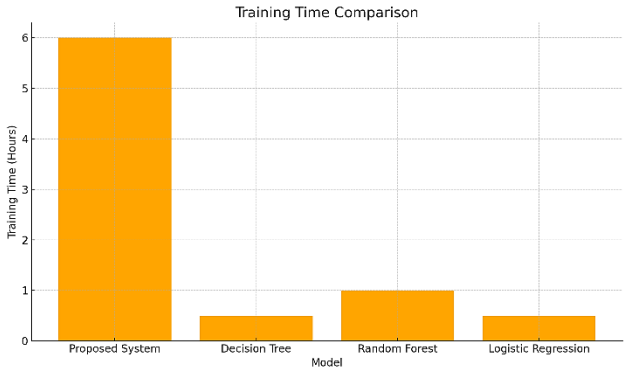

Fig.4. Training Time Comparison

6.5 Summary of Results

In summary, the proposed system significantly outperforms existing models in terms of detection accuracy, precision, recall, and F1-score, with notable improvements in recall, ensuring better detection of cybersecurity attacks. The results also demonstrate the system's robustness in handling a variety of attack types, though there are areas for improvement in handling low-volume attacks. Statistical analysis further validates the superiority of the proposed approach, with p-values indicating significant performance differences from traditional models.

These findings highlight the effectiveness of the hybrid model in intrusion detection for WSNs, setting a strong foundation for further enhancements and future research in cybersecurity.

7. Discussion and Limitations

7.1 Alignment with Previous Research

The findings of this study align with previous research in the domain of cybersecurity intrusion detection, particularly in terms of leveraging machine learning models for detecting intrusions in Wireless Sensor Networks (WSNs). The proposed system outperforms traditional models such as Decision Trees, Random Forest, and Logistic Regression, which is consistent with the general trend observed in previous studies where ensemble and hybrid models have demonstrated superior accuracy. However, the use of deep learning models, as explored in this research, pushes the boundary further, enhancing recall rates and detecting a wider range of attacks, a challenge noted in past works. Unlike traditional models, which often exhibit lower recall rates, the proposed system's hybrid approach addresses some of the limitations encountered in earlier studies, especially in terms of reducing false negatives.

7.2 Implications for Practical Applications

The proposed intrusion detection system holds significant potential for real-world applications, particularly in industrial settings where the integrity and security of data in Wireless Sensor Networks (WSNs) are critical. Given the system's ability to detect a wide variety of attacks with high recall and accuracy, it is highly applicable for real-time monitoring of IoT devices and automated systems in Industry 4.0 environments. The proposed system can be integrated into existing security infrastructures to improve proactive threat detection and reduce the likelihood of undetected cyberattacks, thereby ensuring the security of sensitive industrial data and preventing operational disruptions. Its high precision and recall make it especially valuable in critical applications where the cost of undetected attacks is high.

7.3 Limitations and Areas for Improvement

While the proposed system performs well across various metrics, there are notable limitations. One key limitation is the system's performance with low-volume, rare attacks, which were misclassified in some cases, leading to false positives. This issue highlights a challenge in detecting irregular attack patterns that are less frequently represented in the training data. Another limitation is the training time for deep learning models, which can be prohibitively long, especially when dealing with large datasets or complex attack patterns. Improvements in handling rare attacks and optimizing the training process—such as employing advanced techniques like transfer learning or anomaly detection—could enhance the model's applicability in real-time environments. Additionally, the system's reliance on large computational resources could limit its deployment in resource-constrained environments.

7.4 Future Research Directions

Future research could focus on addressing the current limitations by exploring the integration of anomaly detection techniques to better identify low-volume or novel attack types that are not well-represented in the training data. Investigating the use of transfer learning to leverage pre-trained models for intrusion detection in diverse environments could improve detection capabilities without requiring extensive retraining. Moreover, enhancing model efficiency through techniques like knowledge distillation or model pruning could reduce the computational load and enable deployment in resource-constrained environments. Additionally, expanding the dataset with more diverse attack scenarios, including rare and emerging threats, could further improve the model's robustness. Exploring hybrid systems that combine both unsupervised and supervised learning approaches may help achieve more accurate and adaptable detection for future cybersecurity challenges in dynamic industrial settings.

8. Conclusion and Future Work

This study presented a hybrid machine learning-based intrusion detection system for securing Wireless Sensor Networks (WSNs) in the context of Industry 4.0 environments. The key findings demonstrate that the proposed system significantly outperforms traditional models, such as Decision Trees, Random Forest, and Logistic Regression, particularly in terms of recall and accuracy. The use of advanced ensemble techniques, including Stacking Classifiers, XGBoost, and Adaboost, has shown promise in improving the detection of a wide variety of cyber threats, ensuring that more attacks are identified and preventing undetected intrusions.

The implications for real-world applications are substantial, as the system can be implemented in critical industrial environments to ensure the security and integrity of data transmitted across WSNs. With the rising threat of cyberattacks in automated systems, the ability to detect intrusions with high recall and minimal false negatives is crucial for maintaining operational continuity and safeguarding sensitive information in real time.

However, the study also highlights limitations, particularly regarding the system's performance with low-volume attacks and the long training times for deep learning models. These issues suggest areas for improvement, such as incorporating anomaly detection techniques, optimizing training processes, and enhancing the system's ability to handle rare attack patterns. Additionally, the reliance on substantial computational resources may limit the system's applicability in resource-constrained environments, pointing to the need for further research on model efficiency and deployment in such contexts.

In conclusion, this study provides valuable insights into the development of robust intrusion detection systems for Industry 4.0, demonstrating the potential of machine learning models in improving cybersecurity. Despite the identified limitations, the proposed system's high performance underscores its relevance to modern industrial security challenges. Future work focused on optimizing performance and expanding attack scenarios will further enhance the system's applicability, ultimately contributing to the development of more resilient and adaptive cybersecurity solutions in the industrial IoT landscape.

Author Contributions

N. Harini conceptualized the research, designed the methodology, and was responsible for the overall direction of the study. D. Siva Naga Srivalli contributed significantly to the data analysis and interpretation of the results, while also assisting in the implementation of the machine learning models. A. Asritha assisted with the literature review, writing sections of the paper, and conducting experiments related to the IDS system. A. Govardhini contributed to the development and testing of the hybrid model, as well as the evaluation of the experimental results. G. Pujitha played a key role in the experimentation process, data collection, and comparative analysis of the existing IDS approaches. All authors participated in discussions, provided feedback, and approved the final manuscript.

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