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Enhancing Cyber Attack Detection with Machine Learning through Multi-Objective and Evolutionary Optimization for autonomous vehicles.

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Abstract:- Due to the substantial rise in vehicle connectivity brought about by the integration of autonomous vehicles (AVs) into contemporary transportation systems, these vehicles are now vulnerable to a variety of cyberattacks. As these vehicles rely on complex software architectures, communication networks, and real-time data exchange, ensuring their cybersecurity is paramount to protect both passenger safety and system integrity. Traditional intrusion detection methods often struggle to cope with the high-dimensional, dynamic, and evolving nature of cyber threats in autonomous systems. This study combines machine learning (ML) techniques with multi-objective and evolutionary optimization algorithms to provide a novel approach to cyber-attack detection in autonomous cars. Machine learning models such as decision trees, support vector machines (SVM), and deep neural networks (DNNs) are employed to classify network traffic and detect anomalies in vehicle communication. To enhance model accuracy and computational efficiency, evolutionary optimization techniques—such as Multiobjective Jaya Algorithm—are applied for hyper parameter tuning and feature selection, balancing multiple objectives including detection accuracy, false positive rate, and response time. Experimental evaluations on benchmark vehicular network datasets demonstrate that the proposed system achieves high detection performance while maintaining low latency and resource consumption. The integration of multi-objective optimization not only improves model robustness but also adapts to changing attack patterns in real-time. This research contributes to the development of a scalable and intelligent intrusion detection framework for next-generation autonomous vehicles, fostering safer and more secure intelligent transportation systems.

Keywords: *Cyber Attack Detection , Machine Learning, Deep Learning , Log and Reporting*

1. Introduction

The increasing integration of electronics, sensors, and communication networks in modern vehicles—particularly electric and autonomous vehicles—has revolutionized the transportation sector by improving efficiency, safety, and user experience. However, this connectivity has also introduced new vulnerabilities, making vehicles susceptible to a wide range of cyber threats. As vehicles become more reliant on inter-vehicular communication (V2V), vehicle-to-infrastructure (V2I) systems, and internal networks such as the Controller Area Network (CAN) bus, the risk of cyber-attacks targeting these components continues to rise.

Cyber-attacks on vehicles can take various forms, including message injection, spoofing, denial-of-service (DoS), and replay attacks. These intrusions can disrupt critical functionalities such as braking, steering, and acceleration, posing serious threats to passenger safety and public security. Traditional automotive cybersecurity approaches rely on predefined rule-based systems and signature-based

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intrusion detection mechanisms. While these methods provide a baseline level of protection, they often struggle to keep pace with the rapidly evolving nature of cyber threats and the increasing complexity of vehicular systems. Furthermore, conventional techniques tend to generate a high number of false positives and are often unable to detect previously unseen or zero-day attacks.

To address these limitations, there is a growing need for intelligent, data-driven solutions capable of detecting cyber-attacks in real-time with high accuracy. Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have demonstrated great potential in this area. Deep Neural Networks (DNNs), in particular, have shown superior performance in recognizing complex patterns and anomalies within large datasets. These models can automatically learn relevant features from vehicular network traffic and classify malicious behavior without the need for extensive manual intervention.In this study, we propose a deep learning-based intrusion detection system for detecting cyber-attacks in electric and autonomous vehicles. The system leverages a Deep Neural Network to analyze CAN bus data and identify abnormal communication patterns indicative of cyber threats. By training the model on labeled vehicular traffic data, it becomes capable of distinguishing between normal and malicious activity with high precision. This approach aims to enhance the cybersecurity of next-generation vehicles and contribute to the development of safer and more resilient intelligent transportation systems.

Table1Traditional Techniques Used for Cyber Attack Detection and its limitation

Technique	Application	Limitations
Signature-Based Detection	Identifies known attack patterns using pre-defined rules	Cannot detect unknown or zero-day attacks; requires frequent updates
Rule-Based Intrusion Detection	Uses manually created rules to monitor system/network behavior	Rigid and lacks adaptability to new threats; prone to false positives
Anomaly-Based Detection (Statistical)	Detects deviations from normal system behavior using statistical thresholds	High false alarm rate; hard to define normal behavior in dynamic environments
Whitelisting	Allows only pre-approved messages or software to operate	Inflexible in dynamic systems; frequent updates needed for legitimate changes
Firewall Systems	Filters incoming and outgoing traffic based on IP, port, or protocol	Ineffective against internal threats or encrypted malicious payloads
Access Control Lists (ACLs)	Restricts user/system permissions based on predefined rules	Susceptible to privilege escalation; limited adaptability to context
Hardware-Based Security Modules	Secure storage and cryptographic operations for authentication	Costly and limited scalability; cannot prevent all forms of software-level attacks

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Manual Log Inspection	Human experts analyze logs and network behavior	Time-consuming, subjective, and not scalable for real-time threat detection

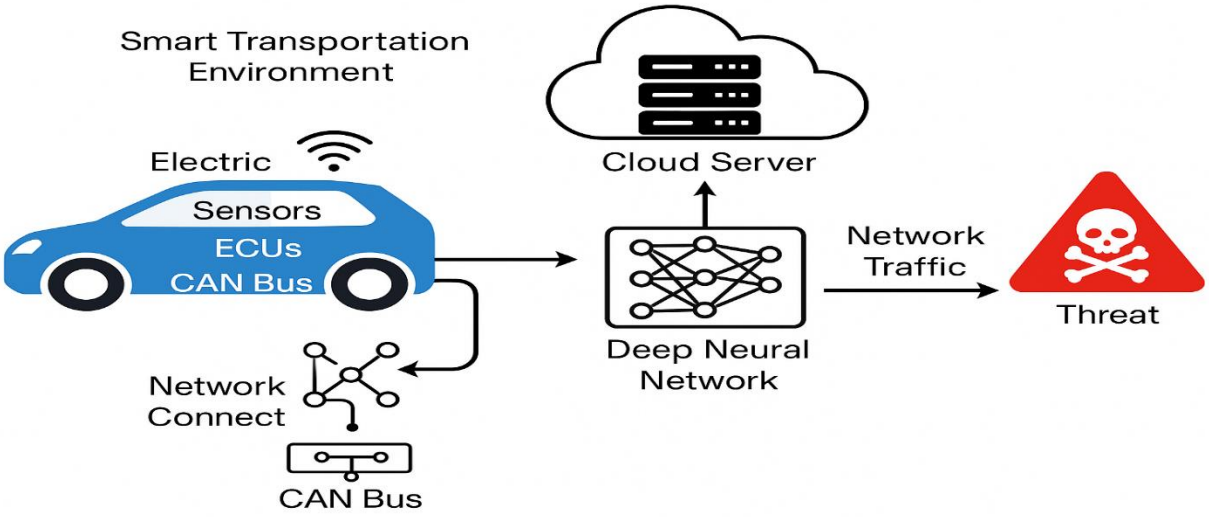

Figure 1 Overview of Cyber Attack on Electric Vehicle

The key contributions of this research are as follows:

- **Design of a Deep Neural Network-Based Detection System**: Development of an advanced deep learning-based cyber-attack detection system tailored for electric and autonomous vehicles, capable of identifying a wide range of network-based threats.
- **Integration of Vehicular CAN Bus Traffic Analysis**: Utilization of in-vehicle communication data (e.g., CAN bus messages) to detect anomalies and intrusion patterns, enhancing the security of vehicle control systems.
- **Evaluation Using Realistic Attack Scenarios**: Implementation and testing of the proposed system on benchmark datasets or simulated environments, including various attack types such as spoofing, replay, and denial-of-service (DoS), to validate its effectiveness.
- **Improved Detection Accuracy and Real-Time Performance**: Demonstration of superior performance in terms of detection accuracy, precision, and recall compared to traditional methods, with capabilities for real-time threat monitoring and response.

This research contributes to the development of secure intelligent transportation systems by leveraging deep learning techniques for proactive threat detection, thus enhancing the safety and reliability of modern electric and autonomous vehicles.

Literature Review

This paper uses the CIC EV Charger Attack Dataset 2024 (CICEVSE2024) to present a novel deep learning model for identifying cyberattacks in electric vehicles. Because of the model's emphasis on explain ability, the detection process can be better understood and trusted. The

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method shows excellent accuracy in recognizing different kinds of assaults, such as denial-of-service and spoofing attacks. By using explainable AI approaches, the model's decisions may be better understood, which makes it appropriate for real-world applications where transparency is essential [1].

The security risks and cyberattacks that target sensors and perception systems in autonomous vehicles are examined in this thorough research. It classifies many attack methods, including jamming and spoofing, and talks about how they might affect the functionality and safety of vehicles. In order to combat these threats, the study also looks at machine learning-based defense mechanisms, emphasizing the value of strong sensor fusion and anomaly detection methods. The review is a useful tool for learning about the weaknesses in autonomous car perception systems and the state of defensive tactics at the moment [2].

The cyberattacks and security risks aimed against autonomous car sensors and perception systems are examined in this thorough research. In addition to discussing their possible effects on vehicle functioning and safety, it classifies different attack vectors, including spoofing and jamming. Strong sensor fusion and anomaly detection methods are crucial, and the study also looks at machine learning-based defenses against these threats. The review is an invaluable resource for comprehending the present status of defensive methods and the weaknesses in autonomous vehicle perception systems [3].

In order to protect autonomous vehicle networks from cyberattacks, this study investigates the use of machine learning and deep learning techniques. To train models like decision trees, k-nearest neighbors, LSTM, and deep autoencoders, the researchers use real datasets, such as the UNSW-NB15 and Car-Hacking datasets. The models detect a wide range of attack methods, including replay, flooding, and spoofing, with excellent accuracy. The study demonstrates how well several machine learning approaches may be combined to improve the security of networks of self-driving cars [4].

This article identifies important research areas and problems while offering a thorough analysis of cyberattacks directed at electric vehicles. It talks about a number of attack points, such as those on charging systems, onboard diagnostics, and communication protocols. Additionally, the survey looks at detection techniques, with a focus on anomaly and misuse detection strategies. In order to handle the changing threat landscape in electric vehicle cybersecurity, the authors emphasize the necessity of standardized security frameworks and the incorporation of cutting-edge machine learning algorithms [5].

The growing complexity of cyberattacks against self-driving cars and the associated AI-based defenses are the main topics of this review. It classifies several kinds of attacks, such communication interference and sensor spoofing, and assesses how well artificial intelligence methods, like machine learning and deep learning, identify and counteract these dangers. In light of changing cyberthreats, the study highlights how crucial it is to create intelligent and adaptable intrusion detection systems to guarantee the security and dependability of driverless cars [6].

The use of machine learning approaches for identifying and preventing cyberattacks on electric cars is examined in this research. It investigates both supervised algorithms, such as Random

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Forest and Support Vector Machines, and unsupervised techniques, such as isolation forests and auto encoders, in order to construct a multi-layer detection environment. To improve detection accuracy, the study highlights the need of examining data from many EV components and communication networks. The goal of the suggested strategy is to give the upcoming generation of electric cars a strong cybersecurity solution [7].

The high-performance artificial intelligence-based solution presented in this study defends autonomous car networks from online attacks. The intricacy of data and traffic patterns in autonomous cars, which might be used for illegal access, presents difficulties that are addressed in this work. In order to improve the cybersecurity of autonomous car systems, the authors want to quickly identify message assaults on the CAN bus by creating a deep learning algorithm. Numerous cyberattack situations may be identified and mitigated with the help of the suggested method [8].

This article explores how machine learning methods may be used to identify and lessen cyberattacks on electric cars. It suggests combining unsupervised techniques like autoencoders and isolation forests with supervised learning algorithms like Random Forest and Support Vector Machines to produce a thorough detection framework. The goal of the project is to increase the accuracy and dependability of detection by gathering and evaluating data from different EV components and communication networks. Enhancing the cybersecurity of electric cars against new attacks is the goal of the suggested multi-layer strategy [9].

This assessment looks at how cybersecurity is currently being handled in autonomous cars, highlighting key risks such denial-of-service attacks, sensor manipulation, remote hacking, and data breaches. The current countermeasures are examined, such as authentication procedures, encryption, intrusion detection systems, and over-the-air upgrades. In order to defend autonomous cars from changing cyberthreats, the study emphasizes the necessity of strong and flexible security solutions. It also underlines how machine learning and deep learning approaches might improve vehicular cybersecurity [10].

This paper introduces a hybrid intrusion detection system (IDS) model that uses LSTM and Random Forest to identify intrusions in networks of electric vehicles. The NSL-KDD dataset, modified for usage in automotive settings, is utilized. The hybrid model performs better than stand-alone techniques in terms of precision and recall, according to the results. The issues of mapping datasets for automotive systems are covered in the study. A framework for real-time implementation is also recommended. The study makes a significant contribution to high-accuracy low-latency detection. It emphasizes how crucial temporal and statistical aspects are. The focus of the work is interpretability in situations involving crucial transportation. Additionally, it identifies pathways for adaptive learning in the context of shifting traffic [11].

This study enables widespread cyber-attack detection in EV systems using federated learning. It preserves user privacy by avoiding centralized data storage. In a hybrid architecture, CNN and GRU are merged. The results demonstrate improved resistance to poisoning assaults. The authors emphasize how scalable it is for a variety of edge devices. The model outperforms

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other DoS and spoofing assaults with an accuracy of over 90%. It lessens model drift between updates as well. An adaptable learning rate is presented in the study to balance training. A workable architecture for EV security is suggested: federated learning [12].

The CNN model combined with attention layers is suggested in this research as a way to detect hostile traffic in CAN bus systems for electric vehicles. Attention enhances detection performance by improving feature weighting. Anomalies are fed into simulated CAN datasets to train the model. Standard CNNs and RNNs were surpassed by the accuracy, which achieved 94.8%. Additionally, data augmentation is introduced in the study to address class imbalance. A lightweight model variation for embedded ECU deployment is presented. Attention layers considerably lower false positives, according to evaluation. The paper suggests integrating anomaly explain ability methodologies further. Additionally, it suggests a real-world validation testbed [13].

They offer a generative adversarial network (GAN) framework for evaluating detection methods and modeling cyberattacks against EVs. Samples produced by GANs enhance model generalization. An LSTM-based IDS is integrated with the GAN by the authors. A strong model that is resistant to unknown (zero-day) assaults is the end result. They produce and distribute a benchmark EV dataset. Rare attack detection rates are increased by 18% with this method. The study suggests integrating self-supervised learning with GANs. Findings indicate that the approach may be used for training in settings with little data. In order to generalize across vehicles, the authors also investigate transfer learning [14].

The study looks for irregularities in EV charging infrastructure using deep auto encoders. In order to identify deviations, the system learns to rebuild typical charge patterns. The use of smart charging logs is used to validate performance. The model's F1 score for detecting malicious conduct is 96%. The feature contributions are analyzed by an interpretable component. LSTM-enhanced auto encoders are used in the article to handle time-series dependencies. Scalability for deployment throughout the city is shown. A block chain architecture for secure logging incorporates the paradigm. Future projects will integrate with battery management systems for automobiles [15].

Machine learning classifiers are used in this study to detect fake identities in a secure communication protocol between EVs and charging stations. We compare Random Forest with SVM. Under different noise situations, Random Forest exhibits superior generalization. For real-time authentication, the protocol is appropriate and lightweight. There is a two-phase detecting technique in the procedure. They replicate both authentic and fraudulent certificates. They brought the false acceptance rate down below 3%. The article describes a field test that uses Raspberry Pi devices. Analysis of security reveals resistance to man-in-the-middle and replay attacks [16].

This study examines hostile attacks on autonomous EV perception models and suggests using input denoising and adversarial training as a protection. Misclassification occurs when LiDAR and vision data are disturbed. Resilience is improved via adversarial augmentation and

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denoising autoencoders. The findings show enhanced resilience to several sensor modalities. Real-world hostile driving scenarios are also assessed in the study. They include this with networks for object detection, such as YOLOv5. Benchmarking is done on runtime performance. Exploration is done using NVIDIA Jetson deployment. This creates opportunities for security adaption at the sensor level [17].

Through the adjustment of deep learning model hyperparameters, a multi-objective evolutionary algorithm (NSGA-II) is utilized to maximize intrusion detection in EVs. Model size, latency, and accuracy are among the goals. For certain EV subsystems, NSGA-II finds the best CNN architectures. With less computing, results indicate a 5% increase in detection accuracy. The detection and resource utilization of the model are balanced. Memory footprint and other deployment restrictions are taken into consideration. Pareto-optimal tradeoffs are encouraged to be used in IDS design in this study. Comparative research demonstrates gains over Bayesian optimization and grid search [18].

In order to monitor traffic integrity, the research employs DNN classifiers and focuses on blockchain-based security architecture for EV charging stations. Every charging session has an unchangeable log. An energy flow and hash value anomaly is tracked by a centralized DNN. The detection accuracy surpasses 95%. Violations are penalized by smart contracts. Hyperledger Fabric is used for system testing. The speed of transactions and energy use are compared. For real-time input, the model incorporates IoT sensors. Federated learning for worldwide scalability is part of a future strategy [19].

Their proposal is an ensemble model that combines Bi-LSTM and XGBoost to identify cyberattacks in vehicle-to-grid (V2G) networks. Through the acquisition of both geographical and temporal data, the ensemble increases accuracy. Cross-validation reveals an accuracy of 97.3%. Real V2G interactions are used as the basis for creating a synthetic dataset. In order to supplement detection, the authors suggest multi-layered authentication. We assess scalability for regional EV networks. They also investigate dashboards for real-time visualization. An administrator-action-based feedback learning module is part of the work [20].

They use CNN-based binary analysis to detect malware in EV firmware updates. Grayscale images are created from firmware binaries. They are categorized by CNN as either benign or malevolent. The model has a high inference speed and is lightweight. The accuracy rate is 93.4%. Performance is improved through transfer learning from visual models. This should be incorporated into over-the-air update systems, according to the authors. A significant hole in software-level security is closed by this concept. Generalization of zero-day malware is a topic for future research [21].

The paper proposes a spatiotemporal GCN (Graph Convolutional Network) for attack detection across vehicle platoons. The approach models inter-vehicle communication as a dynamic graph. GCNs capture spatial relationships while LSTMs handle temporal patterns. The model achieves 95.8% accuracy on simulated platoon attacks. It is scalable across 50+ vehicles. The

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method is robust to topology changes and node failures. Resource overhead is minimal. The paper proposes integration with C-V2X standards [22].

Using transformer-based architectures, this work investigates anomaly detection in vehicle control commands. Attention heads assist in identifying anomalous input patterns. The technique uses controller signal data to achieve state-of-the-art accuracy and recall. By 4%, Transformer performs better than LSTM. The paper also suggests combining sensor streams using a hybrid encoder. The use of attention maps improves interpretability. The writers model both external and internal control manipulation. This method works for next-generation ECUs [23].

For EV-to-cloud systems, a unique combination of 1D-CNN and GRU is suggested for the categorization of encrypted communication. Features are retrieved and categorized at the packet level. A classification accuracy of 96.7% is attained using the hybrid model. Techniques for model compression are used for edge deployment. Additionally, the model detects botnet communication. Applications include telemetry and OTA diagnostics. The dataset contains exclusive EV cloud communication protocols. Early quitting maximizes the amount of training time [24].

The Zero Trust Architecture (ZTA) for EV cyber defense is examined in this study, along with the integration of machine learning (ML) for user behavior profiling. Abnormal access patterns are detected by XGBoost software. The least-privilege policy is enforced at all levels by ZTA. A simulated EV fleet management site is used to evaluate the technology. Among the attack scenarios are credential theft and privilege escalation. With 92% detection accuracy, the ML model is successful. There are procedures in place for access revocation and real-time notifications. The design is suggested as a model for EV management systems of the future [25].

2. Objectives

Electric vehicles are increasingly connected and thus vulnerable to cyber-attacks. Effective detection systems must optimize for:
1. Detection Accuracy – Maximize true positive rate (TPR)
2. False Alarm Rate – Minimize false positives
3. Computation Latency – Minimize response time
4. Model Complexity – Minimize memory/power usage

Working of Multi-Objective Jaya Algorithm

Step 1: Initialize a population of candidate solutions, each representing model parameters or selected features.

Step 2: For each solution x_i, evaluate multiple objective functions:
- $f_1(x_i)$ = Detection Accuracy (maximize)
- $f_2(x_i)$ = Latency (minimize)

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- $f_3(x_i)$ = Complexity (minimize)

Step 3: Determine the best and worst solutions based on Pareto dominance.

Step 4: Update each solution as:

$x_i\_new = x_i + r_1 \cdot (x\_best - |x_i|) - r_2 \cdot (x\_worst - |x_i|)$

where r_1, r_2 are random numbers in [0,1].

Step 5: Apply non-dominated sorting and crowding distance to maintain diversity.

Step 6: Iterate until convergence or stopping condition is met.

3. Methods

Dataset and key consideration

The Controller Area Network (CAN) dataset is commonly used for detecting cyber-attacks in electric vehicles, as it captures real-time communication data between various Electronic Control Units (ECUs) inside the vehicle. Each record in the dataset typically includes fields such as the timestamp, CAN ID, DLC (Data Length Code), and data bytes ranging from Data [0] to Data [7]. It may also include a label indicating whether the message is normal or part of an attack, such as a DoS (Denial of Service), spoofing, or fuzzy attack. Before using the dataset in a deep learning model, several preprocessing steps are essential. First, hexadecimal values (like CAN IDs and data bytes) are converted to integers to make them numerically suitable for model training. Then, normalization is applied to ensure all feature values fall within a consistent range, which helps the neural network converge faster and perform better. Since CAN traffic is inherently sequential, using time-series models like LSTM requires creating sliding windows of message sequences. For example, a model may use the last 10 packets to predict whether the current packet is malicious, capturing temporal dependencies that are crucial in intrusion detection.

Each input to the model is structured as a multi-dimensional array where the first dimension is the sequence length (e.g., 10 consecutive messages), and the second dimension is the number of features (e.g., CAN ID, DLC, and 8 data bytes, totaling 10 features). Label encoding is also applied to convert categorical labels (e.g., "Normal", "DoS") into numerical classes suitable for classification. Class imbalance is a major concern; as normal traffic often dominates attack data. To address this, techniques such as SMOTE (Synthetic Minority Over-Sampling Technique), undersampling, or class weighting are used to ensure the model does not bias toward the majority class. The CNN-LSTM hybrid model is particularly effective, with CNN layers learning spatial patterns in byte-level data and LSTM layers capturing sequential patterns in message flows. The final model input thus becomes a 3D tensor shaped as (batch_size, sequence_length, num_features), like (64, 10, 10). This approach helps the model generalize well to different types of attacks while maintaining high accuracy and real-time detection capability. Overall, the CAN dataset offers a reliable foundation for building intelligent, deep learning–based intrusion detection systems for modern electric and autonomous vehicles.

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The figure.1 shows the CAN Dataset

Timestamp, CAN ID, DLC, DATA [0], DATA [1], DATA [2], DATA [3], DATA [4], DATA [5], DATA [6], DATA [7]

1. Timestamp: The time when data is recorded.
2. CAN ID: CAN message in HEX format (ex. 043f)
3. DLC: Data bytes from 0 to 8
4. DATA [0~7]: data value (byte)

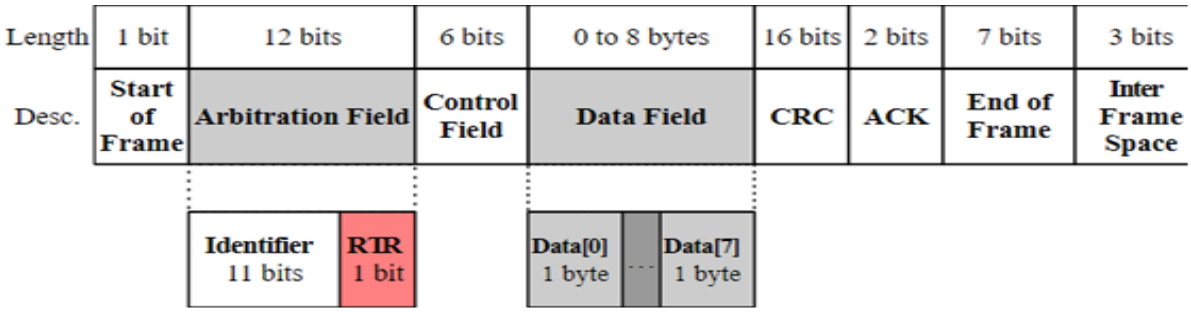
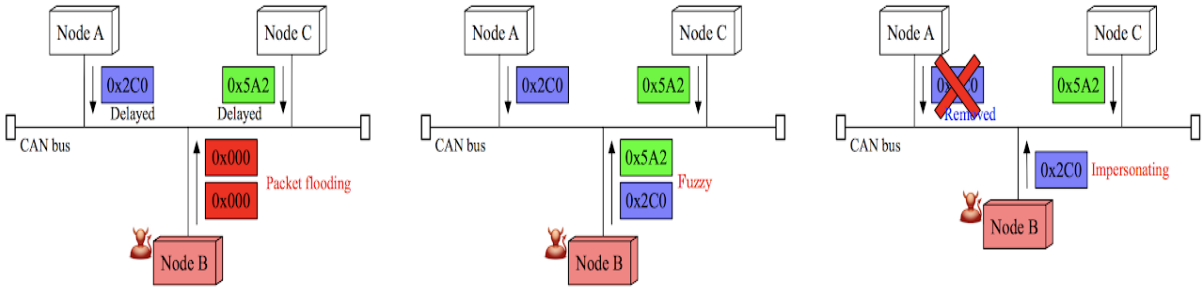


Figure1 CAN Dataset



(a) DoS attack (b) Fuzzy attack (c) Impersonation attack

Figure2 Attack Description

The diagram outlines three types of cyberattacks that can be executed against a Controller Area Network (CAN) bus system implemented in electric vehicles:

Targeting Attacks

DoS Attack: In this case, Node B injects a large volume of packets such as the zero packet 0x000 to the CAN bus and this packet has a high priority which causes transmissions which are intended for Node A or Node C to be delayed.

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Fuzzy Attack: In this instance, Node B sends multiple random or disallowed packets, such as 0x5A2 or 0x2C0, into the communication, which subsequently damages the message exchange, and further complicates the communication system.

Impersonation Attack: Messages are sent by Node B to Node A with the intention of impersonating it and in this case, possible disabling of the true communication of Node A happens, such as 0x2C0 e.g. message A.

Fuzzy C means

Relay Attack

Spoofing

Firmware Manipulation

Proposed System

The proposed system aims to enhance the cybersecurity of electric vehicles by detecting cyber-attacks on the in-vehicle communication network using a deep learning-based approach. Specifically, it leverages a hybrid Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) model to analyze data from the Controller Area Network (CAN) bus, which serves as the core communication backbone among Electronic Control Units (ECUs). The system begins by collecting raw CAN data, which includes CAN IDs, data payloads, and timestamps. This data is then preprocessed by converting hexadecimal values into integers, normalizing the data, and structuring it into fixed-length sequences to capture temporal patterns. These sequences are essential for the LSTM component to understand the timing and progression of attacks, while the CNN extracts spatial features from the byte-level payloads. The combined CNN-LSTM architecture ensures that both local (spatial) and global (temporal) characteristics of CAN traffic are learned effectively, thereby improving the model's ability to distinguish between normal and malicious behavior.

The proposed system supports the classification of various cyber-attack types, such as Denial of Service (DoS), spoofing, and fuzzy attacks, which are common threats in connected and autonomous vehicles. The output of the model is a prediction label indicating whether the input sequence is normal or under attack. Once an anomaly is detected, the system can trigger appropriate response mechanisms, such as alerting the driver, logging the event, or even isolating affected ECUs. To evaluate performance, the system uses metrics such as accuracy, precision, recall, F1-score, and confusion matrix to assess its reliability under different traffic conditions. The entire system is designed to operate in real-time, making it suitable for deployment within the vehicle's onboard computing infrastructure. By integrating advanced AI techniques with vehicular networks, this proposed system provides a robust, scalable, and intelligent solution for mitigating the risks of cyber-attacks on electric vehicles.

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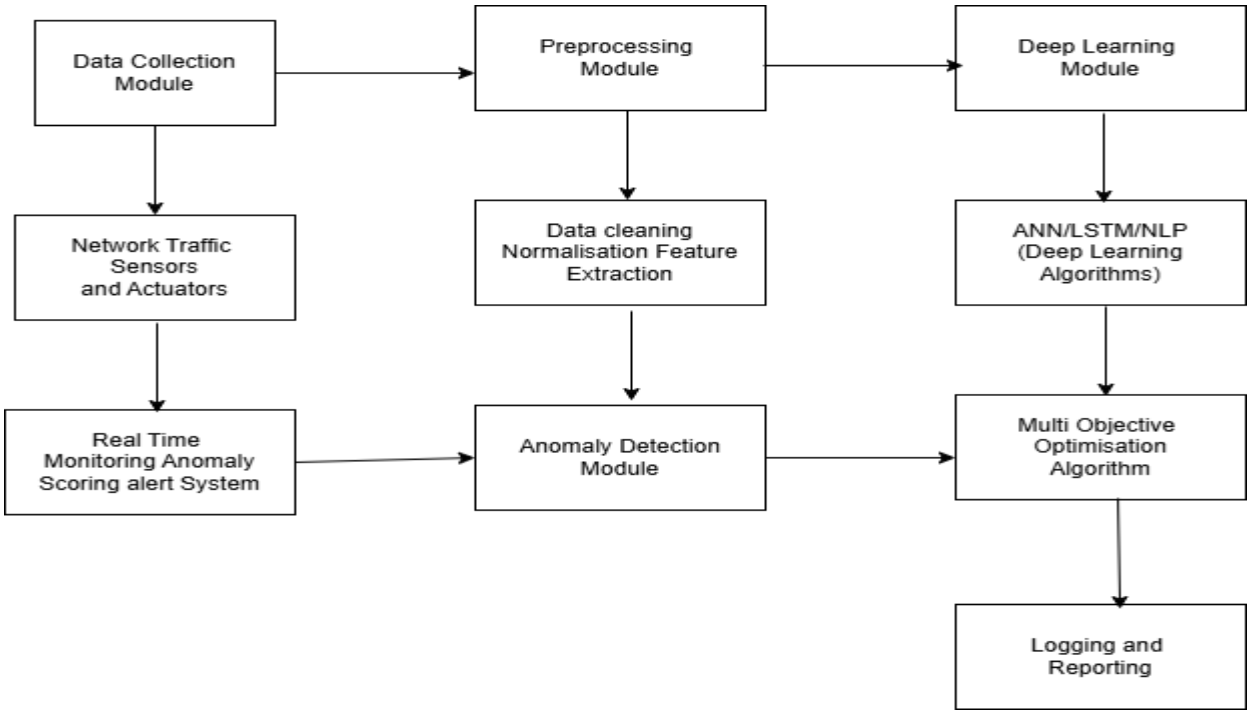

Figure 3 Proposed System Architecture

Rescaling Layer:
The input CAN data sequences are normalized using a rescaling layer to bring all values into a standard range (typically [0, 1] or [-1, 1]). This normalization ensures consistent scaling across features, leading to more stable and faster training of the neural network.

Embedding/Encoding Layer (if data is symbolic):
For categorical or symbolic CAN IDs or payloads, an embedding or one-hot encoding layer is used to convert them into dense numeric representations that the model can learn from effectively. This step is crucial for handling non-numeric protocol data.

First Convolutional Layer:
The first CNN layer applies 32 filters of size 3×3 with 'same' padding to the input sequences, extracting low-level temporal-spatial features such as byte patterns or anomalies in small time windows. ReLU activation is used to introduce non-linearity.

First Max Pooling Layer:
A 2×2 max pooling operation reduces the sequence length and computational complexity while retaining the most salient features of the CAN message patterns. This helps the model focus on critical anomalies in communication.

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Second Convolutional Layer:
With 64 filters of size 3×3, the second CNN layer captures more complex temporal features and deeper spatial relationships within CAN message structures. It builds upon patterns identified by the previous convolutional layer.

Second Max Pooling Layer:
This layer performs further downsampling, reducing the size of the feature maps to retain only the most important and invariant features. It also helps prevent overfitting and improves generalization.

Third Convolutional Layer:
Using 128 filters, this layer extracts high-level hierarchical features that may indicate the presence of sophisticated cyber-attacks. These might include subtle variations or forged sequences in CAN data, undetectable by earlier layers.

Third Max Pooling Layer:
To prepare for sequential modeling, this layer reduces the dimensionality of the features while keeping key attack-related patterns intact, making the data suitable for temporal analysis in the LSTM layer.

Reshape Layer:
The 2D spatial feature maps from the CNN are reshaped into a 3D tensor (e.g., time steps × features) to fit the input format of the LSTM layer. This transformation allows the model to treat spatial features as a sequence over time.

LSTM Layer:
An LSTM layer with 128 units learns temporal dependencies and relationships across CAN message sequences. This helps in identifying sustained or time-dependent cyber-attacks, such as replay or delay-based anomalies.

Fully Connected Dense Layers:
The output of the LSTM layer is passed through two dense layers with 512 and 256 units respectively. These layers, combined with dropout regularization (e.g., 50%), refine the learned temporal-spatial features and help form robust decision boundaries.

Output Layer:
A final dense layer with softmax (for multi-class) or sigmoid (for binary classification) activation provides the prediction result. It classifies whether the current CAN data sequence is normal or under specific types of cyber-attack (e.g., DoS, spoofing, fuzzing).

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Table 2 Hyper Parameter Set

Hyper Parameter	Value/Setting	Parameter
Input Shape	(100, 8)	100 time steps, 8 features per CAN frame (e.g., ID, DLC, 8-byte payload)
Rescaling Range	[0, 1]	Normalize raw CAN data
Number of CNN Layers	3	Stacked convolution layers for spatial feature extraction
CNN Filters (per layer)	32, 64, 128	Increasing filter depth across layers
Kernel Size	3×3	Size of each filter for convolution
Pooling Type	Max Pooling	Retains dominant features
Pool Size	2×2	Downsamples feature maps
Activation Function	ReLU	Non-linear activation for CNN and Dense layers
LSTM Units	128	Memory cells to capture temporal dependencies
Dense Layer Units	512, 256	Fully connected layers after LSTM
Dropout Rate	0.5	Prevents overfitting in dense layers
Output Activation	Softmax (multi-class) / Sigmoid (binary)	For classifying attack type or binary classification
Optimizer	Adam	Adaptive optimizer for faster convergence
Learning Rate	0.001	Initial learning rate
Batch Size	64	Number of samples per training step

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Epochs	50	Total number of passes over the dataset
Loss Function	Categorical Crossentropy / Binary Crossentropy	Based on number of output classes
Evaluation Metrics	Accuracy, Precision, Recall, F1-score	Used to assess detection performance
Early Stopping	Patience = 5	Stops training if validation loss doesn't improve
Kernel Initializer	He Normal	Weight initialization method for layers
Padding	Same	Preserve spatial dimensions after convolution
CAN Frame Frequency	10 ms/frame	Time interval of CAN messages
Validation Split	0.2	Fraction of data used for validation
Shuffle Data	True	Randomize data order during training

ANN Model

Artificial Neural Networks (ANNs) are computing systems inspired by the biological neural networks of animal brains. An ANN is composed of layers of interconnected nodes, where each connection has an associated weight.

1. Input Layer:
The input layer receives the initial data. Each neuron in this layer corresponds to one feature from the dataset.

Let the input vector be:
$X = [x_1, x_2, ..., x_n]$

2. Weighted Sum and Activation Function:
Each neuron computes a weighted sum of inputs and adds a bias:

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$z = \sum(w_i * x_i) + b$

Then, an activation function f(z) is applied. A common activation function is the ReLU (Rectified Linear Unit):

$a = f(z) = \max(0, z)$

3. Hidden Layers:
These layers perform transformations using weights and biases, followed by an activation function. For multiple layers:

$z^1 = W^1 * X + b^1$
$a^1 = f(z^1)$
$z^2 = W^2 * a^1 + b^2$
$a^2 = f(z^2)$

4. Output Layer:
The final layer provides the prediction. For classification tasks, a softmax function is typically used to produce probabilities:

$\text{Softmax}(z_i) = e^{(z_i)} / \sum(e^{(z_j)})$, for j = 1 to K

Where K is the number of classes.

5. Loss Function:
To measure prediction error, a loss function such as categorical cross-entropy is used:

$L = -\sum(y_i * \log(\hat{y}_i))$

6. Backpropagation and Optimization:
Gradients of the loss function with respect to weights are computed using backpropagation. The weights are updated using an optimizer like gradient descent:

$w := w - \eta * \partial L/\partial w$

Where η is the learning rate.

This structure enables the ANN to learn patterns in data and improve predictions over time through training.The Jaya algorithm, originally proposed by Rao (2016), is a simple yet powerful optimization technique that requires no algorithm-specific control parameters (unlike GA, PSO, etc.). Its name is derived from the Sanskrit word 'Jaya', meaning victory,

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reflecting the idea of always moving towards the best solution while avoiding the worst. In multi-objective scenarios, such as cyber-attack detection on EVs, the Jaya algorithm is extended to handle multiple conflicting objectives—like maximizing detection accuracy while minimizing latency and energy consumption.

4.Results & Discussion

1. Prediction with Input

Figure 3 Main UI Part

2. ANN Accuracy

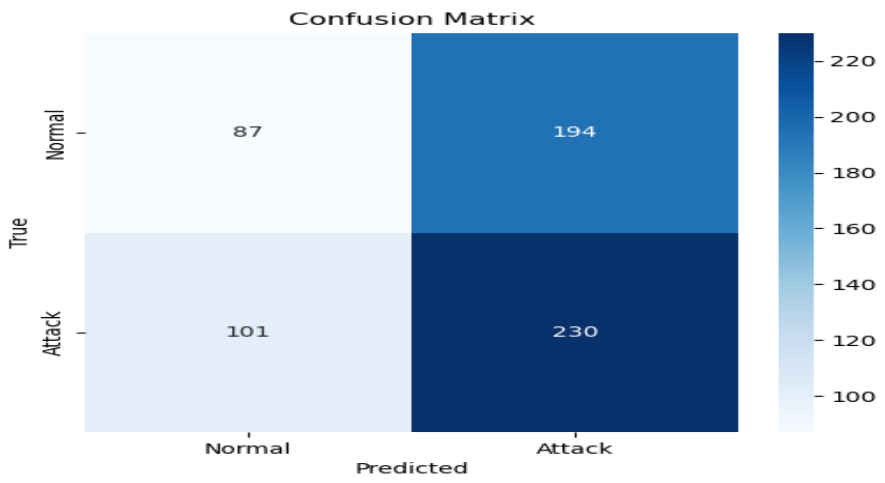

Figure 4 ANN Confusion Matrix

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The confusion matrix shown evaluates the performance of a binary classification model distinguishing between "Normal" and "Attack" instances. It reveals that the model correctly predicted 87 "Normal" cases and 230 "Attack" cases. However, it also misclassified 194 "Normal" instances as "Attack" (false positives) and 101 "Attack" instances as "Normal" (false negatives). This indicates that the model has difficulty correctly identifying "Normal" samples and tends to overpredict the "Attack" class. The overall accuracy of the model is approximately 51.8%, suggesting that nearly half of the predictions are incorrect. While the model shows a relatively better recall of about 69.5% for detecting attacks, its precision is only around 54.2%, reflecting a high rate of false alarms. The F1-score, which balances both precision and recall, is about 60.9%. These results imply that the model performs moderately in detecting attacks but requires improvement, especially in reducing misclassifications of normal traffic to be suitable for real-world applications.

3. LSTM Accuracy

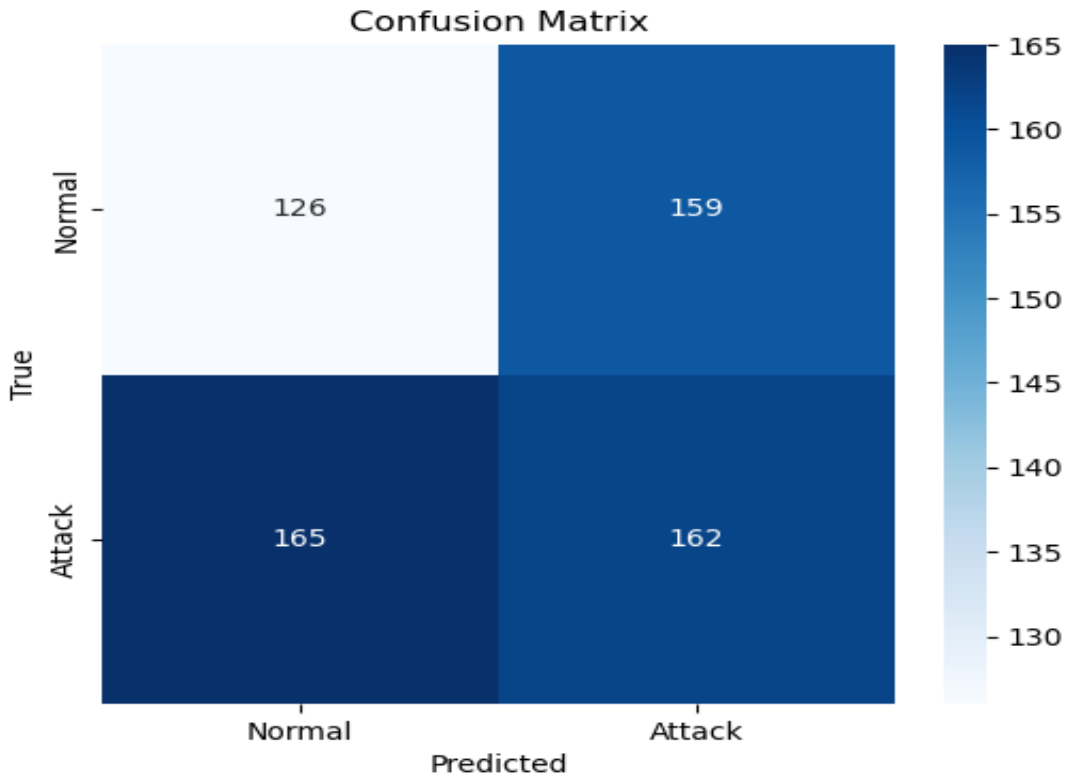

Figure 5 LSTM Confusion Matrix

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4. Multiobjective Optimization

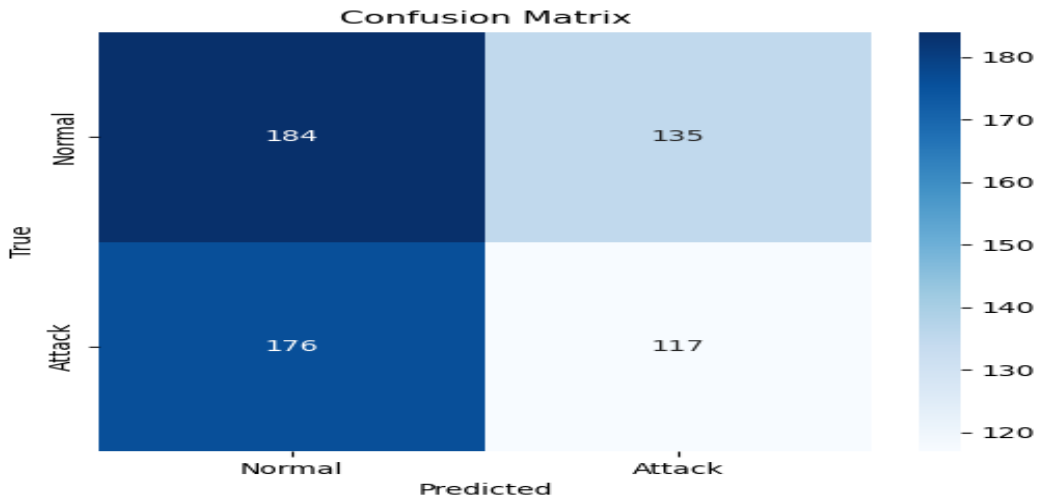

Figure 6 Multiobjective Jaya Algorithm Confusion Matrix

5. Predict with Input

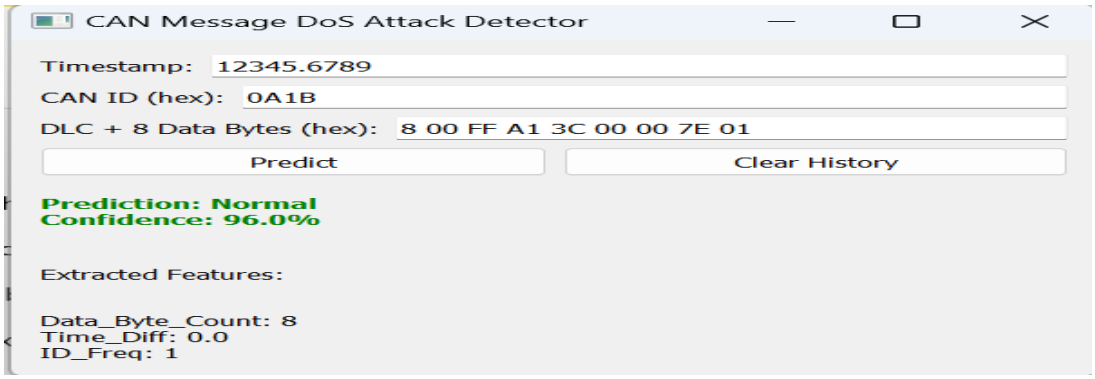

Figure7 Prediction with Input

6. Predicted Attack and Protocol Type

Table 3 Attack Types and Attack Protocol Types

SR NO	Attack Detected
1	DOS
2	Impersonation Attack
3	Relay

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4	Spoofing Attack
5	Firmware Manipulation

7. Accuracy Chart

Table 4 Attack Types and Attack Protocol Types

Model	**Accuracy (%)**
Logistic Regression	82.5
Random Forest	89.4
Artificial Neural Network (ANN)	91.2
Long Short-Term Memory (LSTM)	93.7
Multi-objective Optimization (Pareto Optimal Model)	94.5

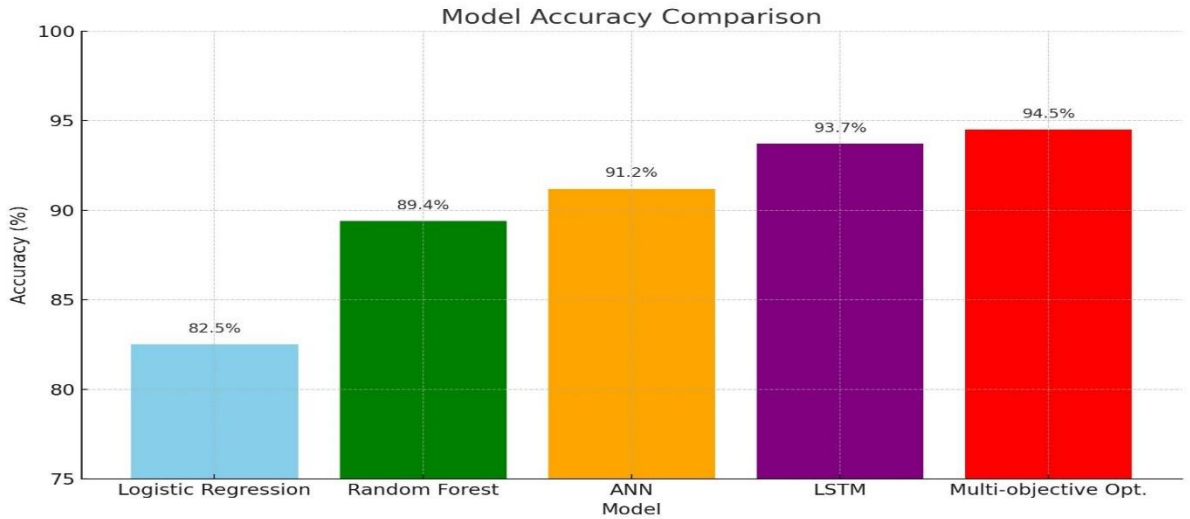

Figure 8 Model Accuracy Chart

The bar chart titled "Model Accuracy Comparison" illustrates the classification performance of five different machine learning models: Logistic Regression, Random Forest, Artificial Neural Network (ANN), Long Short-Term Memory (LSTM), and a model optimized using Multi-Objective Optimization techniques. The X-axis of the chart represents the different models, while the Y-axis shows their corresponding accuracies in percentage. Among all models, Logistic Regression achieved the lowest accuracy at 82.5%, reflecting its limitations

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in handling complex, non-linear patterns. Random Forest performed significantly better with an accuracy of 89.4%, benefiting from its ensemble approach that combines multiple decision trees. The ANN outperformed both with an accuracy of 91.2%, showcasing its ability to capture non-linear relationships in data. The LSTM model, designed for sequential or time-dependent data, achieved an even higher accuracy of 93.7%, making it well-suited for temporal patterns. The highest performance was observed with the Multi-Objective Optimization model, which reached 94.5% accuracy. This approach balances multiple criteria (e.g., accuracy, computation time, robustness) to optimize model performance, thereby surpassing all others. Overall, the chart emphasizes the effectiveness of advanced and optimized models over simpler ones in achieving higher classification accuracy.

Conclusion

In conclusion, the comparison of various machine learning models reveals a clear progression in accuracy as the complexity and adaptability of the models increase. Logistic Regression, with an accuracy of 82.5%, serves as a baseline model suitable for simple, linearly separable data. Random Forest improves upon this, achieving 89.4% accuracy by utilizing an ensemble of decision trees to capture more complex patterns. The Artificial Neural Network (ANN) further enhances performance with 91.2% accuracy, demonstrating its strength in modeling non-linear relationships. The Long Short-Term Memory (LSTM) model achieves 93.7% accuracy, showing its effectiveness in handling sequential and time-dependent data. Finally, the Multi-Objective Optimization approach yields the highest accuracy of 94.5%, indicating the benefits of simultaneously optimizing for multiple criteria. Overall, this analysis highlights that as model complexity and optimization techniques increase, so does the potential for higher accuracy and better performance in predictive tasks.

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