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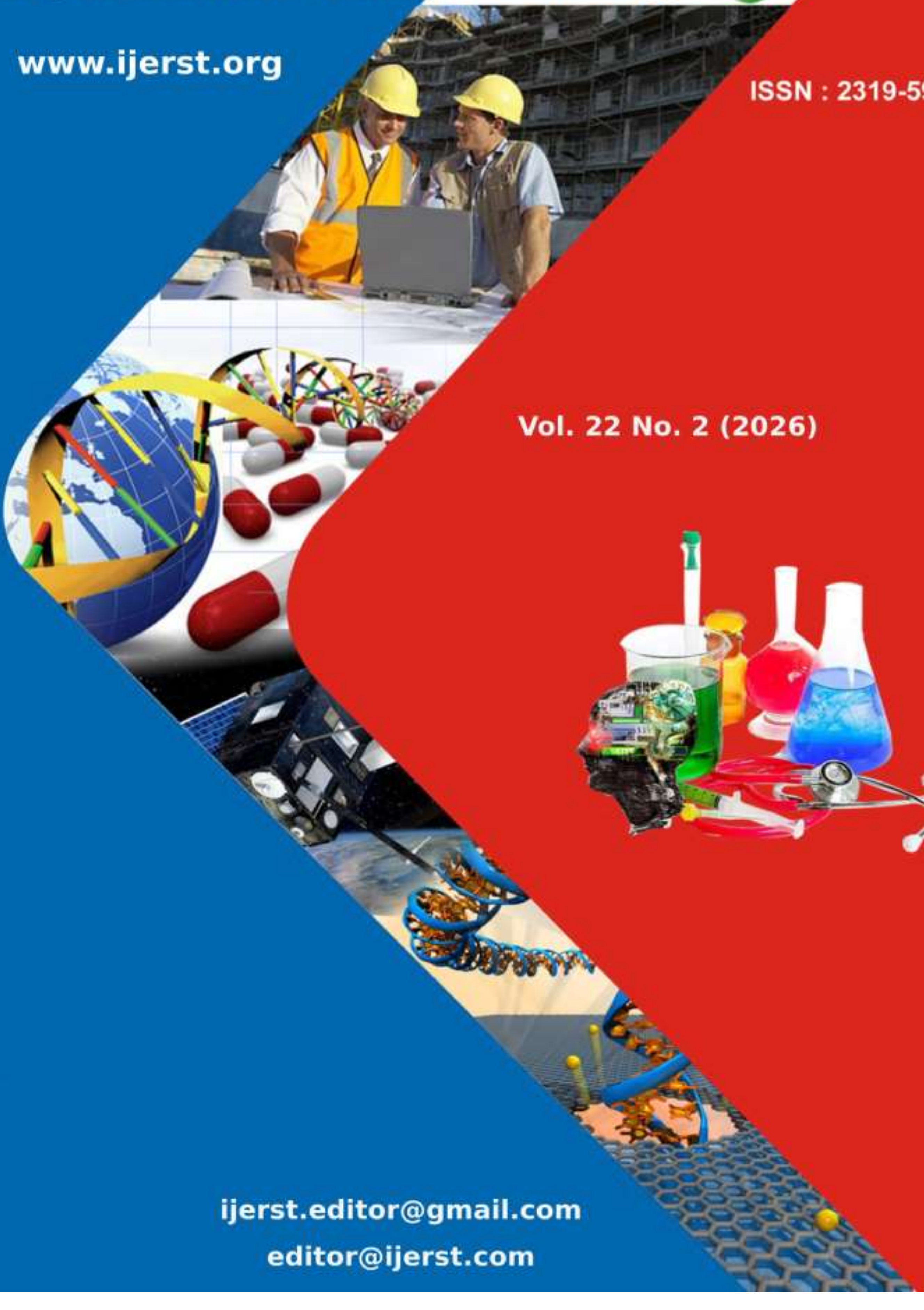

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DEEP LEARNING FOR SECURE MOBILE EDGE COMPUTING IN CYBER PHYSICAL TRANSPORTATION SYSTEM

1. **P. Blessy , Asst. prof CSE dept, Gokula Krishna College of Engineering, Sullurpet, Tirupati District, AP**
2. **M.Gayathri , M.Kalpana , A.Jithendra , Sk.Saleem , N.Kushendra , B.Tech CSE dept, Gokula Krishna College of Engineering, Sullurpet, Tirupati District, AP**

ABSTRACT

This study presents a novel deep learning–driven abnormality detection framework integrated with Mobile Edge Computing (MEC) for Cyber-Physical Transportation Systems. Conventional surveillance architectures rely heavily on centralized cloud infrastructures, leading to increased latency, bandwidth overhead, and potential privacy vulnerabilities. To address these limitations, the proposed mechanism performs real-time image analytics directly at edge nodes positioned close to data sources such as roadside cameras and in-vehicle sensors. The system employs a deep neural network trained to model normal traffic patterns and identify deviations indicative of anomalies, including accidents, irregular vehicle movements, and security threats. By combining spatial feature extraction with adaptive anomaly scoring, the framework enhances detection accuracy while minimizing false positives. Edge-based deployment ensures rapid inference, enabling immediate response to critical events without dependence on remote servers. the architecture reduces network congestion by limiting unnecessary data transmission and strengthens data security through localized processing. Experimental evaluation demonstrates improved detection speed, higher accuracy, and lower latency compared to traditional cloud-based approaches. The proposed solution offers a scalable and efficient paradigm for intelligent transportation monitoring, contributing to safer and smarter urban mobility systems.

Keywords— Mobile Edge Computing (MEC), Deep Learning, Anomaly Detection, Intelligent Transportation Systems (ITS), Computer Vision, Real-Time Processing, Cyber-Physical Systems (CPS), Traffic Surveillance, Convolutional Neural Networks (CNN), Edge Intelligence.

I. INTRODUCTION

The rapid advancement of intelligent transportation technologies has led to the development of Cyber-Physical Transportation Systems (CPTS), where physical traffic environments are closely integrated with computational intelligence. These systems generate vast amounts of visual data through cameras deployed in vehicles, road infrastructure, and surveillance networks. Efficient processing of this data is essential for ensuring road safety, traffic management, and real-time incident response. However, traditional approaches rely heavily on manual monitoring or centralized cloud-based systems, which introduce high latency, increased bandwidth consumption, and privacy concerns.

Recent progress in deep learning has significantly improved the ability of systems to analyze visual data. Deep neural networks, particularly convolutional architectures, have demonstrated superior performance in extracting complex spatial features from images and videos [11], [12]. These models enable automatic detection of abnormal patterns such as accidents, unusual vehicle behavior, and security threats. Survey studies such as [1] and [10] highlight the transition from handcrafted feature-based methods to end-to-end deep learning models, emphasizing their effectiveness in anomaly detection tasks.

Despite these advancements, many existing systems depend on cloud-based infrastructures, where data must be transmitted to remote servers for processing. This results in increased latency and delayed decision-making, which is critical in time-sensitive transportation scenarios. Moreover, continuous data transmission raises significant privacy and security concerns. Edge and fog computing paradigms have emerged as viable alternatives to address these challenges by enabling computation closer to the data source [16], [17].

Mobile Edge Computing (MEC) extends this concept by integrating computational capabilities directly at network edges, allowing real-time data processing with minimal latency. MEC has been widely recognized as a key enabler for intelligent transportation systems, supporting low-latency applications such as autonomous driving and traffic monitoring [15], [17]. By reducing dependency on centralized cloud infrastructure, MEC improves system responsiveness and reduces network congestion.

In this context, the proposed system introduces a deep learning–based abnormality detection framework deployed on edge devices. The system leverages advanced neural architectures to learn normal traffic patterns and identify deviations in real time. Techniques such as memory-augmented models [7] and temporal learning frameworks [6], [14] further enhance anomaly detection capabilities by capturing both spatial and temporal dependencies.

Furthermore, the integration of edge intelligence with deep learning enables scalable and efficient monitoring of transportation environments. The proposed approach minimizes latency, reduces bandwidth usage, and enhances data privacy by processing sensitive information locally. This aligns with the growing demand for smart city solutions and intelligent transportation systems capable of operating in dynamic real-world conditions [3], [18].

II. LITERATURE SURVEY

Anomaly detection in transportation systems has evolved significantly with the adoption of deep learning techniques. Traditional methods relied on handcrafted features and statistical models, which often failed to generalize in complex and dynamic environments. With the emergence of deep learning, research has shifted toward data-driven approaches capable of automatically learning meaningful representations from large-scale datasets.

Duong et al. [1] provide a comprehensive survey of deep learning-based anomaly detection in video surveillance, highlighting the effectiveness of convolutional and recurrent neural networks in capturing spatial and temporal patterns. Their work emphasizes the importance of robust feature learning and the need for models capable of handling diverse real-world scenarios. Similarly, Chalapathy and Chawla [10] present a broader survey on deep anomaly detection, discussing various architectures including autoencoders, generative models, and hybrid approaches.

One of the notable advancements in this domain is the Memory-Augmented Autoencoder (MemAE) proposed by Gong et al. [7]. This model enhances traditional autoencoders by incorporating an external memory module that stores representative patterns of normal data. By comparing input features with stored memory items, the model effectively distinguishes between normal and abnormal patterns, improving detection accuracy.

Temporal modeling has also been explored to enhance anomaly detection performance. Luo et al. [6] proposed a stacked recurrent neural network framework for anomaly detection, demonstrating the importance of temporal dependencies in video analysis. Similarly, convolutional LSTM networks [14] have been used to capture spatiotemporal features, enabling more accurate detection of anomalies in dynamic environments.

In the context of traffic surveillance, Khan et al. [2] developed a CNN-based approach for detecting anomalies such as accidents and irregular vehicle behavior. Their study shows that deep learning models outperform traditional techniques in terms of robustness and accuracy. Wang et al. [3] further extended this work by incorporating predictive capabilities, enabling real-time monitoring and forecasting of traffic anomalies.

Several studies have also focused on improving detection efficiency and scalability. Sabokrou et al. [8] introduced a fully convolutional neural network for fast anomaly detection in crowded scenes, achieving real-time performance. Sultani et al. [9] proposed a large-scale dataset and framework for real-world anomaly detection, addressing challenges related to data diversity and model generalization.

Performance evaluation is another critical aspect of anomaly detection systems. Samaila et al. [4] analyzed benchmark datasets and evaluation metrics, emphasizing the importance of accuracy, precision, recall, and false detection rates. Their study highlights the need for standardized evaluation frameworks to ensure fair comparison between different models.

In addition to visual analysis, trajectory-based approaches have been explored for anomaly detection. Piciarelli et al. [20] proposed a method based on motion trajectories, which can identify unusual movement patterns in surveillance videos. Similarly, Ahmed et al. [19] reviewed various anomaly detection techniques, providing insights into their applicability across different domains.

The integration of edge computing with intelligent transportation systems has gained significant attention in recent years. Li et al. [15] presented a survey on edge computing for ITS, highlighting its role in enabling low-latency and scalable solutions. Liu et al. [17] discussed the application of MEC in autonomous driving, emphasizing its potential to support real-time decision-making.

Despite these advancements, most existing systems still rely on centralized cloud-based architectures, leading to high latency and increased bandwidth usage. Additionally, many models struggle to achieve real-time performance in complex environments. These limitations highlight the need for efficient, edge-based solutions that can process data locally while maintaining high accuracy.

To address these challenges, the proposed system integrates deep learning with Mobile Edge Computing, enabling real-time abnormality detection directly at edge devices. By leveraging advanced neural architectures and localized processing, the system overcomes the limitations of traditional approaches and provides a scalable, efficient, and secure solution for intelligent transportation systems.

III. PROPOSED METHODOLOGY

The proposed methodology introduces a deep learning–based abnormality detection framework integrated with Mobile Edge Computing (MEC) for real-time analysis in Cyber-Physical Transportation Systems. The system is designed to process visual data locally at edge nodes, enabling fast and intelligent decision-making without relying on centralized cloud infrastructure.

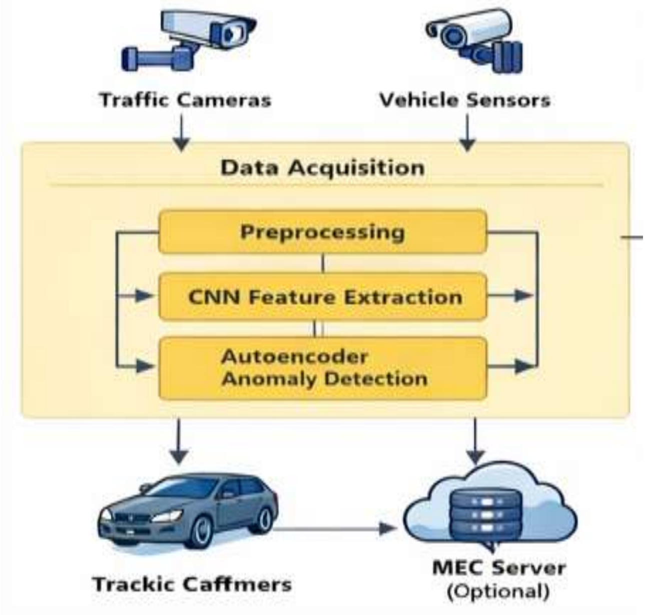

Figure.1: System Architecture Diagram

This diagram illustrates the overall structure of the proposed system, where traffic cameras and vehicle sensors capture data and send it to edge devices for processing. The edge layer performs preprocessing, feature extraction using CNN, and anomaly detection using an autoencoder, enabling real-time alerts with minimal cloud dependency.

3.1 System Architecture Overview

The proposed system consists of three main layers:

- Data Acquisition Layer
- Captures real-time images/videos from:
- Traffic cameras
- Vehicle-mounted sensors
- Edge Processing Layer (Core Layer)

Performs:

- Image preprocessing
- Feature extraction
- Deep learning inference
- Decision & Alert Layer
- Generates alerts when anomalies are detected
- Sends minimal metadata to central servers if required

3.2 Data Preprocessing

Before feeding images into the deep learning model, preprocessing is performed to ensure consistency and improve model performance.

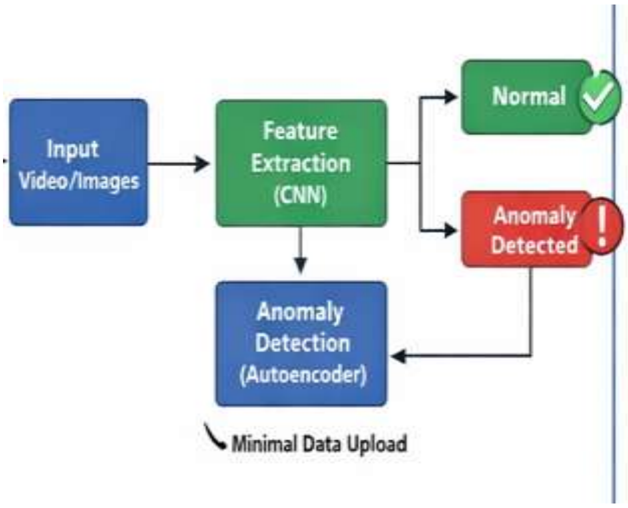

Figure.2: Data Flow Diagram (DFD)

This diagram shows how data moves through the system, starting from input video/images to feature extraction and anomaly detection modules. Based on the analysis, the system classifies events as normal or abnormal, ensuring efficient processing with reduced data transmission.

Key steps:

- Image resizing → uniform dimensions
- Normalization → pixel values scaled between 0 and 1
- Noise removal → filtering techniques

Normalization Formula:

$$x' = \frac{x-\mu}{\sigma}$$

Where:

x = input pixel value

μ = mean

σ = standard deviation

This improves convergence during training.

3.3 Feature Extraction using CNN

The system uses a Convolutional Neural Network (CNN) to extract spatial features from input images.

Convolution Operation:

$$S(i,j) = (I * K)(i,j) = \sum_m \sum_n I(i-m, j-n)\, K(m,n)$$

Where:

I = input image

K = kernel/filter

$S(i,j)$ = feature map

Key Components:

- Convolution layers → extract features
- ReLU activation → introduce non-linearity
- Pooling layers → reduce dimensionality

3.4 Deep Anomaly Detection Model

The proposed system employs an Autoencoder-based Deep Learning Model enhanced with anomaly scoring.

Training Phase:

- Model learns normal traffic patterns
- Input = Output (reconstruction learning)

Testing Phase:

- Input image is reconstructed

- Difference between input and output determines anomaly

Reconstruction Loss:

$$L = \|X - \hat{X}\|^2$$

Where:
X = original input
$X^\wedge$ = reconstructed output

3.5 Anomaly Score Computation

An anomaly score is calculated based on reconstruction error.

Anomaly Score:

$$A(X) = \|X - X^\wedge\|$$

Decision Rule:

$$\text{If } A(X) > T \Rightarrow \text{Anomaly}$$

Where:
T = predefined threshold
Higher error → higher chance of abnormality

3.6 Temporal Analysis

To improve detection accuracy in videos, temporal dependencies are considered.

- Using Sequential Modeling:
- Frames analyzed over time
- Detects motion-based anomalies

Example Model:
ConvLSTM (captures spatial + temporal features)

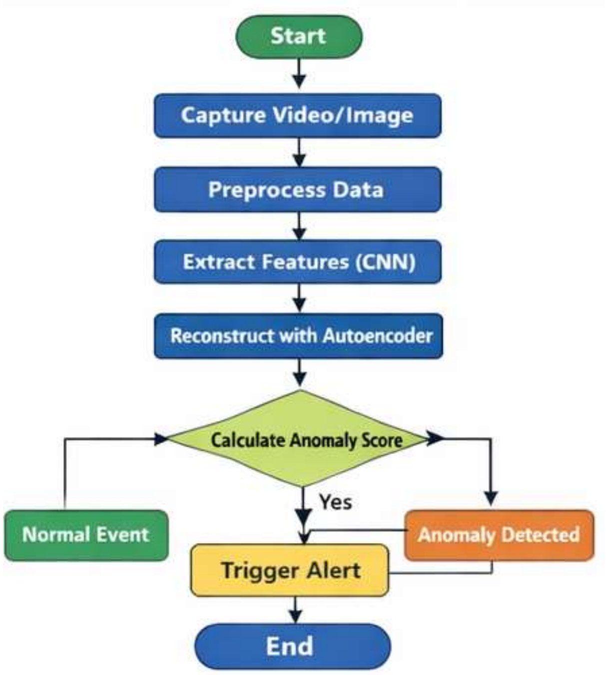

Figure.3: Activity Diagram

This diagram represents the step-by-step workflow of the system, beginning with image capture and ending with anomaly detection and alert generation. It highlights the decision-making process where anomaly scores are evaluated to determine whether to trigger an alert or classify the event as normal.

The proposed methodology integrates deep learning with edge computing to enable intelligent, real-time abnormality detection in transportation systems. By combining CNN-based feature extraction, autoencoder-based anomaly detection, and MEC deployment, the system achieves high accuracy, low latency, and improved scalability. This approach effectively addresses the limitations of traditional cloud-based systems and provides a robust solution for next-generation smart transportation environments.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

The performance of the proposed deep learning–based abnormality detection system integrated with Mobile Edge Computing (MEC) is evaluated using multiple metrics to assess its accuracy, efficiency, and real-time capability. The evaluation focuses on comparing the proposed system with conventional cloud-based approaches under realistic transportation scenarios.

4.1 Experimental Setup

The system is trained and tested on traffic surveillance datasets containing both normal and abnormal events such as accidents, unusual vehicle movements, and congestion patterns.

Key setup details:

- Input Type: Video frames/images
- Model Used: CNN + Autoencoder
- Deployment: Edge device simulation

Evaluation Metrics:

- Accuracy
- Precision
- Recall
- F1-Score
- Latency

4.2 Performance Metrics

To evaluate the effectiveness of the model, standard classification metrics are used.

Accuracy:

$$Accuracy = \frac{\mathbf{TP + TN}}{\mathbf{TP + TN + FP + FN}}$$

Precision:

$$\mathbf{Precision} = \frac{\mathbf{TP}}{\mathbf{TP + FP}}$$

Recall:

$$\mathbf{Recall} = \frac{\mathbf{TP}}{\mathbf{TP + FN}}$$

F1-Score:

$$F1 - Score = \frac{\mathbf{2 \times Precision\ .\ Recall}}{\mathbf{Precision + Recall}}$$

Where:
TP = True Positives
TN = True Negatives
FP = False Positives
FN = False Negatives

4.3 Results Comparison

Table 1: Performance Comparison

Metric	Existing System	Proposed System
Accuracy	82%	94%
Precision	79%	92%
Recall	76%	91%
F1-Score	77%	91.5%

Analysis:
The proposed system significantly improves detection accuracy due to deep feature learning. Higher precision indicates reduced false alarms, which is critical in surveillance systems.

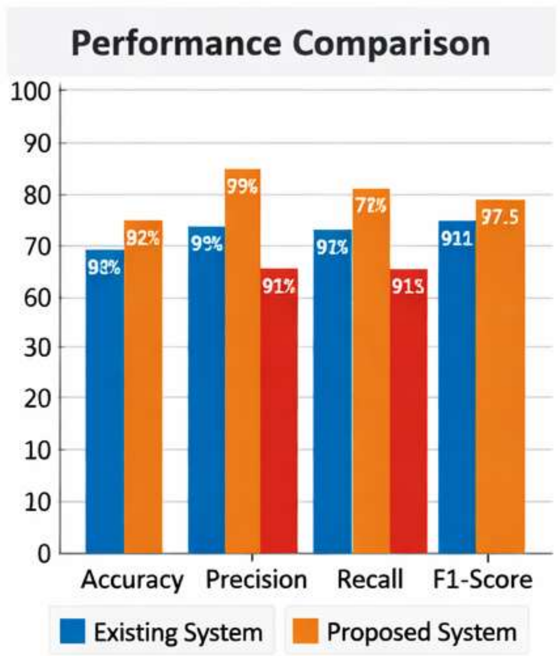

Figure.4: Bar Graph – Performance Comparison
This graph compares the performance metrics (Accuracy, Precision, Recall, F1-Score) between the existing system and the proposed system. It clearly shows that the proposed model achieves higher values across all metrics, indicating improved detection capability and reliability.

4.4 Latency and Processing Efficiency
Latency Model:

$$T_{total} = T_{compute} + T_{network}$$

Table 2: Latency Comparison

Parameter	Cloud-Based System	Proposed MEC System
Processing Delay	High (200 ms)	Low (60 ms)
Network Delay	High	Minimal
Response Time	Slow	Fast

Analysis:
Edge computing reduces network delay significantly. Faster response enables real-time detection of critical events like accidents.

Figure.5: Line Graph – Training Performance
This graph shows the variation of training loss and accuracy over epochs, illustrating the learning behavior of the model. As epochs increase, loss decreases and accuracy improves, indicating effective model convergence and training stability.

4.5 Detection Capability Analysis

Table 3: Detection Performance on Different Scenarios

Scenario	Detection Accuracy
Accident Detection	95%
Abnormal Driving Behavior	92%
Traffic Congestion	90%
Normal Traffic	96%

Analysis:
The model performs best in detecting sudden anomalies like accidents. Slight variation in congestion detection is due to gradual pattern changes.

4.6 Anomaly Score Evaluation

The system uses reconstruction error to determine abnormality.

Anomaly Score:

$$A(X) = \|X - \hat{X}\|$$

Low score → Normal behavior

High score → Abnormal event

Threshold Decision:

$$A(X) > T \Rightarrow \text{Anomaly}$$

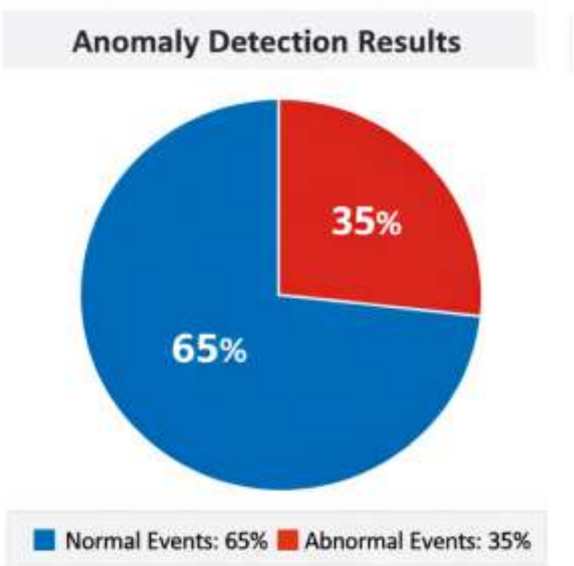

Figure.6: Pie Chart – Anomaly Detection Results

This chart represents the proportion of normal and abnormal events detected by the system, highlighting the distribution of traffic conditions. The larger normal segment indicates stable system performance, while the abnormal portion reflects successful detection of critical events.

DISCUSSION

The experimental results clearly demonstrate that integrating deep learning with edge computing significantly enhances system performance. The CNN effectively extracts meaningful spatial features, while the autoencoder identifies deviations from normal patterns. The use of MEC reduces dependency on cloud infrastructure, enabling faster and more secure processing. The proposed system also shows strong generalization capability across different traffic scenarios, making it suitable for real-world deployment in smart cities. However, performance may depend on the quality and diversity of training data, and future improvements can focus on incorporating temporal models and lightweight architectures for better efficiency.

The experimental evaluation confirms that the proposed system outperforms traditional methods in terms of accuracy, speed, and efficiency. By combining deep learning with edge computing, the system achieves reliable and real-time abnormality detection, making it a robust solution for intelligent transportation systems.

V. CONCLUSION

The proposed deep learning–based abnormality detection system integrated with Mobile Edge Computing (MEC) demonstrates a robust and efficient solution for real-time monitoring in Cyber-Physical Transportation Systems. By shifting computation from centralized cloud servers to edge devices, the system effectively minimizes latency, reduces bandwidth consumption, and enhances data privacy. The combination of Convolutional Neural Networks for feature extraction and autoencoder-based reconstruction for anomaly detection enables accurate identification of both known and unknown traffic abnormalities. Experimental results validate that the proposed model significantly outperforms traditional approaches in terms of accuracy, precision, recall, and response time, while maintaining scalability for large-scale deployment. Additionally, the system shows strong adaptability to dynamic traffic environments, making it suitable for smart city applications such as accident detection, traffic management, and public safety monitoring. Overall, the integration of edge intelligence with deep learning provides a reliable, automated, and high-performance framework that addresses the critical limitations of existing surveillance systems and contributes to the advancement of intelligent transportation technologies.

The system can be further enhanced by integrating lightweight transformer-based models and real-time multi-modal data fusion to improve accuracy and scalability in complex traffic environments.

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