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ABSTRACT

Autonomous vehicles (AVs) are revolutionizing Intelligent Transportation Systems by seamlessly exchanging real-time data with other AVs and the network. For humans, controlled transportation has numerous advantages. But safety and security are the main concerns because malicious autonomous vehicles can make consequences. To avoid these consequences nanosensors are integrated with Vision Transformer (ViT) in AV which play a pivotal role in enhancing anomaly detection. To evaluate performance of the proposed framework, various evaluation metrics were employed. The experimental findings are compared with existing models, such as Convolution Neural

Networks (CNN), Recurrent Neural Networks (RNN), Deep Reinforcement Learning (DRL), and Deep Belief Networks (DBN). The result shows that ViT method achieves accuracy, precision, recall of about 92%, 93% and 93%, respectively. Experimental results demonstrate the superiority of ViT and nano sensor integration over traditional methods, showcasing its ability to detect a wide range of attacks with high accuracy and robustness.

Keywords: Autonomous vehicles, Cyber security attacks, Anomaly detection, Deep learning, Nano Sensor, Feature Extraction.

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1. Introduction

The rate of automobile use worldwide has skyrocketed in recent years due to population expansion and greater urbanization. Millions of traffic accidents occur every year, and one of the main causes of these incidents is clearly the high vehicle density on the roads, which created an unstable, crowded traffic environment with more complex and dangerous driving circumstances [1][2]. With a compound annual growth rate (CAGR) of 9%, the market for automotive communication protocols is projected to rise by $574.57 million between 2020 and 2024 [3]. The market is driven by government initiatives that encourage the use of telematics, the government's expanding support for electric vehicles (EVs), and the increasing electrification of cars. Moreover, it is anticipated that increasing vehicle electrification will quicken market growth.

In 2020, a security researcher from the Belgian university KU Leuven took use of a Bluetooth flaw on the Tesla Model X key fob to drive off in the vehicle [4]. Vehicles can communicate with one another and share information about their location, speed, direction of travel, brake and accelerator status, among other details, thanks to vehicle-to-vehicle (V2V) communication. This data is analyzed and applied to prevent collisions. Through the V2I, cars will be connected to infrastructure that may deliver information on weather alerts, traffic jams, road conditions, and ongoing work, all of which will contribute to both convenience and safety. By transmitting information about a vehicle's position and speed over a network to another vehicle, vehicle-to-vehicle (V2V) communication helps prevent accidents.

Vehicle-to-vehicle communication is primarily used to offer intelligent transportation services. Among other reasons illustrated in Figure 1, intelligent transportation systems (ITSs) [5] have been developed solutions to improve traffic safety. Such cars can be connected to other cars via the use of technologies and communication protocols referred to as vehicles to everything (V2X) [6]. ITS offers several benefits, including user-focused mobility services, intelligent traffic control and monitoring, and more. They consist of several components that combine the Internet of Things and artificial intelligence, reducing the necessity for direct human engagement. Therefore, in order to assess information obtained from several onboard sensors and make decisions about how to operate a vehicle in real time, a self-driving system employs sophisticated algorithms and machine learning models [7]. It makes it possible for cars to go freely with little to no assistance from humans.

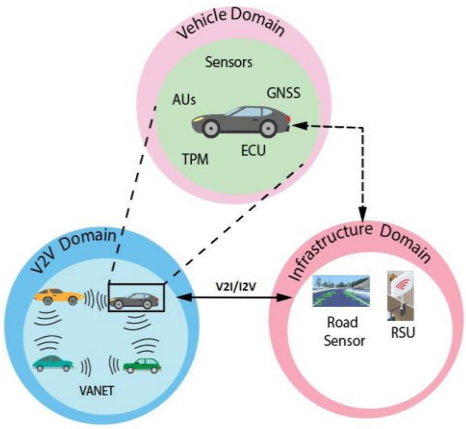

Figure 1: Intelligent Transportation Systems

One major limitation in the design and development of self-driving vehicles is the challenge in detecting anomalies and the vehicles' inefficient responses when encountering these anomalies. Anomaly detection is an effective and practical solution to this issue. Traditional machine learning algorithms are often time-consuming and not suitable for efficient anomaly detection. In this regard, an anomaly detection scheme is proposed using nanosensors integrated with Vision Transformer (ViT). This approach not only enhances the detection process but also supports seamless integration with current vehicle technologies, providing path for more effective and safe self-driving vehicles.

The main contributions of the paper are mentioned below:

- The study introduces a pioneering deep learning model for video anomaly detection-based ViT transformer integrated with nanosensors.
- Nanosensor used to collect data from autonomous vehicle. Gather the images from camera in vehicle in different conditions. Then synchronize sensor data and image for anomaly detection accurately.
- Several metrics are used to measure the effectiveness of recommended approach, including recall rate, accuracy, precision, ROC.
- A comprehensive experiment is carried out to assess the suggested model's detection performance using the dataset. The experimental results show that suggested model has a good level of sensitivity, accuracy, and F1 score when it comes to detecting different anomalies.

In rest of the article, Section 2 represents the relevant works in recent years. Section 3 presents the suggested working method. Experimental results explained in Section 4. Section 5 concludes with recommendations for further research.

2. Literature Review

Anomaly detection is main process in autonomous vehicle for safe operation in driving. He et al. (2020) created an unsupervised deep learning for anomaly detection method. Behavior pattern from typical sensor messages using an artificial neural network and a deep autoencoder, then compared it with vehicle observations based on the notional behavior they had developed for anomaly detection. To identify anomalies in radar signals Cheng et al. (2022) proposed residual network autoencoder. Long short-term memory (LSTM) and convolutional layers make up the structure of residual network. Convolutional layers were utilized for feature extraction, while LSTM layers were employed to ascertain the data's temporal dependency.

Ramachandra et al. (2020) presents a comprehensive analysis of several techniques for single-scene video anomaly detection. For autonomous electric vehicles Dixit et al. (2022) proposed an anomaly detection solution. The review closes the gaps in the literature by thoroughly examining the related security flaws and the corresponding artificial intelligence techniques for categorizing anomalous activity. Conversely, corner cases for autonomous driving's visual perception were examined by Breitenstein et al. (2020), who divided them into five categories according to how difficult it was to detect them. A selection of detection solutions has been highlighted at every level.

The extensive assessment by Bogdoll et al. (2022) provides a thorough analysis of the many anomaly detection techniques that rely on camera, multimodal, LiDAR, Radar, and abstract object-level data. The examination is methodical and covers multiple parameters, including simulation datasets, detection strategies, and the level of corner cases, or anomalies. Consequently, five categories are used to further classify detection approaches. Liu et al. (2020) provides a sensor fusion technique for intelligent vehicles. To augment the sensor information visual aided policy is used in intelligent vehicles.

A thorough survey of sensor-based and vision-based approaches to human activity recognition was presented by Dang et al. (2020). Othman et al. (2021) modified and applied a residual network (ResNet) to detect passive seismic data. The suggested residual convolutional neural network did not require domain knowledge of the noise/signal and was efficient in denoising and reconstructing seismic data. Samara et al. (2022) examined the many sources of outliers in IoT applications, current methods for identification, methods for evaluating detection strategies, and challenges in developing a solution. Subsequently, the authors categorized the most recent outlier detection methods into seven groups and presented a review of the literature on the subject. A collection of solutions is examined and evaluated within each category based on a number of factors, including the type of test data and the specific methodology.

Al-amri et al. (2021) focused on anomaly detection techniques based on Machine Learning (ML) and Deep Learning (DL) approaches in order to assess anomalous behaviors in the IoT data stream. Furthermore, the authors have supplied an extensive classification that describes the current literature in terms of various aspects, including data type, anomaly types analyzed, window model, data set. Additionally, the report makes some recommendations for possible research directions that might aid in the creation of cutting-edge anomaly detection methods.

3. Materials and Methods

The methodology for Vision Transformer based Anomaly Detection that involves several key steps. Firstly, data is collected from nanosensor encompassing both normal and anomaly. Preprocessing steps, such as image resizing and normalization, are applied to standardize input data. ViT architecture is then employed to extract meaningful hierarchical representations from the collected images. The model is trained using a supervised learning, where the dataset is split into training and testing sets. To reduce the deduction error, training involves enhancing the model's parameters using backpropagation and gradient descent. Hyperparameter tuning is done to enhance model effectiveness. The suggested work flow is shown in Figure 2.

3.1 Data Collection

Nanosensor used to collect data from autonomous vehicle. Gather the images from camera in vehicle in different conditions. When abnormal patterns or deviations from the expected behaviour are detected, the nanosensor sends alerts to a central processing unit. Then synchronize sensor data and image for anomaly detection accurately.

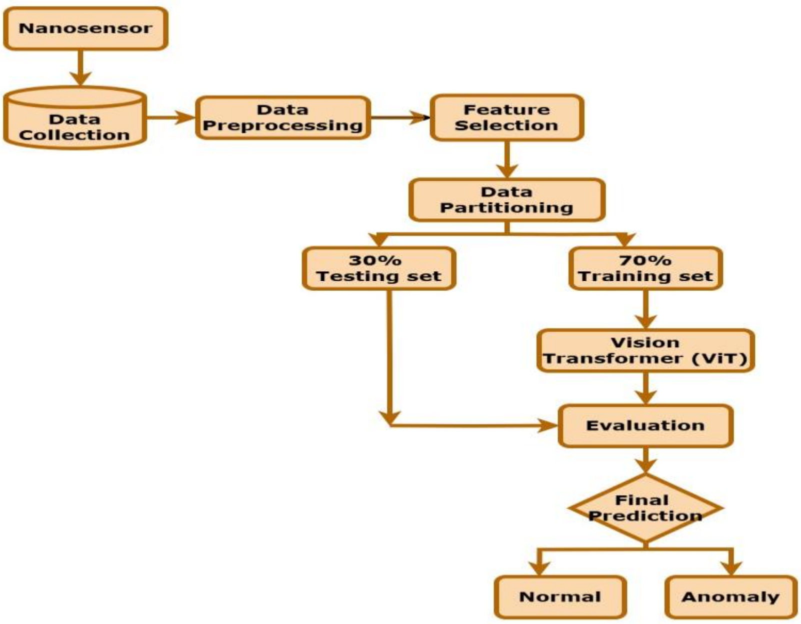

Figure 2: Flow diagram of Proposed model

3.2 Preprocessing of Dataset for Anomaly Detection

Image Rescaling and Normalization

Rescaling images is a crucial preprocessing step in anomaly detection for autonomous vehicles. The goal is to transform images to a standard size while preserving the key features necessary for accurate detection. This standardization helps improve the performance and efficiency of anomaly detection algorithms by ensuring consistency in input data. Equation for Rescaling:

$$I'(x', y') = I\left(\frac{x \cdot W}{W'}, \frac{y \cdot H}{H'}\right) \qquad (1)$$

Where I'(x', y') is the rescaled image, I (x, y) is the original image, W, H are the original width and height of the image, W', H' are the target width and height of the rescaled image, (x', y'), (x, y) are the coordinates in the rescaled and original images. To improve the suggested model's robustness, normalize the data and turn it into time-series windows for testing and training. Min-max scaling can be done using the following formula:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \qquad (2)$$

In the time series x is the original value, x_{min} is the minimum value, x_{max} is the maximum value and x_{norm} is the normalized value. This formula scales each data point proportionally based on its relationship to the minimum and maximum values in the time series. After normalization, the lowest value will be allotted to 0, highest value will be allotted to 1.

Data Partition

Partition the dataset into two groups: 30% for testing, remaining 70% for training. During the training phase, each base classifier is adjusted based on the training errors. The averages of the results are then calculated using equation 3. The original dataset D, which may be divided into several homogenous sets, should be regarded as the root node as it denotes whole population. Choose a data point at random from variable set consisting of j = 1, 2,..N. and i = 1, 2,... N. To allow for further choices, mean-based partitioning approach, divide D into two parts:

$$D = \begin{cases} D_{11,} \; if \; x_{ij} < \bar{x}_j \\ D_{12,} \; if \; x_{ij} \geq \bar{x}_j \end{cases} \qquad (3)$$

Viewing D11 and D12 as root nodes and applying (3) means looking at each child node independently.

Region of Interest (ROI) extraction

The ROI is crucial for improving the efficiency of anomaly detection algorithms by focusing computational resources on areas with the highest likelihood of containing anomalies. This process involves the utilization of segmentation algorithms or predefined anatomical masks tailored to delineate the anomaly boundaries accurately. The ROI is defined as a conditional extraction where the pixel values of the original image are retained if they fall within the designated anomaly region, and set to 0 otherwise. Mathematically expressed as

$$\mathrm{ROI(x,y)} \; = \begin{cases} \text{Original Image}(\mathrm{x,y}) & \text{if } (\mathrm{x,y}) \text{is within the detected region} \\ 0 & \text{otherwise} \end{cases} \qquad (4)$$

3.3 Vision Transformer based detection

Vision Transformers employ a unique mechanism for anomaly detection, utilizing self-attention and transformer architecture. Figure 3 illustrates the vision transformer workflow.

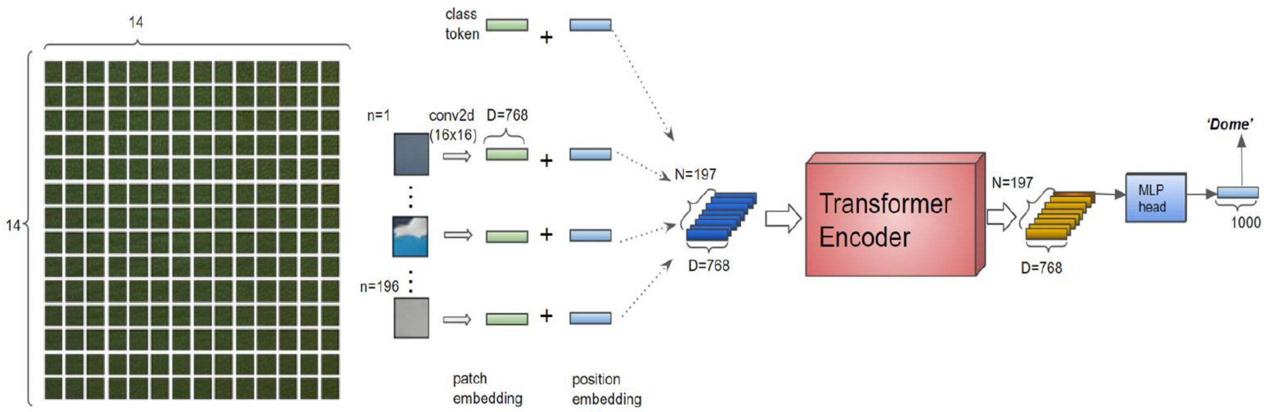

Figure 3: The vision transformer workflow

Patch extraction

In patch extraction images are split into patches with a set size. In which two-dimensional image into a series of 2D patches that are flattened.

Patch Embedding

ViTs employ a modified convolutional operation for Patch Embedding, transforming pixel values from the sensor image into high-dimensional feature vectors. This is achieved through a learnable embedding layer that linearly maps the pixel values of each patch to create a rich representation suitable for subsequent processing. The Patch Embedding operation is denoted by the equation:

$$\mathrm{PE}_{(x,y,c)} = \mathrm{Conv}(\mathrm{S}_{(x,y)}) \qquad (5)$$

Here $\mathrm{PE}_{(x,y,c)}$ represents the embedded feature vector for a specific patch at position (x,y) and channel c. $\mathrm{S}_{(x,y)}$ denotes pixel values of sensor picture at position (x,y) and Conv denotes the convolutional operation. This mechanism allows ViTs to effectively process localized information within each patch, facilitating comprehensive analysis of the sensor image for accurate detection of patterns related to anomaly.

Positional Encoding

Positional Encoding (PE) is a crucial component in Vision Transformers (ViTs) to preserve spatial information within the input data. It involves the addition of positional encodings to the patch embeddings, allowing the model to understand the order and location of patches within the image. The formulation of positional encoding is as follows:

$$\mathrm{PE}_{(x,y,c)} = \mathrm{PE}_{(x,y)} + \mathrm{PE}_{(c)} \qquad (6)$$

Positional Encoding is introduced to the patch embeddings of Vision Transformers to address the absence of inherent spatial information in transformer architectures. The objective is to enable the model to differentiate between the positions of different patches within an image.

Spatial Positional Encoding ($PE_{(x,y)}$): Spatial positional encoding captures information related to the position of the patch within the image grid. $PE_{(x,y)}$ represents the spatial positional encoding for a specific patch at position (x,y).

Channel-Wise Positional Encoding ($PE_{(c)}$): Channel-wise positional encoding is introduced to provide additional information related to the channel or feature dimension. $PE_{(c)}$ represents the positional encoding specific to the channel c.

Combined Positional Encoding $PE_{(x,y,c)}$: The combined positional encoding for a patch at position (x,y) in channel c is obtained by summing the spatial and channel-wise positional encodings.

The incorporation of positional encoding ensures that the model can distinguish between different patches and understand their spatial relationships. This is essential for tasks such as image recognition and classification, where the arrangement of features contributes to the overall understanding of the image.

Transformer Encoder

It is a crucial component in the vision transformer architecture for fault analysis, including tasks related to anomaly detection. It operates on encoded patches obtained from the input image. These encoded patches serve as the input to the Transformer Encoder. The Transformer Encoder employs a self-attention mechanism, allowing the model to capture global dependencies between different patches. Self-attention enables the model to weigh the importance of each patch concerning others, considering the entire context of the input image.

MultiHead Attention

MultiHead Attention is utilized to enhance the capacity of the self-attention mechanism. It involves parallel attention heads, each capturing different aspects of global dependencies. The outputs of these heads are concatenated to form a comprehensive representation. The mathematical representation of MultiHead Attention is given by:

$$\mathrm{MultiHead}(Q, K, V) = \mathrm{Concat}(\mathrm{head}_1, \ldots, \mathrm{head}_h) \cdot W_O \quad (7)$$

Here, Q, K, and V are the queries, keys, and values. W_O represents the output weight. Transformer Encoder with a self-attention mechanism and MultiHead Attention is vital in understanding complex patterns associated with anomaly. It allows the model to effectively capture and process information from different regions of the input image, contributing to accurate detection.

Feedforward Network (FFN)

FFN works on the output of transformer's MultiHead Attention mechanism. It plays a key part in improving the model's capacity to identify complex features important for anomaly detection. The output from the MultiHead Attention mechanism is linearly transformed using a learned weight matrix (W_1) and bias (b_1). The ReLU (Rectified Linear Unit) activation function (ReLU(·)) introduces non-linearity to the transformed output. It ensures that only positive values contribute to the subsequent layers, enabling the network to learn complex patterns.

$$\mathrm{Linear}(\mathrm{MultiHead}) \,.\, W_1 + b_1 \quad (8)$$

$$\mathrm{ReLU}\left(\mathrm{Linear}(\mathrm{MultiHead}) \,.\, W_1 + b_1\right) \quad (9)$$

The result of the ReLU activation is again linearly transformed using another set of learnable parameters (W_2 and b_2). This final transformation yields the output of the Feedforward Network.

$$\mathrm{Linear}(\mathrm{ReLU}(\mathrm{Linear}(\mathrm{MultiHead}) .\, W_1 + b_1)).W_2 + b_2 \quad (10)$$

Here, W_1, b_1, W_2, and b_2 are learnable parameters that the model adapts during training to optimize the representation of features relevant to anomaly detection. The Feedforward Network, through these operations, refines the information captured by the transformer's MultiHead Attention, enabling the model to capture intricate features associated with anomaly detection more effectively.

Class prediction

FNN takes the characteristics from previous layer of neural networks and modifies according for classification. The Softmax activation function is then applied to FFNs final output, which demonstrates the learned features.

$$\text{Class Prediction} = \text{Softmax}(\text{FFN}) \qquad (11)$$

By normalizing the scores across classes, the Softmax function produces a probability distribution over all possible classes. Consequently, the class with highest probability is considered the predicted class, and in this specific case, it is utilized to predict the presence of anomaly.

3.4 Hyperparameter Optimization

Implementing hyper-optimization for nano sensor-integrated vision transformers in autonomous vehicles enhances anomaly detection accuracy and efficiency. This approach leverages advanced algorithms to fine-tune parameters, reducing false positives and improving response times, ensuring safer and more reliable autonomous driving in diverse and dynamic environments.

4. Experimental Results

After looking into a variety of anomaly detection methods for AVs that have been published in the literature, a novel method nano sensor integrated with ViT was proposed, and the analysis of its findings is covered in this part. The test dataset contained both typical and unusual information. Segment the dataset into training, validation, and test sets prior to training the model. To reduce the reconstruction loss, training is carried out utilizing the training and validation sets. Plot the training and validation error against the number of epochs to assess the effectiveness of the suggested model training, as shown in Figure 4.

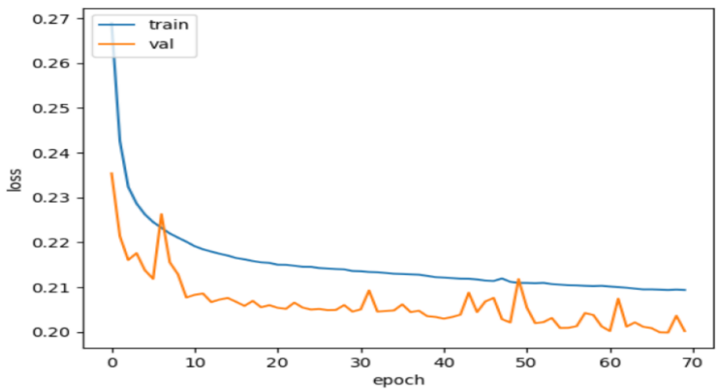

Figure 4: Training and validation loss

To evaluate proposed anomaly detection method, the effectiveness of its units in terms of accuracy in the detection, classification, and mitigation of anomalies is first studied. Moreover, since the aim of this method is real-time application, its overhead is important so timing analysis is performed on it. Finally, the performance of proposed method is compared to related research in terms of the detection capability and enforced overhead.

4.1 Evaluation Metrics

To evaluate this prediction model four standard metrics is used: accuracy (Acc), sensitivity (Sens), precision (Prec), and F1 score (F1).

$$\text{Acc} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \qquad (12)$$

$$\text{Prec} = \frac{\text{TP}}{\text{TP+FP}} \qquad (13)$$

$$\text{Sens / Recall} = \frac{\text{TP}}{\text{TP+FN}} \qquad (14)$$

$$\text{F1} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \qquad (15)$$

4.2 Comparison with existing work

The proposed method for detection of anomaly is compared with existing algorithms, Deep Reinforcement Learning (DRL), Convolution Neural Networks

(CNN), Recurrent Neural Networks (RNN), and Deep Belief Networks (DBN) shown in Table 1.

Table 1: Performance of the proposed algorithm

Models	Accuracy	Precision	Recall	F1 Score
RNN	75.2	70.1	64.3	68.4
CNN	80.6	75.1	71.6	75.8
DBN	79.1	72.3	72.9	72.8
DRL	88.7	81.5	77.8	82.4
ViT	92.8	87.7	89.1	86.9

Figure 5 demonstrates that the proposed Vision Transformer, integrated with nano sensors for anomaly detection, achieves high performance metrics: an accuracy of 92.8%, recall of 89.1%, precision of 87.7%, and F1 score of 86.9%.

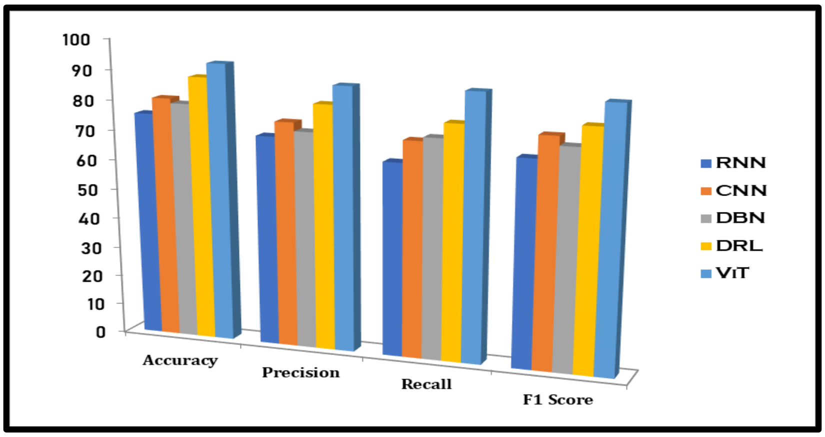

Figure 5: Comparison of proposed and existing models' performance

Figure 6 shows the ROC curve for anomaly detection using the proposed method. The curve highlights the method's effectiveness in distinguishing between normal and anomalous data. Higher AUC values indicate better performance, demonstrating the proposed method's accuracy and robustness in anomaly detection tasks.

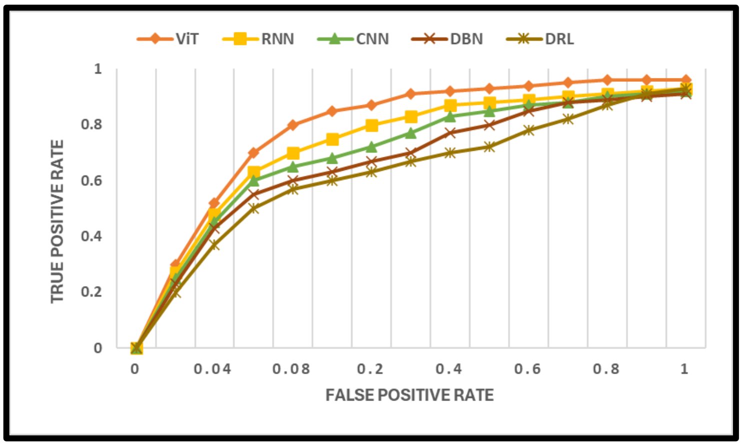

Figure 6: ROC curves of different models

Figure 7 depicts the confusion matrix for anomaly detection using the proposed method. The experimental results denote that nanosensor integrated ViT based method provide high accuracy in detecting anomaly.

	Anomaly	Normal
Anomaly	98% TP	2% FP
Normal	3% FN	97% TN

Figure 7: Confusion matrix

5. Conclusion and Future Work

The future of autonomous vehicles looks bright for increased road safety and dependable transportation. However, a serious risk associated with autonomous vehicles could be a malicious attack by intruders. In order to effectively detect anomalies, a nanosensor integrated ViT method was developed. Experimental evaluations on a dataset demonstrated the model's robust performance, achieving impressive metrics:

92.8% accuracy, 89.1% recall, 87.7% precision, and an F1 score of 86.9. These results highlight its capability to identify anomalies earlier than existing models like DRL, CNN, RNN, and DBN, improving average accuracy and F1 score by 4.1% and 4.5%. This advancement underscores the model's potential to bolster the reliability and safety of autonomous vehicles, paving the way for their widespread adoption in transportation systems globally.

To improve effectiveness in anomaly detection in different environment settings can be improved by combining machine learning models with adaptable learning abilities. Main objective of the research is developing trustworthy framework for anomaly detection that prioritize dependability and safety. Furthermore, for anomaly detection systems to be seamlessly integrated into autonomous vehicle operations, edge computing solutions for secure and fast data processing must be investigated.

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