Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

Enhancing Autonomous Vehicle Safety via DF-GRU and VAE Based Anomaly Detection

Keerthana B[1], Dr. Jayanthi B[2]

[1]*Assistant Professor, Department of Computer Applications, Kongu Arts and Science College (Autonomous), India*
[2]*Associate Professor& Head, Department of Computer Science (PG), Kongu Arts and Science College (Autonomous), India*
Email: keerthikec@gmail.com

The development of autonomous vehicles (AVs) has accelerated the need for advanced safety mechanisms to ensure reliable and secure operation in real-world environments. A crucial aspect of maintaining AV safety is anomaly detection, which helps identify irregularities in vehicle behavior, sensor data, and system performance. This paper introduces a framework designed for detecting anomalies that utilizes a Convolutional Dual Flow Gated Recurrent Unit (DF-GRU) and Variational Autoencoder (VAE) model, designed to enhance AV safety. The initial convolutional layers focus on extracting spatial features and highlighting semantic details, whereas the DF-GRU is responsible for capturing the temporal context from multivariate time series data. Additionally, suggested Framework incorporates a VAE to identify anomalies. A threshold setting strategy is developed in the Variational Autoencoder to enhance the performance of anomaly detection. Anomalies are detected by analyzing the reconstruction loss of the output alongside the log-likelihood score, using a defined threshold value. To evaluate the effectiveness of the proposed framework, use various metrics such as accuracy, precision, recall, F1 score, and an analysis of the loss curve. The experimental outcomes express that the suggested approach excels existing competing algorithms. The model's performance and results in detecting anomalies show that it effectively identifies unusual patterns in multivariate time series data. Ultimately, it is concluded that the model's output can be leveraged to intelligently identify and prevent cyber-attacks on autonomous vehicles.

Keywords: Autonomous vehicles, convolutional Dual Flow Gated Recurrent Unit, Variational Autoencoder, Multivariate time series data, Anomaly detection and threshold.

1. Introduction

Recent advancements in connectivity and Advancements in automation have led to the creation of autonomous vehicles. This mechanisms aims to reduce colliding events, lower energy demand, decrease roar, alleviate blockage, and enhance accessible mobility. An autonomous vehicle can operate and perform necessary tasks without human intervention, thanks to its ability to sense its environment. An AV employs a completely automated driving system to handle situations that would usually need human intervention. Additionally, AVs offer benefits like enhanced connectivity, improved mobility, and better land use. By facilitating effective and real-time data sharing between the cars, automated cars are revolutionizing the automobile sector. While connected and automated cars offer numerous advantages, they might also bring about new concerns regarding privacy, security, and safety. Moreover, AVs are totally dependent on data of sensor, as well as data from other cars. However, the sensor data is vulnerable to abnormalities brought on by mistakes, malfunctions, and cyberattacks, which can lead to mishaps and fatalities. Therefore, before AVs are widely used, methods for detecting anomalies and determining their causes must be developed [1]. Anomaly detection is a classic yet important problem, and numerous deep learning-based algorithms have been developed that typically outperform traditional methods in terms of detection accuracy. Anomalies can indicate serious situations, unusual events, or failures across various domains, such as abnormal data or cyberattacks in networks [2]. Accurate detection of anomalies in multivariate time series data is crucial for many applications, which has led to significant interest in this area. The difficulty of obtaining well-labeled data has resulted in the development of various unsupervised outlier detection for multivariate time series. However, creating an effective system is complex, as it needs to capture the temporal dependencies within each time series while also encoding the inter-correlations between different pairs of time series [3]. Most time series frequently lack anomaly labels due to high labor costs and the need for substantial domain expertise. Therefore, using unsupervised techniques becomes essential for real-world industrial applications. Nevertheless, complex underlying correlations and temporal dependencies in time series are difficult for current reconstruction-based anomaly detection techniques to capture. [4].

The navigation of autonomous vehicles, monitoring of traffic flow, recognition of obstacles, and ensuring passenger safety all rely on time series sensor data. The reliability of this data can be influenced by anomalies caused by sensor malfunctions, environmental conditions, or unexpected road incidents. Thus, it is crucial to identify anomalies in both spatial-temporal and semantic features to ensure safety. Reconstruction-based Anomaly Detection identifies abnormal patterns through the reconstruction capacity of deep neural networks. This variation seeks to find and localize anomalies by comparing the rebuilt data with the original input after reconstructing the input data using generative deep models. While there exist numerous reconstruction-based networks suitable for the AD task [5], focus in this work is on Variational Autoencoder and its various adaptations.

While the deep learning methods mentioned above have proven effective, a significant drawback is their reliance on labeled normal or abnormal data for training, thus classifying them as supervised or semi-supervised models. In this paper, explore the issue of detection of anomalies in multivariate time series sensor data collected from autonomous vehicles. A novel low-complex unsupervised method named convolutional DF-GRU and VAE model is developed. The proposed approach combines the generative capabilities of variational auto-encoders with the learning abilities of convolutional neural networks (CNN) for spatial and semantic features and Dual Flow GRU networks for temporal dependencies from multivariate time series data. The proposed mixture of deep learning techniques seeks to tackle the challenges inherent in AD within pre-processed multivariate time series data, where conventional approaches may prove inadequate.

The following is a summary of the primary contributions made by this study:

- The proposed system improves the model's capability to enhance the quality of input data by applying lower and upper bound normalization during preprocessing. This step ensures that the results are both reliable and consistent.

- Process of feature extraction using Convolutional DF-GRU Model. The Dual Flow GRU layer leverages the spatial, semantic, and temporal relationships within the input data to provide time series data with a summary of the relevant contextual information. The Utility of dual-flow Data Managing Improves the Perception of the multivariate time series data and Provides autonomous vehicles safety.

- To employ a VAE model. to latent space for anomaly detection is conducted by computing the Reconstruction loss and log-likelihood score, which serves as the anomaly score

The project is arranged in the following way, Section 2 explains Literature Review, In Section 3 Illustrate the proposed method for detecting anomalies in AV. The results are explained in Section 4. Ultimately, Section 5 provides the conclusion of the proposed work

2. Literature Review

This study seeks to offer a thorough overview of the existig research, highlighting key findings, methodologies, and gaps in the current knowledge. By synthesizing these contributions, this survey sets the foundation for understanding the anomaly detection in autonomous vehicle and identifying potential avenues for future research.

The work [6] represented a significant advancement in predictive vehicle maintenance. By combining graph outlier detection alongside the distinct aspects of vehicle sensor data, this method could greatly improves the consistency and productivity of transport services. By modeling the sensor network as a graph and using self-supervised learning to grasp the temporal relationships among the features, can achieve better outcomes. This technique finds flaws in the sensor data. In [7], a novel unsupervised framework for detecting anomalies on highways, named Structural Attention-Based Recurrent VAE (SABeRVAE), was introduced. This framework leverages the environmental structure to enhance anomaly detection. It includes a lane-vehicle attention module that evaluates the significance of allowable lanes for predicting trajectories, as well as a vehicle self-attention module that understands the interactions between vehicles on the road. The architecture employs a recurrent encoder-decoder design with a stochastic Koopman operator-propagated latent space, which predicts the next states of vehicles based on the outputs from the attention modules. This model successfully detects anomalies in both normal and unusual situations and is trained end-to-end to minimize prediction loss associated with typical vehicle behaviors.

An unsupervised approach [8] is introduced to anomaly detection in data with a temporal dimension. This study adapted the VAE-GAN architecture to learn the proxy task of temporal sequence continuation. The variational decoder decodes to a future sequence forecast instead of recreating the input. In order to separate structural uncertainty (which the model can reconstruct by fitting to observed data) from stochastic uncertainty, this approach introduced an additional decoder that outputs the pointwise confidence of the prediction, after the optimal latent-variable has been found. This model can use this for zero-shot anomaly detection, separating anomalies from stochastic variation that cannot be modelled, without any examples. This study [9] presented a DSA-CNN, a technique for detecting abnormal behavior of CAV velocity and acceleration sensors that is based on CNN and the self-attention mechanism. A dual-channel self-attention structure enhances the model's sensitivity to small anomalies, allowing for the integration of spatiotemporal feature learning into the deep learning training process.

A new architecture for a Variational Autoencoder (VAE) aimed at Multivariate sequential modeling was proposed in [10], which includes an innovative incremental training method. This approach includes a progress-based latent space that is effective for both offline and real-time anomaly detection. Unlike many current techniques that are trained in a semi-supervised manner and rely on large batches of normal observations, this approach utilizes unlabeled data from a robot executing tasks that encompass both normal and anomalous behaviors. Additionally, [11] presented VSAD, An anomaly detection algorithm for multivariate time series (MTS) that utilizes spatial-temporal graph networks in conjunction with a VAE. This approach leverages spatial-temporal graph networks to capture intricate temporal and spatial relationships within MTS data and it includes an autonomous method for threshold selection. Its VAE framework facilitates unsupervised learning of data distribution patterns.

A traffic flow prediction model called the Dual Spatial Convolution Gated Recurrent Unit (DSC-GRU) was introduced in [12] which integrates the DSC unit with the Gated Recurrent Unit (GRU) to capture both global and local spatiotemporal dependencies. Traditional prediction models often overlook or simply overlay global spatial characteristics when considering spatial correlation, focusing only on nearest-neighbor spatial features. The DSC-GRU model addresses this by using a novel dependency graph that represents global geographical relationships through the correlation coefficient between nodes, while the classic static graph in the DSC unit captures adjacent spatial dependencies. A modified gated mechanism in the DSC unit assesses the impacts of both global and local spatial correlations. In contrast, [13] presented a VAE prediction model that employs Planar Flow, using LSTM for both the encoder and decoder. This model reconfigures the internal structure of the VAE with planar flow to improve its capacity for learning intricate time series data. Planar flow adapts the VAE to better handle the nonlinearity inherent in time series data, allowing for more accurate predictions.

A method for anomaly detection that utilizes the reconstruction probability from a Variational Autoencoder (VAE) was introduced in [14]. This approach incorporates the probabilistic characteristics of VAE by considering variability, making the reconstruction probability a more objective and principled anomaly score compared to reconstruction errors from autoencoders or PCA-based methods. As a probabilistic measure, it offers a more robust evaluation of anomalies. Additionally, the generative nature of VAE allows for the reconstruction of data, facilitating the analysis of the underlying causes of the anomalies. In [15], an unsupervised anomaly detection model called GGU-VAE was proposed, which combines a GRU-based architecture with a Gaussian Mixture VAE for multidimensional time-series data. This model employs a deep latent embedding based on GRU to capture temporal correlations. Unlike traditional VAE models that use a single Gaussian distribution as the earlier, GGU-VAE employs a model of Gaussian Mixture to more accurately describe the space of latent using multiple Gaussian distributions, improving its ability to detect anomalies.

2.1. Research Gap and Novelty

Existing deep learning frameworks for AV safety focus primarily on either spatial or temporal data. However, the lack of integrated spatiotemporal modeling limits their ability to capture the full dynamics of complex driving scenarios. Traditional anomaly detection methods in AV systems are deterministic or rely on pre-defined thresholds, which struggle to generalize to unseen or rare failure modes. Many state-of-the-art architectures (e.g., Transformers, 3D CNNs) are computationally intensive, making real-time inference challenging on resource-constrained AV system. A significant portion of existing methods depend on a single sensor modality, like cameras or LiDAR, neglecting the advantages of multi-modal data integration for more reliable safety measures. Models trained on specific datasets often fail to adapt to variations in driving environments, such as adverse weather or dynamic traffic. This research introduces a novel architecture combining Convolutional DF- GRU and VAE model to address the limitations in AV safety systems. By addressing the research gaps, this approach improves the robustness, efficiency, and safety of autonomous vehicle systems, especially in dynamic and unpredictable scenarios.

3. Methodology

The approach used in this study is organized around several essential elements. The initial phase of training and testing the model focuses on collecting a substantial dataset pertaining to autonomous driving. The next step in data processing is normalizing the values using lower and upper bounds, which means scaling the multivariate time series data to a default range. At the core of the methodology is the suggested convolutional DF-GRU and VAE model, a deep learning framework tailored for detecting anomalies. This combination of convolutional DF-GRU and VAE for analyzing multivariate time series data aims to leverage the extraction of feature strengths of CNNs, modeling the temporal capabilities of DF-GRU, and the generative learning aspects of VAE. The goal of this architecture is to identify unusual patterns by learning both the temporal dynamics and latent representations from normal data. Ultimately, this system is intended to enhance the autonomous vehicles safety by helping to prevent accidents and collisions, while also being very effective at spotting anomalies, which helps ensure safer interactions with autonomous vehicles on the road.

Figure-1 illustrates the complete structure of the convolutional DF-GRU combined with a Variational Autoencoder. It consists of four primary phases as outlined below

- Data Collection
- Data preprocessing using normalization
- Feature extraction using convolutional DF-GRU
- Anomaly detection with VAE

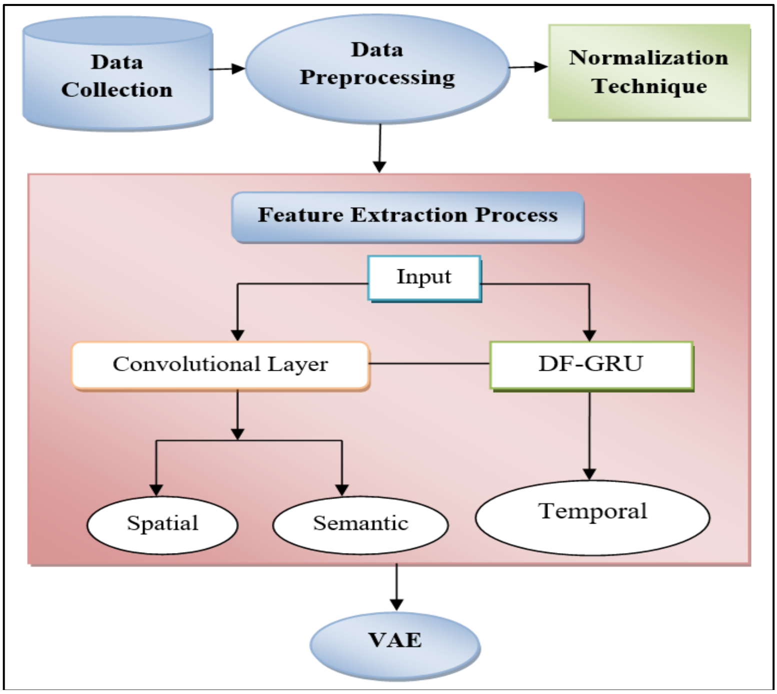

Fig-1: Architecture Diagram of Proposed Model

3.1. Data Collection:

Data collection for anomaly detection in autonomous vehicles involves gathering extensive and diverse datasets to detect unusual behaviors that diverge from the norm. Data is collected from various sensors which capture real-time information about the vehicle's surroundings, including distances, speeds, and obstacles. Recording the vehicle's internal states such as fast, acceleration, brake pressure, and steering angle. This helps in understanding the vehicle's operational dynamics. Logging incidents like sudden stops, collisions, or system malfunctions to identify potential anomalies.

DF-GRU and VAE performance in detecting anomalies is assessed using six open databases. Table 1 presents statistical data for these sediments. Assess model's performance on univariate time series even though it is intended for multivariate data. NAB and UCR were thus selected as the two databases. The time series characteristics chosen from this data span the specified time frame and can be utilized to inform multivariate statistics and evaluate the model's consistency.

Table 1: Datasets

Type	Dataset	Test	Dimension	Anomalies
Univariate	NAB	4022	1	0.93
	UCR	5800	1	1.87
Multivariate	MBA	100000	2	0.13
	MSL	73724	54	10.73

	SMAP	427618	26	13.13
	WADI	172802	124	5.98

NAB (Numenta Anomaly Benchmark)

The evaluation of anomaly detection algorithms is simplified by NAB, which offers a diverse set of real-world time-series data that includes labeled anomalies. It is appropriate for testing an anomaly detection models in autonomous cars since it includes a variety of domains, such as server metrics, network traffic, and environmental sensors.

UCR (HexagonML)

A variety of time-series datasets are available for classification, clustering, and anomaly detection applications through the UCR Time Series Classification/Clustering Repository. It is helpful for comparing anomaly detection algorithms in autonomous car systems since it contains datasets with varying features and levels of complexity.

MBA (Multi-source Background Autoencoders)

MBA is a dataset designed specifically for multi-source anomaly detection tasks, where data from multiple sensors/sources are combined. It provides labelled data for training and evaluation, enabling the development of robust anomaly detection systems for autonomous vehicles.

MSL (Mars Science Laboratory)

MSL dataset comprises telemetry data collected from the Mars Science Laboratory mission, including rover sensor readings and environmental data. It offers an opportunity to test anomaly detection algorithms in extreme and remote environments, simulating challenges faced by autonomous vehicles in unfamiliar terrains.

SMAP (Soil Moisture Active Passive)

Soil moisture readings obtained from satellite sensors make up the SMAP dataset.While not directly related to autonomous vehicles, it provides valuable environmental data that can be used to detect anomalies affecting vehicle operation, such as changes in terrain conditions or weather patterns.

WADI

Real-world sensor data from a water distribution system, such as flow rates, pressure readings, and valve statuses, is included in the WADI dataset.It offers a unique environment for testing anomaly detection algorithms relevant to autonomous vehicles operating in infrastructure networks, such as detecting leaks or malfunctions in the water distribution system.

3.2. Data Pre-Processing:

To enhance the robustness of the suggested model, it's important to normalize the data and convert it into time-series windows for both testing and training. Lower bound and upper bound scaling, often referred to as normalizing, is a data processing technique where the values in a time series dataset are adjusted to fit within a specific range, typically from 0 to a higher value in computer vision applications. This approach ensures that each data point falls within a defined range, which is crucial for this study. By doing so, we can develop a deep learning model that operates smoothly [16]:

$$t_n = \frac{t - t_{lb}}{t_{ub} - x_{lb}} \qquad (1)$$

Eq(1) illustrates, that in the time series t represents the actual value, t_{lb} denotes the lower bound, t_{ub} signifies the upper bound , t_n indicates the normalized value. This formula proportionally scales each data point according to its relationship with the lower and upper bounds in the time series. After normalization, the lowest value will be assigned a score of 0, while the highest value will receive a score of 1.

3.3. Feature Extraction using Convolutional DF-GRU Model:

Finding the most pertinent features in a dataset in order to enhance model performance and lessen over fitting is known as feature selection. By utilizing the Convolutional DF-GRU Model along with a deep learning approach for feature extraction and anomaly detection, this model improves the safety of autonomous vehicles through the use of Pre-processed feature vectors in the input layer. These vectors capture key attributes crucial for identifying anomalies in multivariate time series sensor data. The proposed model integrates temporal patterns (time-wise focus) and spatial patterns (sensor-wise focus) based on the DF-GRU framework. This study effectively explores and understands the various characteristics of time series, thanks to these preconfigured vectors that encode information from sensor data. Time series operations focus on the temporal dependencies between sequential data points. The input layer acts as the gateway for data entering the neural network, without performing any computations.

$$T_i = (t_1, t_2, \dots \dots .. t_{n-1}, t_n) \quad \text{-----} \quad (2)$$

In Eq. (2), the feature vector for the i^{th} instance of time series data is represented as T_i, while the attribute vector for the i^{th} characteristic in the time series data is denoted as t_i. The length or dimensionality of the input data is represented by T. The Dual Flow Gated Recurrent Unit layer is intended to capture the temporal dependencies within a time sequence. It can analyze data in dual flows (forward and backward), allowing it to gradually grasp the context.

The output of this layer consists of a series of feature vectors that capture the temporal characteristics of the input data.

As shown in Figure 2, this model uses features that represent time series scenarios as input data. The input x comes from the convolutional layer after being processed through Dual Flow GRU layers. The DF-GRU layer consists of two components, each evaluating the features in both forward and backward flows at the same time. Y represents the output produced by the two GRU layers.

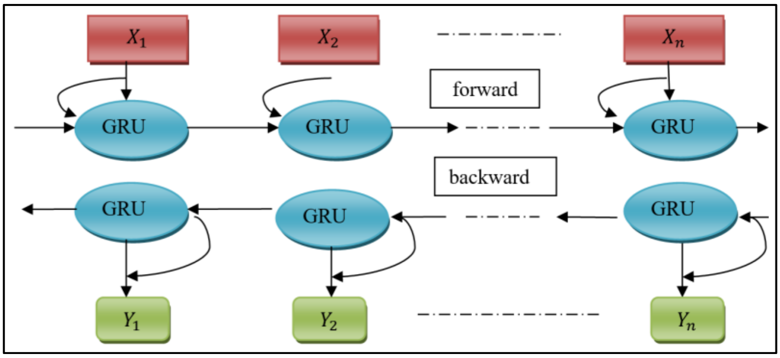

Fig-2: Structure of DF-GRU Model

The GRU algorithm [17] processes these sequential features to generate an output vector of defined dimensions. Its operation involves four main components. The reset gate is part of the initial element. The outcomes from the previously discussed operations form the basis for the GRU to calculate the output. The DF-GRU layer effectively captures contextual information regarding each element in the input data.

Using the Convolutional Layer on the spatial representation of input data is a common practice in Convolutional Neural Networks (CNNs). The convolution layer takes in its input and produces intermediate semantic information. In Eq. (3), $C_{a:b}$ represents the cluster of features related to the a^{th} and b^{th} items in the context of time series data analysis. The calculation within the convolution layer is performed as follows:

$$C_{a:b} = C_a \oplus C_{a+1} \oplus \dots \dots \oplus C_a \qquad (3)$$

After that, the model uses maximum pooling to combine the results from the convolution and emphasize the important features. The final output of the convolution layer is produced by combining these pooled results. Here, number of convolution results is denoted as $'nr'$, while number of convolution kernels denoted as $'p_i'$. Following equations represents the computations.

$$p_i = [p_1, p_2, \dots \dots p_{nr-1}, p_{nr}] \qquad (4)$$

$$\widehat{p_i} = \max(p_i) \qquad (5)$$

$$\hat{p} = [\widehat{p_1}, \widehat{p_2}, \widehat{p_3}] \qquad (6)$$

In this study, the fully connected layer receives its input from the output of the convolutional layer. Next, apply the SoftMax function to maximize the results in each segment. The part of the input that detects spatial-temporal features shows the greatest efficiency. The following formula expresses the computation. Where w_m indicates the weighting parameters of the mesh and b_m denotes the bias term.

$$m_i = w_m \hat{p} + b_m \qquad (7)$$

$$op_i = \frac{\exp(m_i)}{\sum_i \exp(m_i)} \quad (8)$$

The convolutional layer identifies significant features by applying weights that the model assigns to essential characteristics, which are then classified reliably through the SoftMax activation and the fully connected layer that it offers for the final output. This method explains potential for enhancing the autonomous vehicles safety by aiding in collision avoidance and improving anomaly detection.

3.4. VAE Based Anomaly Detection:

Generative models include Variational Autoencoders. During the training of the VAE, the inputs are obtained from the Convolutional DF-GRU model is encoded into a latent space this is succeeded through an integration of two primary aspect encoder and decoder. Encoder projects input data of high-dimensional (multivariate time series) to a latent space using a probabilistic distribution (mean and variance). Learns parameters $\mu(z)$ (mean) and σ^2(variance) for each input sample. After these input samples are decoded using the sampled latent points, the decoder recreates the real time series data.

VAE model applied for anomaly identification on multivariate time series data, both the reconstruction loss, the approximate log-likelihood score (via the ELBO) can help detect anomalies. This setup enables the VAE to generate accurate reconstructions while also regularizing the latent space to better approximate the standard data propagation.If the input is standard, reconstruction should closely match the original sequence. If it contains anomalies, the reconstruction will be poor. Fig-3 shows the architecture of a VAE contains two core concepts: encoder and decoder.

The Encoder converts the input data into a latent space and produces a probability distribution's parameters. Given a multivariate time series input $i=\{i_t\}_{t=1}^{T}$ where $i_t \epsilon R^f$(with T time steps and f features at each time step) the encoder encodes i into a latent variable z characterized by a mean vector μ and variance vectorσ. Decoder Reconstructs the input data using samples of latent variables taken from the encoder's distribution. For multivariate time series data, the decoder reconstructs each time step of the sequence based on the latent representation z Given a latent variable z, the decoder f_θ (with parametersθ) maps z to a reconstruction$\hat{\imath} = \{\hat{\imath}_t\}_{t=1}^{T}$ typically generated by feeding z.

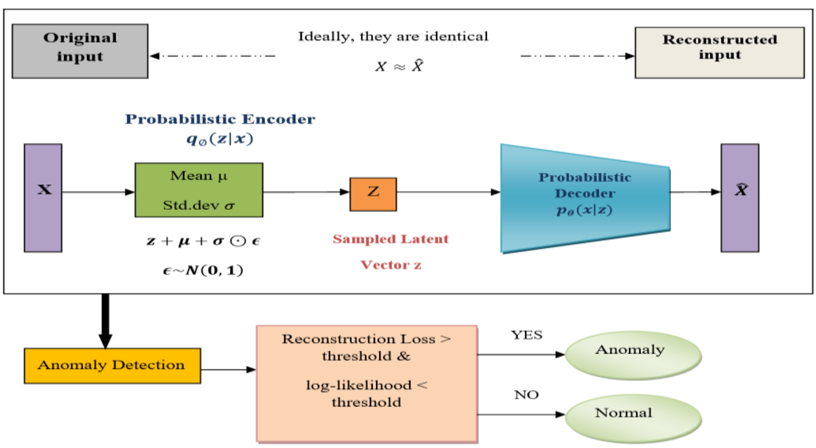

Fig-3: VAE Architecture with Anomaly Detection

3.4.1 Reconstruction Loss:

The reconstruction loss for VAE is typically calculated utilizing the Mean Squared Error (MSE) among the i - the original input, î - the reconstructed output. The reconstruction loss using Mean Squared Error is computed as follows:

$$L_{rc} = \frac{1}{T}\sum_{t=1}^{T} \|i_t - \hat{i}_t\|^2 \qquad (9)$$

Where

i_t= Original input time series data at time step t

$\hat{i}_t$ = Reconstructed time series data at time step t

T = Number of time steps in the sequence.

Based on the reconstruction loss distribution for normal data, set a threshold (th_{rc})Values of the reconstruction loss above this threshold the sample might be anomalous.

Anomaly if: Reconstruction Loss>th_{rc} (10)

KL Divergence:

The Kullback-Leibler (KL) divergence term is used to measure how much the learned latent distribution deviates from a prior distribution. The KL divergence term L_{KL} between the learned distributiony$(z|i)$ and the prior $p(z)$ for each data instance

$$L_{KL} = D_{KL}(y(z|i)||x(z)) = \frac{1}{2}\sum_{k=1}^{d_z} 1 + \log\sigma^2{}_k - \mu_k^2 - \sigma_k^2 \qquad 11$$

Where d_z - Dimensionality of the latent space (or number of latent features)

3.4.2 Log-Likelihood Score (ELBO):

Evidence Lower Bound (ELBO) acts as an approximate log-likelihood score, helping quantify how well a given input fits within the learned distribution of "normal" data. In an anomaly detection context, the ELBO is used to identify samples that fall outside this distribution, signaling a possible anomaly.

$$\log x(i) \approx \text{ELBO}(i) = R_{y(z|i)}[\log x(i|z)] - D_{KL}\big(y(z|i)||x(z)\big) \qquad (12)$$

A lower ELBO score indicates a lower likelihood, suggesting the sample may be anomalous.

Anomaly Score:

Create a weighted composite score using both the reconstruction loss and ELBO. The weighting factors α and β are used in calculate an anomaly score and Then, set a threshold on the anomaly score.

$$AS = \alpha \times L_{rc} - \beta \times \text{ELBO} \quad (13)$$

Setting thresholds [18] on both reconstruction loss and ELBO allows for a greater definitive Segregation between usual and aberrant data, reducing false positives and making detection more reliable. Using both metrics makes the model more resilient to missing subtle patterns, enhancing anomaly detection accuracy in complex datasets.

4. Experimental Results

After looking into a variety of anomaly detection methods for AVs that have been published in the literature, a novel method called Convolutional DF-GRU and VAE Model was proposed, and the analysis of its findings is covered in this part. The test dataset contained both typical and unusual information. Divide the dataset into three types, termed as training, validation, and test sets before you start training the model. To reduce the reconstruction loss, training is carried out utilizing the validation and training sets. During training phase, the loss functions result is illustrated in Fig. 4. Over the course of 50 epochs, the loss values progressively decrease during both training and validation steps until reaching a minimum value for training and validation.

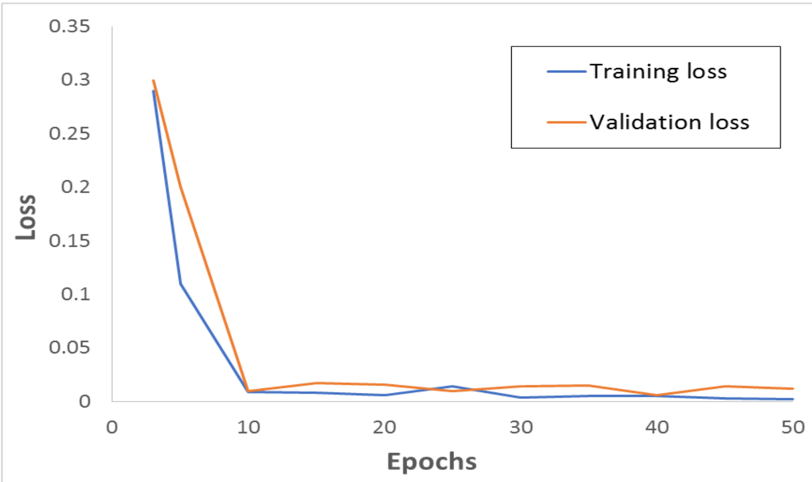

Fig.4: proposed model Loss curves.

4.1 Performance Metrics for Evaluation

During the testing phase, the metrics are employed for evaluating the proposed scheme. The evaluating metrics are precision (P), the F1 score (F1), which is a way to evaluate the effectiveness of a test, calculated as the harmonic mean of precision and recall (R), which is also referred to as the true positive rate, is used for this calculation. These metrics gauge the model's capabilities to detect anomalies and are derived from both detected anomalies and ground-truth labels.

4.2 Comparison with existing work

In this part present the training, validation, and testing outcomes of proposed framework comparing these results with existing deep learning models. For this evaluation, four existing models are compared with the proposed work. The existing models are deep auto encoder based framework named as LSTM-AE[19], CNN-BiLSTM VAE [17], Modified-Convolutional Neural Network (M-CNN) [20],GRU-AE which is a fully unsupervised Anomaly Detection approach.

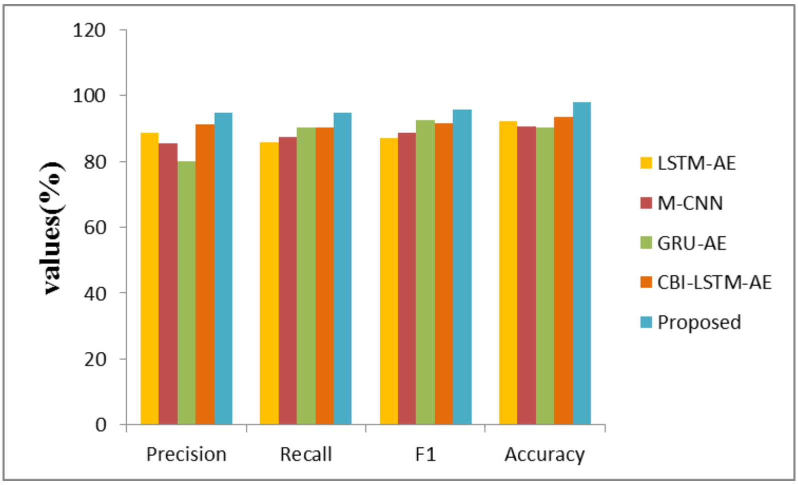

Fig.5: Comparison of Proposed Model with existing Models

Figure 5 presents the evaluation metrics of existing deep learning methods alongside the outcome of the proposed model. The values indicate a comparative performance evaluation between the proposed work and several existing models. The comparisons describes the superiority of the proposed work in terms of accuracy, precision, recall, and F1 score. The Convolutional DF-GRU and VAE model achieved the highest accuracy of 97.8%, as well as leading scores in F1 (95.6%), recall (94.7%), and precision (94.8%).

Fig 6 illustrates the time series anomaly score produced by the proposed design. The optimal threshold was represented by the red dotted line. It is evident that the scores for normal points generally fall under this threshold, while the scores for anomaly points tend to exceed it. Given that the reconstructed segments are relatively smooth [18], The variations in reconstruction that lead to the anomaly score cause the anomaly score curves to closely mirror the shape of the time series.

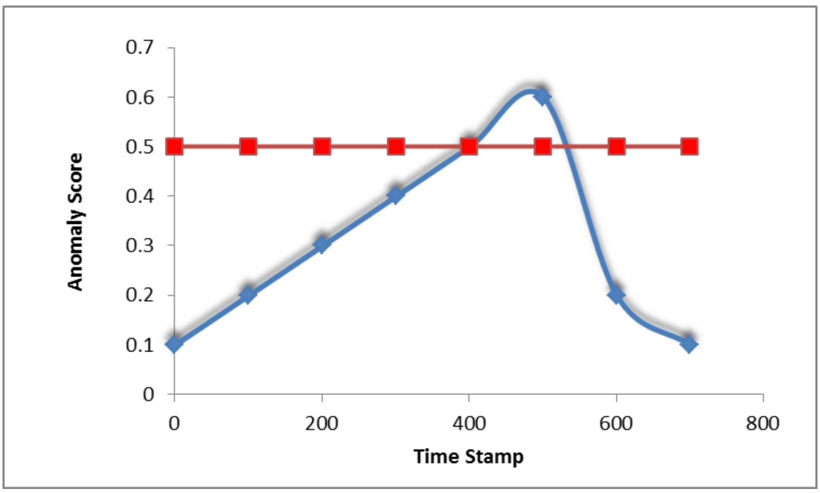

Fig 6: The anomaly score for the time series

A Strong Anomaly Detection method was improved for pre-processed multivariate time series data integrating VAE architecture with CNN and DF-GRU networks to jointly manage the spatial, semantic and temporal dependencies. This technique enhances the learning of latent representations, leading to exact anomaly detection. A DF-GRU processes data in both forward and backward flows, allowing it to understand relationships between past and future data points at the same time. This is particularly useful for autonomous vehicles, where understanding the sequence of events needs both past and future contextual information. DF-GRUs offers a balance of computational efficiency and robust temporal modeling, making them a valuable component in the design of autonomous vehicle safety systems. By using both reconstruction loss and log-likelihood score, VAEs can reach a comprehensive and complex approach to anomaly detection. Reconstruction loss excels at capturing visible deviations in the input-output mapping, while log-likelihood identifies latent anomalies that deviate from the probabilistic structure of the data. The collaboration of these metrics ensures a more robust, accurate, and versatile anomaly detection system.

This study has achieved a notable incremental improvement in performance compared to existing methods applied by this study. The outcome of the experiment indicates that the suggested design excels at multivariate time series data anomaly detection, significantly enhancing sensitivity across all determined conditions. This indicates that the suggested approach effectively detects anomalies that could be detrimental in real-world systems, outperforming other methods found in the literature.

5. Conclusion:

This work offers a thorough and effective approach to improving the protection of self-sustaining vehicles. Incorporation of Convolutional DF-GRU and VAE suggested a robust solution for anomaly detection in autonomous vehicle safety. Convolutional DF-GRU effectively captured the complex spatiotemporal and semantic relationships within multivariate time series data, ensuring a deep understanding of sensor dynamics. VAE offers a probabilistic framework for determining sophisticated Variations and indeterminacies permitting Powerful and Consistent detection of anomalies. Together, these technologies improved the resilience and flexibility of autonomous systems, Assuring safer and more reliable tasks. This integrated methodology shows notable improvements over current DL techniques. The evaluation of the proposed model through 5-fold cross-validation demonstrated its remarkable performance. With average detection accuracy, precision, sensitivity (recall), and F1-Score the model showcased superior capabilities compared to existing approaches. These results show how effectively the proposed model can identify anomalies, which in turn improves the security and reliability of autonomous vehicle systems.

In future work, discuss how the model can be modified to handle data from several sensor types, an extreme operational circumstance (such as bad weather or sensor failure) that arise in the real world. The model could Progress to use weather-aware sensors that are enhanced for particular circumstances (e.g., infrared sensors for fog, or radar for rain). By integrating these sensor types and their corresponding data into the anomaly detection model, autonomous vehicles will be better trained to handle diverse environmental factors. The VAE, with its probabilistic nature, could learn to model sensor noise introduced by weather conditions and distinguish between true anomalies and environmental distortions. This continued adaptation will be essential for assuring that autonomous vehicles are not only safe and dependable but also of navigating the unpredictable and dynamic nature of human-driven environments.

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