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Improving fault diagnosis in elevator systems with GAN-based synthetic data

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Abstract: Elevator maintenance and fault diagnosis are critical in ensuring reliable and safe operation. Elevator systems are complex electromechanical systems prone to various faults, such as sensor failures, motor malfunctions, and mechanical wear and tear. Detecting these faults promptly and accurately ensures elevators' safe and reliable operation. However, there is a lack of labelled data that may be used to train machine learning models, making it difficult to diagnose problems with elevators. This paper presents a novel approach for elevator fault diagnosis based on optimised generative adversarial networks (GANs). The proposed method employs a GAN model that generates synthetic data to augment the limited amount of labelled data and then trains a classifier on the augmented dataset. To improve the performance of the GAN, the authors introduce an optimisation algorithm that combines gradient ascent and descent, resulting in better-quality synthetic data. The efficiency of the system is evaluated using real-world elevator sensor data and compared its performance to traditional fault diagnosis methods. The results show that the proposed system can accurately diagnose faults with high accuracy and can potentially reduce maintenance costs and downtime. The proposed system provides a promising solution for elevator fault diagnosis, especially when labelled data is limited.

Keywords: fault diagnosis; optimised generative adversarial networks; GANs; elevators; augmented dataset; and maintenance costs.

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1 Introduction

As the construction sector expands rapidly, more and more people are opting to use elevators as a convenient mode of transportation between floors (Awatramani et al., 2021). Elevators, an important part of modern infrastructure, provide great convenience for individuals with limited mobility and emergencies. Accidents involving elevators pose a significant risk to human and material well-being (Xiao et al., 2021). The public has high expectations for the security and dependability of elevators, which is both a challenge and an opportunity for innovation. Elevators are usually subject to routine inspections by maintenance experts (Niu et al., 2021); however, it requires a lot of money, time, and effort. Maintainers' inspection results are frequently too amorphous to reliably guarantee elevator safety (Olalere et al., 2018). Researchers and engineers have developed several systems and gadgets to address this gap, monitor elevator conditions, and provide fault diagnostics (Mishra et al., 2019). The technology is developed to aid elevator maintenance engineers in their quest for greater defect detection and efficiency (Tayyeb et al., 2021).

Even then, relying on a simple mistake-matching mode, especially for elevator door systems, is insufficient for meeting the objectives of speed and generality in fault diagnosis (Chew et al., 2022). This research requires intelligent methods to diagnose faults in complex mechanical and electrical systems effectively, and the advent of artificial intelligence (AI) and machine learning has opened up new avenues to address these challenges. Today, numerous intelligent approaches have proven effective in addressing the problem of failure diagnosis of complicated mechanical and electrical systems (Oya et al., 2020). Central to this research is the concept of an agent, characterised by four fundamental properties: responsiveness, autonomy, object orientation, and adaptation (Mishra et al., 2019). An agent is a computer program or other algorithmic entity that can act independently of its creator or user to perform a predetermined set of tasks in a given environment (An et al., 2021). The proposed method provides a new approach, GAN, to assessing elevator performance by integrating data from the tracking platform's record of breakdowns with the results of a fuzzy mathematics estimate of the risk associated with the elevator system (Wu et al., 2021).

This paper discusses using a combination of gradient ascent and descent to improve synthetic data quality, which can diagnose problems in rotatory devices such as elevators (Geng et al., 2022). To enhance the functionality of the conventional fault diagnostic technique, GAN generates synthetic data to augment (Suzuki et al., 2020). The limited amount of labelled data then trains a classifier on the augmented dataset for defect detection in elevator systems based on deep learning feature extraction techniques (Balaji et al., 2022). Researchers are evaluating the probable lifetime of faulty elevator parts through remote monitoring (Chatterjee et al., 2022). Troubleshooting and analysing elevator systems are essential for proper operation (Kim et al., 2022). Users can estimate the service life of damaged elevator components through remote monitoring, which is important in planning elevator maintenance schedules and minimising interruptions.

Through remote monitoring, users calculate how long the broken elevator components will likely last. Monitoring and analysing possible problems is crucial for smoothly operating elevator systems (Frid-Adar et al., 2018). Several real-world engineering applications, such as aircraft and elevator motors, have been explored using an informed decision system for failure detection (Jia et al., 2021). As a result, GANs have been increasingly popular in recent years, and their use has proven highly effective in helping academics tackle challenging pattern recognition problems (Zhou et al., 2018). The challenge of generative modelling is addressed by AIA known as generative adversarial networks (GANs) (Olalere et al., 2018). A generative model's function is to understand the probability distribution that produces a collection of training instances by analysing those examples (Zhou et al., 2023). In GANs, two machine learning models (usually neural networks) engage in a game in the traditional sense (Niu et al., 2022). One model is used to generate a new instance, and the other is used to evaluate its authenticity, which greatly improves the performance of the generated model.

According to the discussions, the elevator system fault diagnosis process has a crucial role in infrastructure because it helps to improve safety. In addition, the elevator system has very complex patterns because of cables, motors, safety mechanisms, and control systems. Therefore, the system may fail due to potential accidents, safety hazards, and disruptions. An automatic and effective fault diagnosis system must be developed to improve availability, safety, operational efficiency and reduce maintenance costs. The created diagnosis system faces difficulty predicting the exact fault that occurred region because it requires frequent diagnostic tests, leveraging historical data and optimised machine learning techniques. In addition, the system requires the maintenance history, operation conditions, and system designs to improve the accuracy of overall fault detection. Then, the fault detection system is integrated with the monitoring systems to ensure the scalability and complexity issues. The research difficulties are overcome by applying the GAN approach that predicts the faults with maximum recognition accuracy.

The major contribution of this paper is given as,

- We adopt improved quality synthetic data, which is the goal of the gradient ascent and descent optimisation method described here for boosting GAN performance.
- We analyse data collected from actual elevator sensors and compare the results to those obtained using conventional defect diagnosis techniques to determine the system's efficacy.
- The suggested technique, GAN, offers a potentially useful approach to elevator failure diagnostics, especially in cases where labelled data is scarce.

The remaining section of this paper is given as

Section 2 deals with a background study on elevator faults and diagnosis. The proposed framework GAN is designed in Section 3. Section 4 illustrates the software analysis and evaluation; Section 5 describes the conclusion and future scope.

2 Background study

Elevator failures seriously threaten people's safety and property; researchers must find reliable ways to diagnose and prevent them. AI methods, a relatively new area of study, have proven useful in diagnosing and fixing elevator problems and were proposed (Chen et al., 2019). This study provides an overview of the different AIA used for elevator malfunction diagnostics, discussing them from two perspectives: a combined theoretical study with real-world use. It provides a comprehensive literature overview of how these AI algorithms (AIA) have been used in elevator fault diagnostics. Future directions for AI advancement in elevator fault diagnosis were highlighted, too.

Assuring passenger safety and comfort is essential to identifying and fixing problems with critical mechanical parts. The article's authors focus on keeping tabs on the health of vital mechanical parts. Strong interference and indirect signal collecting are two problems proposed to be addressed by a defect diagnosis system (DDS) (Zheng et al., 2021). Analysing real-time elevator operation data determines the small shock signal induced by mechanical equipment damage. In addition, the elevator's essential mechanical parts undergo an intelligent defect diagnosis. The diagnostic information might guide elevator upkeep and ensure passenger safety and comfort.

This analysis and the accompanying app aimed to prevent elevator breakdowns and the resulting stranding of passengers and staff alike by alerting elevator technicians to potential problems ahead of time. The elevator communication systems module sends data to a cloud-based program, which then processes the information and, if necessary, notifies technicians working in the elevators. The authors in the article proposed an elevator communication module based on a cloud program (ECM-CP) (Suárez et al., 2018). This paper explained the modern tools used in this creation, most notably Microsoft Azure, and deeply obtained results.

The elevator sector is becoming increasingly reliant on 'Industry 4.0' initiatives such as the use of big data as well as AI technology. Conventional elevator fault tracking is inaccurate, and this is a problem that needs to be fixed immediately as the volume of data about elevator operations grows and more stringent demands are placed on the elevator's real-time performance. In this study, the authors in the article offer an AI-and big data-driven approach to elevator failure monitoring and diagnostics (EFMD) (Jiang et al., 2022). To keep tabs on the overall elevator control system's operational status, here proposed a pattern recognition technique that utilises finite state machines (FSM), and the experimental simulation has been completed.

In this research, authors discovered a unified framework for defect detection of elevator doors based on control state information. This includes classifying states, pre-processing of that data, and finally, classification. During state classification, doors are categorised as either open or closed, and the accompanying operational circumstances are categorised further depending on the information from the elevator's control board. Because the proposed framework relies solely on state information collected from control boards, it has the potential to be efficient for real-world identification of elevator door failures. Elevator control board measurements taken in the field confirmed the efficacy of the proposed strategy as fault diagnosis and classification on elevator doors (FD-CED) discovered (Chae et al., 2022).

As cities expand, elevator security and dependability concerns have become more prevalent. When an elevator breaks down, it can devastate the efficiency of the entire mechanical transmission system and potentially cause significant injuries (Chien et al., 2022). This research combined the decision tree and rough set theory (DT-RST) to form a novel method for intelligent fault diagnostics. Results show that the provided approach can provide fast fault location and remedies to deal with the situation, and the elevator fault detection method is completed.

Given the prevalence of elevator accidents, an internet of things-based elevator monitoring and control system (IoT-EMCS) was developed. Elevator safety monitoring necessities were first studied functionally and performance-wise, and then the system's viability was assessed from the viewpoints of demands, innovation, and practical operation (Ming et al., 2018). The installation of a system to monitor elevator safety has finally been completed. The test results verified that the presented elevator safety monitoring system worked as intended and could be useful in the real world.

Han and colleagues introduced a fault diagnosis model for railway point machines that is predicated on using vibration signals and is aimed at enhancing Sustainable Railway Transportation. This innovative model leverages pre-trained GANs with empirical mode decomposition to decompose vibration signals into their constituent intrinsic mode functions. This decomposition facilitates detecting and categorising anomalies within the railway points. Furthermore, the system integrates a gradient-boosted decision tree and a discriminative model to derive Mel-frequency cepstral coefficients (MFCCs) from audio data. This approach results in a reduced set of feature dimensions, which is beneficial for the efficiency and accuracy of the diagnostic process. Using MFCCs from audio information is a strategic move that enhances the model's ability to discern and diagnose faults accurately (Han et al., 2023).

Mabrek and co-authors have created a protocol specifically designed to recover drones that have become disconnected during their operational missions while mitigating associated security threats (Mabrek et al., 2023).

Based on the previous research studies AIA, DDS, ECM-CP, EFMD, FD-CED, IoT-EMCS, and DT-RST, the proposed system (GAN) can overcome the main challenges and offers a potentially useful approach to elevator failure diagnostics, especially in cases where labelled data is scarce.

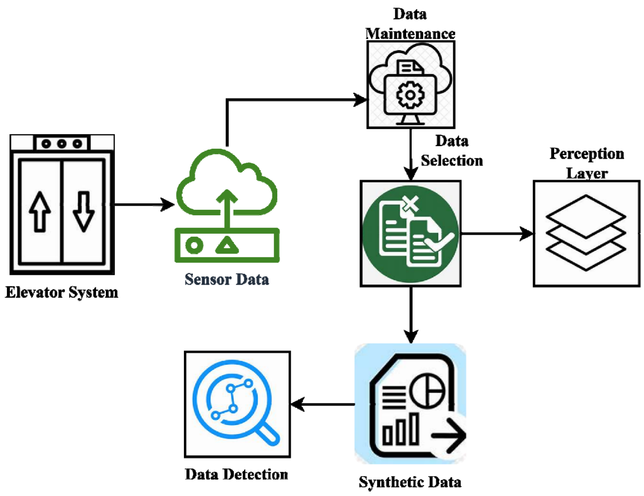
3 Proposed system

To establish a comprehensive operation status monitoring model for the elevator door, it is necessary to monitor the health status of the elevator door in real-time, mainly considering the electromechanical data, environmental data, and physical parameters of the elevator door. Electromechanical data, especially the Door Ball Bearing Sensor, is a critical mechanical component for monitoring elevator doors and is essential for predicting the door's potential failures and maintenance needs. Environmental data mainly takes into account humidity, and changes in humidity may affect the lubrication and wear of mechanical parts of elevator doors, so monitoring humidity can help better understand the operation of elevator doors under different environmental conditions. The physical parameters, mainly vibration parameters, are also key indicators. Vibration data can reveal the dynamic characteristics of elevator doors during operation, which is significant for identifying abnormal vibration patterns and preventing potential structural problems. The data from these datasets can be obtained through gate ball bearings, humidity, and vibration sensors. By comprehensively analysing the data provided by these sensors, it is possible to reduce downtime due to elevator failures, reduce maintenance costs by optimising maintenance schedules, and ultimately achieve efficient and reliable operation of elevator equipment.

GAN is fed vibration signals from different elevator functions, and those signals' energy properties and time-frequency indicators are retrieved using theoretical analysis of the best synthetic data. The generator's job is to create new data nearer to the information supplied as input, while the discriminator's job is to tell the two apart.

Elevator sensor data is retrieved according to timeframes provided by the maintenance data, as shown in Figure 1 of this study, which illustrates the defect identification approach taken. The elevator system data is loaded into a synthetic data-based multilayer perceptron GAN model to extract novel features. The retrieved deep features are then used in a defect detection task. Fault detection using the current features is compared using the synthetic data method. To learn a non-linear function approximator, a multilayer perceptron is a GAN approach. Non-linear layers, known as hidden layers, could exist between the input and output layers. This new method of detecting elevator problems requires fewer devices, making it more cost-effective. This invention relates to diagnosing elevator defects, for instance, when the cab lifts due to a lack of action from an elevator faults diagnostic device.

Figure 1 Elevator fault diagnosis approach (see online version for colours)



$$\left.\begin{aligned} il &= \{(max_i il_l d \mid pi \in bt), (min_i il_l d \mid pi \in ct)\} = \{il_1^+, il_2^+, \ldots il_n^+\} \\ il' &= \{(min_i il_l d \mid pi \in ct), (max_i il_l d \mid pi \in bt)\} = \{il_1^-, il_2^-, \ldots il ?_n^-\} \end{aligned}\right\} \quad (1)$$

$$dt_i^+ = \sqrt{\sum_{il+}^{n} (il_l d)^2} \quad dt_i^- = \sqrt{\sum_{il-}^{n} (il_l d)^2} \quad (2)$$

Many performance indicators *pi* have varied physical dimensions *dt*, so the data associated with each feature must be standardised for diagnosing by + and –. Get the normalised matrix *il* and *il′* after processing, and then use the following formula to derive the normalised decision matrix for this process are explained in equations (1) and (2) by the maximum $\max_i$ $il_l d|pi \in bt$ and the minimum values $\min_i$ $il_l d|pi \in ct$. *ct* and *bt* are two sets of attributes, one dealing with benefits and the other with costs using summation with *n* numbers of input and outputs for synthetic data quality analysis.

To compensate for the dearth of labelled data, the suggested method uses a GAN model to produce synthetic data, subsequently used to train a classifier. Here, we offer an optimisation approach that combines gradient ascent and descent to enhance the GAN's performance, leading to higher-quality synthetic data, which are discussed below.

In this paper, authors present the successful application of supervised training of GAN-based synthetic data process to the problem of elevator malfunction diagnostics. The proposed system employed a two-layer of feature vectors and n numbers of hidden-layer with the multilayer perceptron network model. The generator and discriminator networks make up GAN. New instances are made by the generator using a simple random variable, and the discriminator attempts to tell them apart from real data. While the original framework allows for no input and is entirely reliant on random noise, a subsequent study introduced conditional GAN, which allows the authors to exert some degree of control over the generated content by concatenating the provisional input vector c with the noise vector z before feeding it into the generator shown in Figure 2.

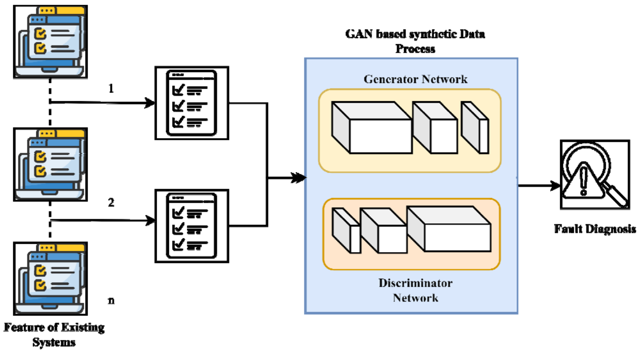


Figure 2 Multilayer perception of GAN-based synthetic data (see online version for colours)

$$\frac{\rho}{dt}(nt)-\frac{\rho}{dt}sn\frac{gn^{n}*\frac{ap}{rp}}{(ac*id*rd)}=\begin{cases} n \\ ef^{n}*\frac{nt}{sn}, \text{ where } n\geq 0 \end{cases} \tag{3}$$

$$sn^{n}*\frac{ap}{rp}=\frac{\rho}{dt}(ac)+\frac{\rho}{dt}(id)+\frac{\rho}{dt}(rd)*\frac{n}{\left(1-ef^{n}\right)} \tag{4}$$

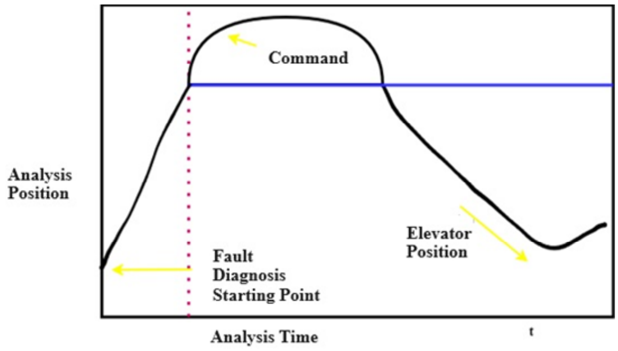
The above equation (3), used for performance comparison with other conventional methods, can be rewritten to calculate accuracy and the efficiency value below in equation (4). A network trained *nt* solely on synthetic data *sn* has a poor generalisation gn^n to actual process *ap* and fails to generalise to real-world one *rp*; however, it is a promising option to get accurate ad and infinite data *id* without having to pay for expensive annotated real data rd. The network can be used to generate data in different modalities as well as to generate realistic training elevator functions ef^n that can be used to train any other machine learning model.

A domain of a certain kind can be specified, and then this conditional GAN can produce relevant instances from that domain. This paves the way for some of GANs' most amazing uses, such as translating one image into another, transferring a user's style to a new image, colouring previously unseen photos, etc. As interest in the efficacy of deep generative learning has grown, several academics have begun attempting to overcome these difficulties through GANs, despite many existing methods already attempting to accomplish this using powerful learning-based approaches. The optimisation algorithm of gradient descent is shown in Figure 3.

The idea behind gradient descent is to move away from the function's gradient, or gradient, at each step to reach its local minimum. If given a function of fault analysis, the objective of the optimisation algorithm of gradient descent is to find its minimum. It does this by repeatedly carrying out the following two procedures:

- Get the function's first-order derivative at that point, often known as its gradient.
- From the current vantage point, advance in the direction opposite the gradient by an amount equal to alpha times the gradient.

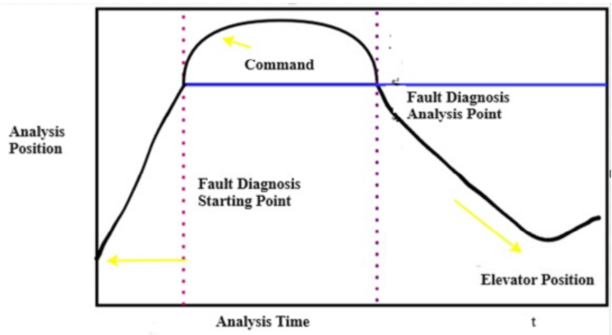
Figure 3 Optimisation algorithm of gradient descent (see online version for colours)



$$\theta_x := \theta_x - \alpha\frac{\sigma}{\sigma\theta_x} * x\left(\theta_0,\theta_1\right), \text{where } x=1 \text{ or } 0 \tag{5}$$

Since there is merely one observable variable θ_x, the dependent variable (here, $x(\theta_0, \theta_1)$,) can be plotted on the y-axis, and theta (θ) can be plotted on the x-axis. In the case of two parameters, it will use a three-dimensional plot, with price forward along an axis and the two specifications $\alpha\frac{\sigma}{\sigma\theta_x}$ Distributed over the other two axes shown in equation (5).

Figure 4 Optimisation algorithm of gradient ascent (see online version for colours)



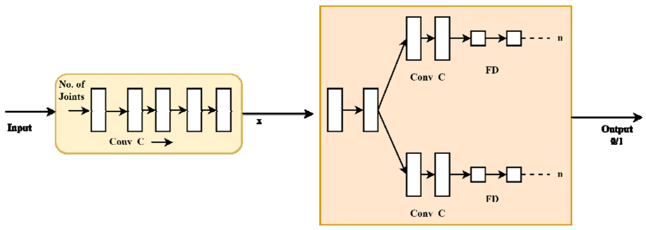
It is overshooting the minima and continuing to bounce about if the training error is too high. It is possible that training will take too long if the training rate is too low for the analysis position. There could be a large number of minimum points in the cost function. The gradient can converge to any minimum depending on the starting position as initial parameters and the number of iterations. As a result, the optimal solution may vary depending on the initial conditions and the rate of adaptation.

Gradient descent is a method for finding the least value of a function by gradually deviating from the gradient. The gradient ascent optimisation algorithm aims to locate the smallest value of a given function. As just one independent variable, theta(t) is available to analyse both fault starting and fault ending time based on the dependent variable, in this case, cost, which can be displayed against time along the y-axis.

$$cf = x(\theta_0, \theta_1) = \frac{1}{2mi}\sum_{i=1}^{n}\left(x_\theta\left((\theta_0, \theta_1) - x_1(\theta_0, \theta_1)\right)\right)^2 \quad (6)$$

From equation (6), the cost function *cf* of $x(\theta_0, \theta_1)$, it employs a three-dimensional graphic in the case of two parameters $\frac{1}{2mi}$, with the forward price along one axis $x_\theta((\theta_0, \theta_1)$ and the two specifications $x_1((\theta_0, \theta_1)$ spread out across the other two, shown in Figure 4. If the training error is too large, the system will overshoot the minima and continue to oscillate $(x_\theta((\theta_0, \theta_1)–x_1((\theta_0, \theta_1))^2$. If the training rate is too low for the analysis position, the training process could take too long to maintain elevator operations. There may be numerous points where the cost function is at its lowest. The gradient converges to one of the minima depending on the initial parameters and the number of repetitions. Hence, the ideal solution may change based on the problem's parameters and the adaptation rate.

Figure 5 Process of GAN (see online version for colours)



Among the most well-known applications of GANs are in elevator fault identification synthesis and modelling. The statistical distribution of a synthetic dataset improved by a GAN can closely approximate that of a real dataset processed in Figure 5. Several methods are mentioned in Section 2 compared with our proposed work and investigate how to employ GAN models to enhance image manipulation. While a physical renderer of GAN can be used to create synthetic images, the image-generation process pays no attention to the distinction between natural and artificial information. The suggested style-transfer network is meant to convert the smooth, optimised algorithms into a more faithful depth to the real thing. The figure depicts the overall design of the implemented procedure using convolutions or the fault diagnosis (*fd*). Although much research has been done on elevator estimation of faults using GANs, Data-driven approaches require extensive amounts of annotated data, which is time-consuming and costly.

$$ps_g(x, x') = ps(x')ps_g(x \mid x') * \frac{ps}{ps_g} \quad (7)$$

when the label fixing for each process ps_g generates output, then optimisation of gradient ascent and descent will be given as

$$ps_l(x, x') = ps(x)ps_g l(x' \mid x) * \frac{ps}{ps_g} - ps_g \quad (8)$$

Based on the mathematical explanations to improve the maintenance, where the process *ps* of both discriminator *dr* and generator gr process, the above equations (7) and (8) are used. When *l* is held constant, this may test if the created data follows the true data distribution using a discriminator. After this occurs, the distribution defined by the generator and classifier $(x' \mid x)$ will have converged to the true distribution by $\frac{ps}{ps_g} - ps_g$. After picking the training dataset from the original data ps_g and ps_l, the classifier will produce a misleading label if the original data are readily available.

Generalised steps of the proposed system

Step 1 The elevator fault real-world dataset is given as input in a GAN-based synthetic system

Step 2 The output from the first step is fed into one part of the GAN (generator).

Step 3 Generator output can be mixed with randomly generated noise, which must be removed in the next step.

Step 4 Data quality is improved in subsequent iterations of the generator due to the discriminator, which distinguishes falsely created data from real data.

Step 5 Using the learned probability distribution, the generator creates random noises to simulate the original data through equations 3 and 4.

Step 6 The experimental results demonstrate the superiority of GAN over conventional methods in preventing elevator fault issues.

The explanation given by the figures and mathematical equations demonstrates that the suggested system GAN can provide a highly accurate problem diagnosis, potentially cutting down on maintenance costs and system downtime.

4 Results and discussions

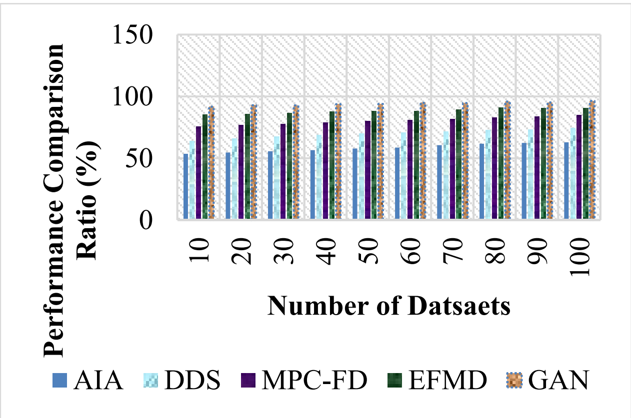
Here, researchers show off the numerical outcomes of our proposed method, GAN, on an analysis of elevator failure diagnostics using a dataset link listed in the reference. This study uses the Elevator Predictive Maintenance Dataset to analyse the system's efficiency. The dataset collects information using various IoT sensors in the elevator industry. The collected information is useful to maintain the elevator doors, minimise unplanned sops, and improve the equipment life cycle. The dataset has 4Hz high peak time series samples using electromechanical sensors, ambiance and physics information. To diagnose a fault in elevators are to identify its cause to figure out what went wrong. Interpreting sensor readings and prior process knowledge, process fault detection determines the current state of the plant. The proposed method combination is built on top of the Keras API and the Flask Python framework for supervised machine learning. The benchmarks are run in Ubuntu 18.07.3 (128GB RAM) on a Central Processing

Unit (Intel Xeon E5-2718L v4) and Graphics Processing Unit (Nvidia GeForce GTX 1080 Ti) (NVIDIA GeForce 2480TI) by charting the characteristics against time in MATLAB, the elevator data can be seen as a graph comparison below.

4.1 *Performance comparison*

In this paper, the activation function of the classification, alternator, and differential amplifier are all updated to make use of the new one; the gradient descent technique is updated to make use of a fixed memory step, while the gradient ascent method is updated to make use of the same change in the discriminator's activation function of elevators. This paper updates previous work by switching the gradient descent approach instead of the gradient rise method of the designator and using the information from equation (8), to step gradient descent method of the classifier and generator are compared with our traditional methods, and these are shown in below Figure 6.

Figure 6 Performance comparison analysis (see online version for colours)



4.2 *Synthetic data quality analysis*

It is hard to evaluate the discriminator of elevators without judging the generator. New data instances can be generated by training the generator network to map locations in the latent space. The generator network is responsible for creating believable visuals using equation (2), while the discriminator network's job is to differentiate between the two apart. A portion of the 96.7% recognition efficiency can be seen in Figure 7 for 100 dataset samples relating to the normal state of elevators and six types of faults. The generator eventually allows visualisation that is like the examples used for training. The discriminator improves the system's detection of fraudulent and real problems of elevator usage. The discriminator loss is based on the discrepancy between authentic and fake labels and can be calculated and compared with other traditional methods with the proposed GAN model. Oversampling solutions may be aided by considering the effects of imbalances and expanding datasets on problems associated with small datasets.

Figure 7 Data quality analysis (see online version for colours)

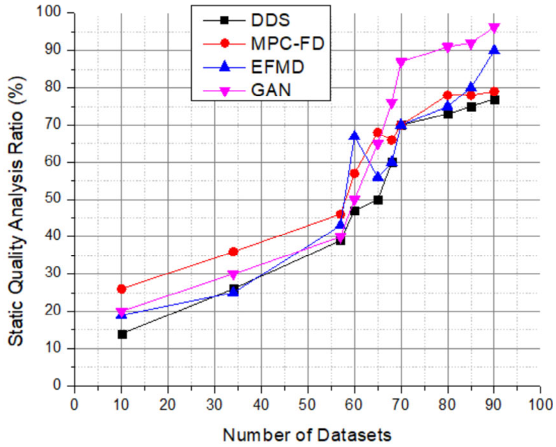


Table 1 Efficiency comparison of GAN

Number of datasets	*AIA*	*DDS*	*DT-RST*	*EFMD*	*FD-CED*	*GAN*
10	53.7	63.7	75.7	85.4	91.7	10
20	54.8	65.8	76.8	85.5	92.8	20
30	55.7	67.7	77.7	86.7	92.7	30
40	56.7	68.7	78.7	87.9	93.7	40
50	57.9	69.9	79.9	88.3	93.9	50
60	58.8	70.8	80.8	88.1	94.8	60
70	60.6	71.6	81.6	89.3	94.6	70
80	61.8	72.8	82.8	90.9	95.8	80
90	62.5	73.0	83.9	90.5	95.1	90
100	63.0	74.6	84.9	90.5	96.3	100

4.3 *Efficiency comparison*

A finite state machine model is compared after identifying the faults occurring while the elevator is operational. Here propose using synthetic data on the GAN platform to monitor elevator faults and assess the quality of the data collected to date on elevator safety faults, too. The values enrolled in the table are obtained by evaluating equation (4) to train other machine learning models; the network may create realistic training elevator functions ef^n and data in many modalities. Input values are given as faults tested samples starting from the range between 50 to 100. The parameter analyses peak-to-peak values from both domains $\frac{n}{\left(1-ef^n\right)}$. The comparison of the efficacy of our proposed system is given in Table 1. The study's findings demonstrate that real-time, efficient monitoring of the elevator's operation state is possible. Elevator fault types can be identified by linking irregular operation states to their respective causes. The result obtained for the suggested system is 96.3%.

4.4 Maintenance comparison

The charge of each occurrence will change as the position moves throughout maintenance in a particular order, necessitating a re-estimation of the cost score by experts. Even though it is absurd to expect an expert to keep scoring even if the venue keeps shifting. As a result, it is important to define the location-related attributes of position time charge and location-related feature, which respectively indicate the costs incurred due to location and the relationships between different places as $x(\theta_0, \theta_1) = \frac{1}{2mi}$. The failure likelihood, monitoring costs, and location time expense of each bottom occurrence are calculated in this research. Using equation (6) probability of failure has a 0–1 range, while search expense and position time cost have a 0–10 range, which is compared with other conventional methods and given in Table 2. The equation parameter $\sum_{i=1}^{n}\left(x_\theta\left((\theta_0,\theta_1\right)-x_1\left((\theta_0,\theta_1\right)\right)^2$ is used to obtain the input values for the table where θ_0, θ_1 are considered as the distance between two elevator faults.

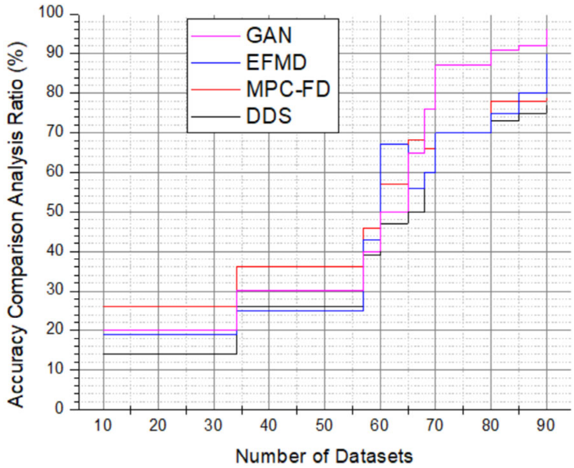
Table 2 Maintenance comparison of GAN

Number of datasets	*AIA*	*DDS*	*DT-RST*	*EFMD*	*FD-CED*	*GAN*
10	44.2	47.5	57.6	65.3	59.3	71.2
20	54.3	69.4	67.8	64.8	67.8	76.5
30	54.5	79.4	70.5	78.2	65.2	88.9
40	72.6	72.5	73.7	73.3	78.5	89.7
50	44.7	53.9	76.5	75.7	79.3	85.1
60	42.8	54.8	58.4	68.8	73.1	83.9
70	49.4	45.7	57.3	57.6	70.2	79.2
80	59.3	56.7	60.2	72.2	75.4	87.3
90	67.2	76.6	77.1	84.7	86.7	92.3
100	63.1	75.7	89.2	87.9	89.8	95.6

4.5 Accuracy comparison of GAN

GAN device is measured using the traditional evaluation method based on synthetic data while operating in various convert modes. This paper employs GAN to generate a boosted sample dataset consistent with the original data to train the optimisation algorithm network. As a final step, the testing set is used to assess the model's performance shown in Figure 8. This paper uses GAN to generate an augmented sample dataset identical to the initial data, which is then used to train a network. To conclude, the model's efficacy is evaluated using the testing set obtained from equation (3). In the early stages of training, the model that uses the supplemented dataset exhibits significant fluctuations. Nevertheless, after it has stabilised, the model's identification accuracy increases.

Figure 8 Accuracy comparison (see online version for colours)



From the above graphical and tabular representations, it is proved that our proposed model GAN has better performance, accuracy, maintenance, and quality when compared with other traditional methods, AIA, DDS, ECM-CP, EFMD, FD-CED, IoT-EMCS, DT-RST. The findings demonstrate that the suggested system can provide highly accurate problem diagnosis, potentially reducing maintenance costs and system downtime.

5 Conclusions

In this research, we build a GAN model for dynamic characteristics that considers fault possibility, enhances maintenance, quality of synthetic data, and position-related bottom events by first establishing an elevator fault using expert information and synthetic data. This study proposes a methodology for objectively identifying the best order to tackle a problem, ultimately leading to a more effective fault diagnosis with a performance achievement of 96.32%. The proposed one is suited for device use in elevator soft switching circuits because it has a simple construction, good dynamic response, and can be used to measure fault diagnosis accurately. The feasibility of using GANs to simulate elaborate and pricey real-world simulations is explored in this paper. Researchers compared the results of a GAN to those generated by a simulation of a technological system. Our research shows that this method can be successfully implemented. Challenges and technical issues encountered during deployment are covered, and this will take for future research to provide quality synthetic data when a fault occurs. Despite our lack of proof-of-concept, here demonstrated that GANs can replace costly simulation runs.

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