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Optimizing Mobile Edge Computing Efficiency through Multidimensional Generative Adversarial Network

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Abstract: Big data Processing and the IoT have recently gained popularity as study topics in MEC and thorough research is sought for well-informed decisions. Mobile edge equipment, such as base stations, routers, and edge servers, usually have limited processing capabilities compared to traditional data centers. According to this perspective, this research constructs MEC using Intelligent Outlier Detection with a Multidimensional Generative Adversarial Network (IOD-MDGAN). The suggested structure uses servers at the edge, mobile phones, and cloud resources to achieve minimal latency, lower bandwidth usage, and more scalability. To eliminate outliers from the data, the suggested model uses an adaptive synthetic sampling-based outlier identification technique. Complete start and completion timings for base station connectivity are included in the statistics to gather the information for every mobile user. Data pre-processing for the Adaptive Median Filter (AMF) filter eliminates the noisy data from raw data samples. Feature selection was used for Particle Swarm Optimization (PSO) to choose a suitable group of characteristics. To differentiate between several class labels, an extended immediate memory-based classification model is needed. The innovative nature of the study is demonstrated by the designs of the PSO algorithm for feature selection with the Synthetic Minority Over-sampling Technique (SMOTE) approach for massive data. The results show that the IOD-MDGAN technique has better latency (78 ms), higher throughput (750 Mbps), a faster detection rate (96 ms), a higher data delivery ratio (900 ms), and a higher cost-effectiveness (79). Adapted big data processing architectures designed for MEC provide significant potential for reshaping data use inside mobile applications.

Keywords: Mobile Edge Computing (MEC), Intelligent Outlier Detection with Multidimensional Generative Adversarial Network (IOD-MDGAN), Big Data Processing

Introduction

Mobile apps are becoming more advanced due to recent improvements in mobile device capabilities, and they are increasingly used for personal and professional purposes. Despite its widespread use and many benefits, integrated cloud substructure has significant challenges meeting the Modern mobile apps that operate on widely used mobile devices, such as media processing, online gaming, and self-driving vehicle applications, have time, energy, cost and security needs (Shakarami *et al*., 2020). Because these widely used mobile devices have resource restrictions, more accessible breakthrough technologies, such as MEC, have been transforming the possibilities of the far-reaching cloud with small limits for some demanding applications. The research exhibits the use of neural networks in medical dataset prediction. Utilizing a data-mining perturbation combined strategy; it employs cryptography methods and association principles (Natarajan *et al*., 2023; Rajesh and Selvakumar, 2019). MEC is a still-evolving Internet-based computing standard many businesses use to set themselves apart from rival technology.

The effectiveness and efficiency of resource management in MEC are largely dependent on data processing. The primary goals of data processing at MEC center on the smooth integration of edge computing infrastructure and big data analytics to achieve optimal resource utilization, improve user experience, and strengthen network performance (Duan *et al*., 2022). MEC uses edge servers that are situated closer to end users to decentralize computing. The localization of resources brings with it new potential and problems for data processing, requiring a well-tuned framework that can handle a variety of data kinds, quantities, and real-time demands (Haibeh *et al*., 2022).

Additionally, MEC is placed close to the mobile devices that are most likely nearby, with essential Server resources positioned at the network's edge to fulfill user-centric needs. The dataset consists of several categories that are further enhanced to carry out sophisticated classifications. The prepared dataset has to be through data pre-processing, comprising feature selection and cleaning before the prediction procedure utilizes an ensemble training strategy (Qin *et al*., 2023; Rajesh and Christodoss, 2021). Realistic, effective resource management is required for edge computing to be a genuinely effective strategy since MEC has built-in restrictions on storage, bandwidth, and CPU. MEC settings employ offloading mechanisms to improve mobile apps' performance. Activities that need a lot of resources are moved to adjacent servers. Combining analytical and clinical data gathered from a Kaggle secondary data source to create a machine learning-based method for the early detection of heart failure. To create a heart failure prediction model, it employed supervised learning techniques. Performance evaluations were conducted on six machine learning algorithms, including the naive Bayes model, support vector machines, Random Forest, decision trees, logistic regression, and K-Nearest Neighbour (Khan *et al*., 2019; Shukla and Kumar, 2023).

The Industrial IoT has drawn much interest from the academic and business communities. Industrial IoT and Wireless Sensor Networks (WSNs) include additional component elements like Mobile Agents. The authors provide a technique for visually impaired individuals that is superior and more precise than the sense of touch and is based on the sense of sound. The following section describes a valuable technique for distilling books into key phrases so you don't have to read the whole thing every time. The system can even help blind people due to various APIs and modules used in the current research, such as Gensim, text ranking algorithms, and other instruments for converting summary text to audio (Wang *et al*., 2019; Irudayasamy *et al*., 2022). These sensor networks are constructed of various sensors dispersed around the industrial setting to provide inexpensive monitoring services. To assist in decision-making, convergence sensor nodes routinely evaluate the data acquired by the sensor. The speed, capacity, flexibility, and other performance traits of WSNs have been greatly enhanced by the Sensor-Cloud System (SCS), which integrates WSNs and Cloud Computing (Wang *et al*., 2020; Jones and Sah, 2023). Unquestionably, the data gathered from the sensor network underneath serves as the basis for all applications and the cornerstone of SCS. Collecting data from several monitoring sites is crucial for improving the accuracy of data analysis. Most sensor nodes are located in challenging, unforgiving conditions, making them susceptible to malicious assaults and changing on purpose to provide false or even deceptive data (Dhaya and Kanthavel, 2020). Statistics show that less than 47% of the information is accurate and dependable.

The dynamic allocation of computational resources in response to changing demand patterns and application needs is a primary goal of data processing in MEC resource management. MEC systems can effectively distribute workloads between edge servers, minimizing latency and optimizing throughput, by evaluating incoming data streams in real-time (Bolettieri *et al*., 2021). Moreover, MEC's data processing makes it easier to deploy latency-sensitive applications like real-time analytics, driverless cars, and augmented reality. MEC improves user experience and opens up new use cases by processing data closer to the point of consumption, which also guarantees near-instantaneous response rates and cuts down on round-trip durations. The stability and dependability of the network depend on effective data processing in MEC. MEC systems can improve overall network performance and resilience by detecting abnormalities, reducing congestion, and optimizing routing decisions through the monitoring and analysis of network data (Qiu *et al*., 2020).

The analysis findings are impacted by abnormal data transmission, which consumes greater upload bandwidth and node energy (Sangaiah *et al*., 2019). Data cleansing is a frequent procedure and data retention and deletion are becoming increasingly important. Data cleaning, or removing "dirty" data, is the final step in identifying and fixing data files' discernible flaws (Wang *et al*., 2020). Sensors' processing capability can match the needs if they need to gather a single feature's data (Ridzuan and Wan Zainon, 2019). Sensors themselves would produce a significant amount of complicated data by introducing 5G and integrating sensors. Because user data is sensitive and edge infrastructure is spread, security is a top priority in MEC contexts. Robust security measures, such as data encryption, access control, and threat detection, must be implemented with effective data processing systems to protect sensitive data and maintain user privacy (Liu *et al*., 2020).

Objective of the Study

The objective of the study is to develop MEC utilizing an innovative approach termed Intelligent Outlier Detection with Multidimensional Generative Adversarial Network (IOD-MDGAN). This framework aims to enhance MEC by employing advanced outlier detection techniques within a multidimensional Generative Adversarial Network (GAN) architecture. By integrating outlier detection intelligence, the proposed IOD-MDGAN model seeks to improve the efficiency, reliability, and security of MEC systems, thereby addressing existing challenges such as optimizing spectrum use and ensuring seamless service delivery in dynamic environments:

- First, we gathered the telecom dataset and pre-processed the data using the Adaptive Mean Filter (AMF) method
- The feature selection process uses PSO and SMOTE, detection approaches based on adaptive synthetic sampling to remove outliers from the data
- The IOD-MDGAN proposed model employs an outlier detection approach based on adaptive synthetic sampling to remove outliers from the data
- The proposed IOD-MDGAN method achieved better outcomes when compared to the other existing methods

Significance of the Study

The paper addresses the issue of restricted processing capacity in edge devices by presenting a unique method, IOD-MDGAN, designed for MEC. The suggested structure delivers impressive efficiency advantages in latency, bandwidth utilization, and scalability by combining outlier identification with a multidimensional Generative Adversarial Network (GAN). Adaptive synthetic sampling and feature selection approaches are utilized to filter noisy data and identify pertinent characteristics, thus improving classification accuracy. Significant gains in latency, throughput, detection rate, data delivery ratio, and cost-effectiveness are shown by the study's results, highlighting the need for big data processing optimization for mobile edge applications.

Related Works

Table (1) represents the summary of a few studies related to approaches.

Table 1: Summary of related work

Ref No	Objective	Result	Limitation
Zhu (2020)	A comprehensive review of the research on edge computing. The report starts with a quick overview of edge and cloud computing and compares the two. Then, quickly go through the background of edge computing, the technology behind it, the precautions that must be taken to protect user data, and the applications that use it	As a result, novel methods for the efficacy and safety assessments of drug candidates based on big data modeling and analysis have been made possible by newly emerging artificial intelligence techniques like deep learning (DL) and pertinent modeling studies	Though there are several potential limitations to consider, such as uninterruptible DL models, potential biases in data, and the requirement for validation through traditional clinical trials to ensure reliability and regulatory compliance, DL and big data modeling offer promising avenues for drug-efficacious and safety assessments
Liu *et al*. (2021)	Complexity theory into the question of what tools and settings work best for analyzing large datasets. They utilized a mixed-methods approach to illustrate that the usefulness of extensive data analytics resources in improving performance depends on the unique circumstances, polling 175 chief information officers (CIO) and information technology (IT) managers at Greek firms and conducting three case studies	The results demonstrate that a hierarchical regional center system, comprising one major center interacting with seven surrounding secondary centers, is represented by the polycentric metropolitan region. Due to the attractiveness of these metropolitan centers, additional neighboring jurisdictions are constantly expanding outside the administrative boundaries	Though there are several potential limitations to consider, such as uninterruptible DL models, potential biases in data, and the requirement for validation through traditional clinical trials to ensure reliability and regulatory compliance, DL and big data modeling offer promising avenues for drug efficacious and safety assessments
Aranda *et al*. (2021)	Combining critique of discourse with topic modeling is an example of research that utilizes multiple methods. That can be used to overcome these roadblocks. Combining the two approaches may go above the limitations of each individually and provide new insights	The tobacco industry's rhetorical legitimation challenges are the subject of our illustrative case. The result shows how an integrated mixed-methods strategy may capture the depth and range of discourses	It contends that integrating the two methods overcomes their drawbacks and offers enormous opportunities for investigating important phenomena in a modern mediatized culture

	into essential occurrences in today's media-driven culture	employed by various tobacco debate actors	
Hajjaji *et al.* (2021)	Many IoT and Big Data Smart Environment Applications. The study aims to provide insight into the sector's origins, current patterns, and persistent problems	The results show that there are several prospects for smart environment applications related to monitoring, and the enhancement of natural resources when big data and IoT technologies are integrated	The potential uses of big data and IoT integration in smart environments are encouraging; but, to assure effective adoption and long-term growth, concerns about data privacy and interoperability addressed
Mikalef and Krogstie (2020)	A large data analytics conception driven by theory. Using this paradigm, they examine the degree to which an organization's capabilities for both radical and progressive innovation in the process are compatible with analytics tools built on massive data sets, including how these resources interact with the organization's environments	The results demonstrate that various combinations of contextual factors have varying effects on the significance of big data analytics resources. ; for example, certain combinations lead to high levels of process creative abilities, both radical and incremental	Though some insight into the relationship between BDA resources and process innovation skills could be gained from the study's findings, the analysis obviously has major limitations

The research (Pääkkönen and Pakkala, 2020) obtained The Reference Architecture (RA) design of a large data system using Machine Learning (ML) techniques in edge computing settings is the contribution of this study. Based on 16 realized implementation architectures that were created for edge/distributed computing contexts, an earlier version of the RA has been expanded. Deployment of architectural components in various contexts is also explained. The article (Shen *et al*., 2021) described the application of Hierarchical Discriminant Analysis (HDA) for unsupervised learning was discussed. A DL and MEC-based intelligent image fusion system is proposed. The hierarchical mode of DL can be utilized to maximize the total distance between classes, extract features from images, and execute distributed computing through the use of edge servers and base stations. The study (Salih Ageed *et al*., 2021) is an example of possible hybridization. Analyzing and displaying enormous data sets is what "data mining visualization" refers to. How changes to computer standards and algorithms affect the volume and speed with which data must be stored and sent has been studied. The article (Bag *et al*., 2023) is helpful for logistics and supply chain managers because it provides recommendations for using Green supply chain operations that might benefit from using the BDA-AI methodology. The article (Majeed *et al*., 2021) proposed a framework that can assist additive manufacturing enterprises through Smart, environmentally friendly manufacturing that uses 3D printing and extensive data analysis. Product managers can benefit from including Sustainable and innovative Additive Manufacturing (BD-SSAM) in their Business Object Layer (BOL) choices.

"Intelligent Outlier Detection and Machine Learning Big Data Analytics (IODML-BDA)" are used in the study (Mansour *et al*., 2023) to develop a method for MEC. It makes use of "Long Short-Term Memory (LSTM)"-based classification, "Oppositional Swallow Swarm Optimization (OSSO)" for choosing features, and an adaptive synthetic sampling-based outlier detection method. Experimental results demonstrating improved accuracy over a wide range of datasets confirm the effectiveness of the proposed strategy. The article (Wan *et al*., 2020) presented that two of the largest barriers to online data processing in the Internet of Things have traditionally been high data loads and widespread coverage. MEC and Unmanned Aerial Vehicle Base Stations (UAV-BSs) have been identified as two IoT methods that show promise. It provides a MEC-based three-layer online data processing network. Local information is reflected in the raw data from widely dispersed sensors on the bottom layer. The study (Kakhi *et al*., 2022) introduced the ETS-DNN model, a novel and efficient training scheme for Deep Neural Networks (DNNs) in edge computing-enabled Internet of medical devices. By utilizing the patterns found in the data, the proposed ETS-DNN seeks to expedite the timely collection and processing of data so that decisions can be made. The IoMT devices first detect the patient's data and send it to edge computing, which uses the data to run the ETS-DNN model to diagnose the patient. The research (Pham *et al*., 2020) examined Lung Severity Score (LSS) literature and Big Data Analytics (BDA) to help LSS decision-makers make better informed and predictable choices. Diligent searches for comparable publications yielded 52. Organizational theories recommend big data and LSS research paths.

The paper (Wang *et al*., 2020) suggested a unique method for designing wireless networks to tackle the difficulties brought about by the increasing demand for the Internet of Things (IoT). It creates a paradigm for combined energy and computation optimization by offloading computation utilizing Frequency-Division Multiple Access (FDMA) and Nonorthogonal Multiple Access (NOMA). Lyapunov optimization is used for short-term resource optimization and long-term workload prediction using LSTM. The outcomes of the simulation show notable reductions in energy use and delay. The research (Habib ur Rehman *et al*., 2017) explores the Red Edge architecture and the associated mechanism using twelve mobile users in real-world experiments. The Red Edge model has been evaluated experimentally and has been shown to decrease massive data flows by up to 92.86% without causing any adverse effects on memory or electricity usage on mobile edge equipment. The study (Miao *et al*., 2020) examines computation strategies for task displacement and discharge based on demand estimation, data generated through mobile user computational tasks, and the performance characteristics of computing edge hardware. It has been brought upwards. Long Short-Term Memory (LSTM) networks, task relocation for edge computing scheduler, and task prediction-based compute loading for handheld devices are all used in the optimization process of the edge computing offloading model. The article (Rui *et al*., 2021) developed innovative cloud-based edge computing for mobile devices methodology to create a compelling prediction scenario. The experimental findings demonstrate the ability of the model in the paper above to evaluate a forest eco-tourism development strategy. The research (Yang *et al*., 2023) examines the MEC scenario to provide a next-generation IoT mechanism for resource scheduling and user task offloading. Our problem formulation aimed to decrease the average user Task Completion Time (TCT). Describe how the problem can be solved by combining the Graph Convolutional Network (GCN) technique with a Reinforcement Learning-based strategy for Container Scheduling (RLCS). The evaluation's findings show that RLCS beats other baselines, such as heuristic algorithms and algorithms based on reinforcement learning, in numerous experimental circumstances. The (Pandiyan and Sasikala, 2023) MEC enables clouds to tackle sizable occupations from nearby mobile devices. The network's dynamic nature causes an ineffective distribution of edge servers.

Massive volumes of big data are generated by IoT devices, which makes computing and analytics difficult. In (Kaur *et al*., 2022), a novel GAN for MEC in IoT-enabled big data environments was introduced, along with a Quantum Elephant Herd Optimization (QEHO) algorithm. Feature selection and data classification procedures were used by the GAN-QEHO algorithm, while the QEHO algorithm expands the search window and strikes the best balance between exploration and utilization. The research (Nie *et al*., 2022) suggested an intrusion detection algorithm for Collaborative Edge Computing (CEC) that was based on DL to tackle security problems like DoS and unauthorized access. The efficacy of the approach, which employed a GAN-based architecture for both single and multiple attacks, was assessed. The study (Liu *et al*., 2023) used GANs and edge computing to introduce a novel design style transfer method for producing high-quality stylized photos in cell phone photography systems. The technique achieved 95-98% detection accuracy while emulating the artistic style of paintings, lowering network latency and bandwidth consumption. (Pandey *et al*., 2023) Presented 5GT-GAN, an innovative approach for creating artificial mobile internet traffic information for applications in smart cities using GAN. By combining supervised autoregressive models with unsupervised GAN schemes, the model outperforms conventional models in terms of mean squared error and mean absolute error.

Problem Statement

Mobile Edge Computing (MEC) is a promising technology that can improve mobile networks' speed and efficiency by placing processing and storage resources closer to end users. Nevertheless, there are still several issues with MEC adoption and execution. One of these difficulties is the absence of standard operating procedures for MEC deployment, which causes inconsistent and ineffective execution. Furthermore, there are several challenges in maintaining integrity and transparency in MEC contexts, especially in settings with high mobility and heterogeneity. To develop shared frameworks and best practices, comprehensive initiatives that bridge the gap between industries, even in the face of continuous standardization efforts within the MEC sector. Resolving these issues is crucial to maximizing MEC's potential and providing mobile customers with streamlined, effective services. In this study, we try to overcome the problem with the help of IOD-MDGAN.

Materials and Methods

Initially, we collected the telecom dataset. The Adaptive Mean Filter (AMF) method is used to preprocess the collected dataset. Next, to eliminate outliers from the data, the feature selection process employs PSO and SMOTE, detection techniques based on adaptive synthetic sampling. PSO to select an appropriate set of attributes. SMOTE method for large-scale data. This study develops MEC by utilizing a multidimensional Generative Adversarial Network (IOD-MDGAN) for intelligent outlier detection. Figure (1) represents the provided strategy's flow.

Data Collection

In this section, the data set using MEC is based on big data processing. For our studies, we used internet data for mobile users accessing 3233 base stations from the Shanghai Telecommunications base station dataset (Wang *et al*., 2019).

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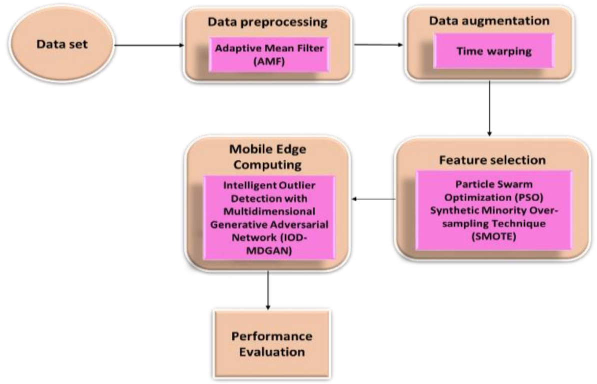

Fig. 1: Block diagram for suggested technique

Table 2: Base station workload data from Shanghai Telecom's dataset

Station-based ID	1927	40	1265	76	328	274 8	531	2748	664
User ID	821	1824	499	6	108	74	81	74	151
Workload-Minus	1042 672	2571 744	62486 6	28 30	140 960	986 23	109 145	9862 3	190 703

Our study reveals that 3000 base stations are indeed in service, while the other base stations are inactive or have erroneous data. The data comprises the start and end times of base station connectivity for each mobile user. Due to its characteristic dense population, Shanghai can fully meet the criteria of a mobile edge computer network. Table (2) shows an example of the workload of the base stations we selected randomly from the dataset. The total request time, or base station burden, can be determined by taking into account the beginning and ending times of requests made by mobile users to base stations.

The Prepared Dataset has to be Through Data Pre-Processing

Data Preprocessing Using Adaptive Mean Filter (AMF)

The Adaptive Median Filter (AMF) is employed to effectively remove noise from raw data, ensuring clean and reliable input for the model. By adapting its filtering window size, AMF preserves important data features, enhancing the accuracy of outlier detection and analysis. The performance of the median filter is highly dependent on the size of the filter window. While certain visual components can be preserved with a tighter filter window, the filtering effect on noise should be amplified. Retaining details and reducing noise cannot coexist. Although there will be a discernible blurring of vision, the wider glass is more effective in reducing noise. According to the median filter concept, if there are more noise points than pixels in the filtering window, the conventional median filter's efficacy likewise significantly drops. During the filtering process, the adaptive median filter can identify whether a particular pixel is noisy and change the window size to the specified values. If a pixel is loud, the median value takes its place. Otherwise, its current value is preserved. The adaptive median filter serves three objectives. The first three phases of this process involve filtering salt-and-pepper noise, lowering other non-impulse noise, and keeping visual characteristics as intact as possible to avoid sharpening or coarsening of the edges.

After discussing the adaptive median filter technique based on the divide-and-conquer strategy, the relevant symbols are described as follows. The sequential array $B[]$ in the filter window $Sr \times r$ can be easily acquired using a divide and conquer-based fast sorting approach; Y_{min} is the lowest value in the filter window, Y_{max} is the maximum value that the filter's window allows, Y_{med} is the filter window's median, Y_{xy} is the value in (*x*, *y*), S_{max} the largest dimension permitted by filter window Sr × r. One follows the Eqs. (1-2):

$$C_1 = Z_{med} - Z_{min} \tag{1}$$

$$C_2 = Z_{med} - Z_{max} \tag{2}$$

Formula (1 and 2) check to see if the median value of $S_{r\times r}$ is noise, $C1 > 0$, and $C2 > 0$:

$$D_1 = Z_{wz} - Z_{min} \tag{3}$$

$$D_2 = Z_{wz} - Z_{max} \tag{4}$$

If $C1 > 0$ and $C2 > 0$ are not satisfied, the mean value Z_{med} of $S_{r\times r}$ is noise and Z_{wz} is a weighted sum. Eqs. (3-4), In this case, raise the filter window size incrementally until the desired non-noise median is reached.

Time Warping

Bringing processing power and storage closer to end users and devices is the goal of MEC or MEC. This is achieved by locating computing resources and services closer to the network edge. When discussing time warping in MEC, we're talking about allocating resources best and scheduling tasks to reduce latency and enhance general application and service performance. Time warping improves the user experience and makes novel applications like augmented reality, driverless cars, and real-time analytics possible by dynamically modifying computing tasks and resources based on real-time conditions, such as network congestion or device proximity.

Feature Selection

The PSO algorithm's designs for feature selection using the SMOTE approach for large data demonstrate the unique nature of the study.

Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is employed for feature selection to optimize the choice of relevant features from a potentially large dataset. By identifying and selecting the most significant features, PSO helps reduce the dimensionality of the data, which is crucial for improving computational efficiency and processing speed in Mobile Edge Computing (MEC) environments. We employed PSO to choose the features after the extraction. It replicates the group communication behavior while exchanging secret information about migratory, flocking, or hunting behavior. This group is called a swarm; its members are particles. Together, they constitute a solution. A particle updates its location based on its knowledge and that of its neighbors. The swarm first creates a collection of random particles with their coordinates (x_i) and speeds (v_i) in the dimension j^{th}. Once the main loop of PSO has started, each particle is evaluated using a fitness function, and the results are checked against the best and overall values. The process for updating the particles' locations is shown in Eqs. (5-6):

$$x_{ij}^{(t+1)} = x_{ij}^{(t)} + v_{ij}^{(t+1)} \quad (5)$$

$$v_{ij}^{(t+1)} = wv_{ij}^{(t)} + c_1 \mathrm{r}\left(x_{ij}^{p(t)} - x_{ij}^{(t)}\right) + c_2 \mathrm{r}\left(x_{j}^{p(t)} - x_{ij}^{(t)}\right) \quad (6)$$

Here x_{ij} is the location of the i^{th} particle in the dimension, v_{ij} is the rapidity of the j^{th} particle in the measurement, t is the current iteration and u denotes an inertia weight used to speed up population convergence. The constants $c1$ and $c2$ express acceleration coefficients. The expressions $x_{ij}^{(t)}$ and $x_{j}^{p(t)}$ define the global best position in the ith dimension $x_{ij}^{(t)}$ and $x_{j}^{p(t)}$ respectively. [0, 1] are the random parameters r_1 and r_2 . This sequence is repeated until the stopping condition (for example, a set number of iterations) is met. Algorithm 1 outlines the PSO's concluding phases.

Algorithm 1 Particle Swarm Algorithm (PSO)
1: Set up the b population W
2: repeat
3: For i = 1 to Population Size, do
4: Determine the value of the objective function.
5: Whenever the fitness value exceeds the best (P Best).
6: Then make the present value the new value P Best.
7: Select the one with the highest fitness value GBest among all the particles.
8: Determine a new speed in line with Eq. (5).
9: Adjust the particle position to reflect Eq. (6).
10: end for
11: until the termination requirement is satisfied

Synthetic Minority Over-Sampling Technique (SMOTE)

SMOTE is applied to handle imbalanced data, generating synthetic samples of underrepresented classes (such as outliers) to ensure the model learns effectively across all classes. SMOTE generates synthetic samples for the minority class by interpolating between existing samples, ensuring a balanced representation. This approach allows the model to learn effectively from both normal and outlier instances, improving overall detection accuracy. Increasing the minority class's oversample leads to the identification of comparable but more precise areas in the feature space as the decision district for the minority class. Samples from the underrepresented group are denoted by +, whereas those from the overrepresented group are denoted. As shown by the plus signs ('+'), it includes three erroneous samples from underrepresented groups. The decision area for the alternative class gets more specialized if we duplicate the alternative course, primary to additional forks in the decision tree. Overfitting occurs when a learning algorithm attempts to learn too much about the minority class, producing too many leaves (final nodes). When a minority class is replicated, the majority-class decision border does not expand into the newly created minority-class territory. Instead of the more common practice of oversampling with replacement, this method represents underrepresented groups by creating "synthetic" examples. This strategy was inspired by a technique used effectively in handwritten character recognition. By applying specific manipulations to actual data, they generated more training data. Specifically, they found that transforming the training data via operations like rotation and skew came naturally. By functioning in "feature space" rather than "data space," we build generic artificial examples across a broader range of use cases.

Each member of the minority group is then over-sampled by adding fake instances along the lines that connect their k closest neighbors. Neighbors are randomly selected from the k-nearest neighbor's pool based on the desired oversampling level. Five-nearest-neighbor is presently being used in our implementation. For instance, if a 200% oversample is required, two of the five closest neighbors would be selected and a sample would be drawn in both directions. Methods for creating synthetic pieces include Subtracting the neighboring feature vector from the one we're interested in the model. Because of this, an arbitrary location between two characteristics is chosen. This strategy successfully compels the minority class to expand the scope of their decision-making zone.

MEC Using Intelligent Outlier Detection with Multidimensional Generative Adversarial Network (IOD-MDGAN)

MEC using Intelligent Outlier Detection with Multidimensional Generative Adversarial Network (IOD-MDGAN) is a cutting-edge approach that leverages advanced machine learning techniques, particularly multidimensional generative adversarial networks, to detect and mitigate outliers efficiently in MEC environments, enhancing overall system reliability and performance. Generative Adversarial Networks (GANs) can be applied to MEC scenarios to generate, enhance, or modify data at the edge. GANs consist of two neural networks, the generator and the discriminator, which are trained adversarial to create high-quality synthetic data. Combining these ideas might result in implementing an outlier detection system inside an MEC environment, where the outlier detection processing is carried out at the network's periphery, close to the data source. By doing this, the delay involved in transferring data to a centralized server for analysis would be reduced. Multidimensional GANs can also create synthetic data that mimics the predicted data distribution at the edge to discover outliers. This artificial data can then be contrasted with incoming real-time data.

A generative model, IOD-MDGAN, creates synthetic data with several attributes through adversarial training. It is a development of the well-known GAN architecture, in which two connections, a discriminative model and a generator, compete in opposition to one another in a two-player softmax game.

While using IOD-MDGAN, the generative model creates samples conditioned on a collection of attribute vectors and a random noise vector as input. On the other hand, the discriminator network seeks to differentiate between genuine and false data according to their characteristics. IOD-MDGAN has a variety of uses, including computer vision, where it can be applied to produce images with particular features, including various haircuts or expressions on the subject's face. It can also be used in natural language processing to create text with specific qualities, such as a topic or attitude. One of IOD-MDGAN's critical benefits compared to traditional GANs is its capacity to produce samples with particular attribute values, enabling more precise control over the output. However, training is required due to the model's increasing complexity.

IOD-MDGAN can be more complex and can require more data and computational power. Researchers communicate pertinent attributes from a trained AE to the determiner to decrease GAN train instability. This indirectly forces the discriminative model to be updated by adequately accounting for equally rearward presumptuous KL variations. Since an AE is created and processed, its goal is to learn a condensed depiction of the provided data. As a result, feature spaces discovered by the AE are effective models for reconstructing the P-data distribution. The AE functionality has been applied in numerous researches as a feature representation for categorization using fine-tuning. Nevertheless, as rebuilding and discriminative visibility are obtained from separate aims and should be presented to their respective tasks for best achievement, a good rebuilding depiction does not necessarily imply a successful categorization.

The discriminator functions as a binary classifier when a GAN is being trained; hence, features taken from the discriminator focus on determining whether the input is authentic. As a result, discriminating qualities and AE's parts are entirely different. Considering these various characteristics, we refer to them as representative and discriminatory features, AE and discriminator features, respectively. Since the original GAN design only included discriminative characteristics to evaluate the quality of data production, we propose using representational and separated to implicitly normalize the discriminator and stabilize GAN learning, as shown in Fig. (2).

The networks A, T, and S in this architecture are used to model, Y_{real} and Y_{fake}, which represent real and artificial pictures, respectively. Features $Z1$ and $Z2$ affect the latent vector, H; these in turn affect the network parameters U_1, U_2, U_T, and the binary output Y, which classifies pictures as natural or artificial. To illustrate the bidirectional propagation inside the system, solid blue and dashed red lines represent the flow of information in both directions.

The suggested MDGAN outcomes of the modified architecture for training the model discriminative model are discussed in this section. Also, we look into how this impact might prevent collapse mode and enhance visual excellence.

MDGAN Architecture

The MDGAN model's primary contribution is the adoption of characteristic attributes from a previously trained AE to construct the GAN. As a result, MDGAN refers to a group of GANs that use representative features and can be built on different GAN architectures. We demonstrate that the MDGAN method is insensitive to parameter collection even though reflective features and data have been taken from the encoder. Using samples from Pdata, the AE is unsupervised, pre-trained, and kept separate from GAN training.

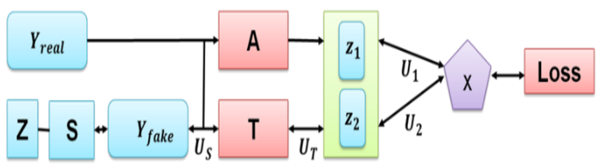

Fig. 2: Generic adversarial network representation based on features

We specifically build the AE so that the encoder and the decoder, which correspond to the generator and discriminator, have the same architecture. Then, we combine two feature vectors, one from the discriminator and the other from the encoder's final convolution layer. Final ratings are developed for the combined feature vector to distinguish between authentic data and false input. Figure (2) demonstrates the encoder's input data model (A) and discriminative model (T) network system. $Z1$ and $Z2$, respectively, denote the symbolic and discriminatory extracted features in this. They are combined and turned into a wholly connected layer with a single stochastic output, X. The discriminator is then updated with the gradient of the loss function through backpropagation after the production is calculated using the sigmoid cross-entropy-based truth label. The encoder does not receive this signal because its parameters have already been taught and fixed. The process for updating gradients is:

$$D(x) = -logY for\, x{\sim}P_{data}, Y = \sigma(h_1w_1 + h_2w_2) \tag{7}$$

$$\nabla w_i = \frac{\partial D(x)}{\partial w_i} = -\frac{1}{y}.Y(1-Y).h_i = (Y-1)h_i, i \in \{1,2\} \tag{8}$$

$$\nabla w_D = \frac{\partial d(x)}{\partial w_D} = (Y-1).w_2.u(w_D). \tag{9}$$

The variables' representation of the GAN goal function:

$$J(\theta_G, \theta_D) = \underset{x\sim P_{data}}{E}[logD(x;\theta_D)] + \underset{z\sim P_z}{B}\big[log\big(1 - D(G(z;\theta_G);\theta_D)\big)\big] \tag{10}$$

$$\theta_D^{t+1} \leftarrow \theta_D^t - \eta D\frac{dI(\theta_G,\theta_D^t)}{dt} = \theta_D^t - \eta D(\nabla w_D + \nabla w_i) \tag{11}$$

$$\theta_G^{t+1} \leftarrow \theta_G^t - \eta_D\frac{dI(\theta_g,\theta_D^t)}{d\theta_D^t} \tag{12}$$

Hence σ and w are sigmoid and step functions correspondingly. We consider discriminator updates because the encoder is predetermined by evaluating a portion of its derivative. The same result is drawn in the case of a bogus sample, but $D(x)$ is now log $(1\ (h1w1 + h2w2))$ since the generator should deceive the discriminative model by maximizing ledger $(S\ (h))$ it is trained by taking into account both representing and discriminative features, Eqs. (7-12). By fixing the encoder parameters, a global depiction to reassemble the data distribution is one of the properties that MDGAN representing characteristics preserve IOD-MGAN.

An IOD-MDGAN that minimizes transport distance in an invertible way is the approach that has been put into practice. It consists of a Generator and an iteratively trained discriminator. While the Discriminator assesses the legitimacy of the generated synthetic data samples, the Generator produces them. In the training process, the Generator modifies its settings based on input from the Discriminator to generate more realistic samples, while the Discriminator is regularly trained on real and false data to increase classification accuracy. To improve the caliber of the samples that are produced, the training procedure alternates between updating the Discriminator and the Generator. The model is initialized, trained for a particular number of epochs and batch size on a given dataset, and then made capable of producing synthetic data samples in the main function. The algorithm's overall goal is to minimize the Invertible Optimal Transport Distance between the real and synthetic distributions to provide high-quality synthetic data.

Results

In this study, we proposed Intelligent Outlier Detection with a Multidimensional Generative Adversarial Network (IOD-MDGAN) to enhance MEC. We analyze the performance evaluation of our proposed method compared to existing methods. We employ the following evaluation metrics: Latency, Throughput, Detection rate, Data delivery ratio, and Cost-effectiveness. Secured Edge Computing-Intrusion Detection System (SEC-IDS), Smart Ant colony Zone-Intrusion Detection system (SAZID), and Enhanced Energy-Aware Clustering and Key management-Intrusion Detection System (EEACK-IDS) are the existing approaches (Alsubhi, 2024).

Latency

Latency is the time delay between task commencing and completion. In MEC, it refers to the time it takes for tasks to be processed at an edge computing server when comparing the suggested approach (IOD-MDGAN attained 78 ms) with the current approaches (SEC-IDS attained 91 ms, EEACK-IDS attained 86 ms and SAZID attained 82 ms). Our suggested strategy is better than the current one as shown in Table (3) and Fig. (3):

$$Latency = \frac{Time\ of\ the\ response}{of\ the\ request}$$

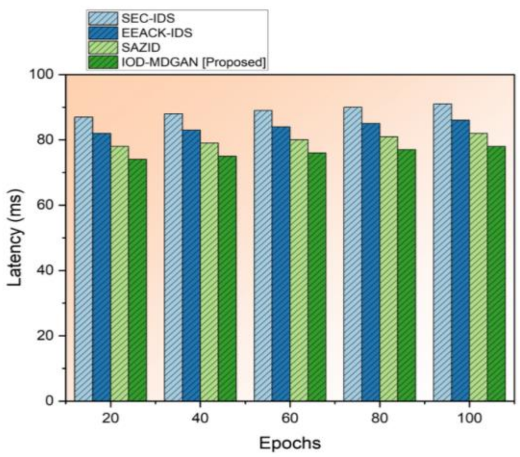

Fig. 3: Outcome of latency

Table 3: Value of latency

Epochs	Latency (ms)			
	SEC-IDS	EEACK-IDS	SAZID	IOD-MDGAN [Proposed]
20	87	82	78	74
40	88	83	79	75
60	89	84	80	76
80	90	85	81	77
100	91	86	82	78

Throughput

Throughput is the quantity of data that is successfully transmitted over a network in a particular period as shown in Fig. (4) and Table (4). It evaluates the efficiency of data transport in MEC when comparing the existing methods (SEC-IDS attained 460 (Mbps), EEACK-IDS attained 540 (Mbps) and SAZID attained 692 (Mbps)) with the suggested method (IOD-MDGAN attained 750 (Mbps)). Our suggested technique outperforms the existing approach:

$$Throughput = \frac{Data\ tranfered}{Time}$$

Detection Rate

The detection rate is the proportion of events or abnormalities accurately recognized by the MEC system out of all occurrences when comparing the present methods (SEC-IDS is attained at 94 (ms), EEACK-IDS is attained at 86 (ms) and SAZID is attained at 92 (ms)) with the recommended method (IOD-MDGAN is attained 96 (ms)). Our recommended technique is superior to the current approach as shown in Fig. (5) and Table (5):

$$Detection = \frac{True\ positive}{True\ positive + False\ Negative} \times 100$$

Data Delivery Ratio

The data delivery ratio is the percentage of successfully transmitted data to the total data created by MEC's applications comparing the suggested approach (IOD-MDGAN attained 900 (ms)) with the current methods (SEC-IDS attained 890 (ms), EEACK-IDS attained 825 (ms) and SAZID is attained 860 (ms)). Our suggested method outperforms the existing method as shown in Fig. (6) and Table (6):

$$Data\ delivered\ ratio = \frac{succefully\ Delivered\ Data}{total\ Data} \times 100$$

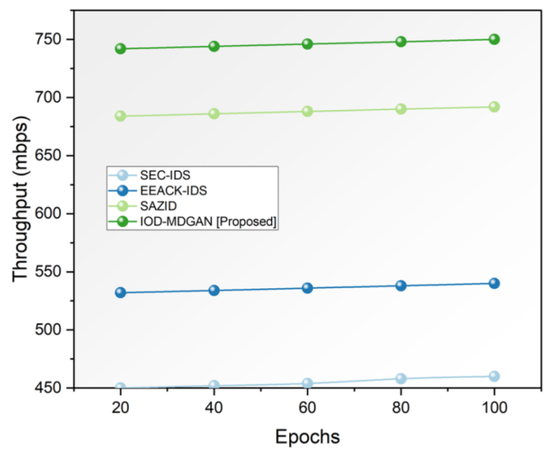

Fig. 4: Outcome of throughput

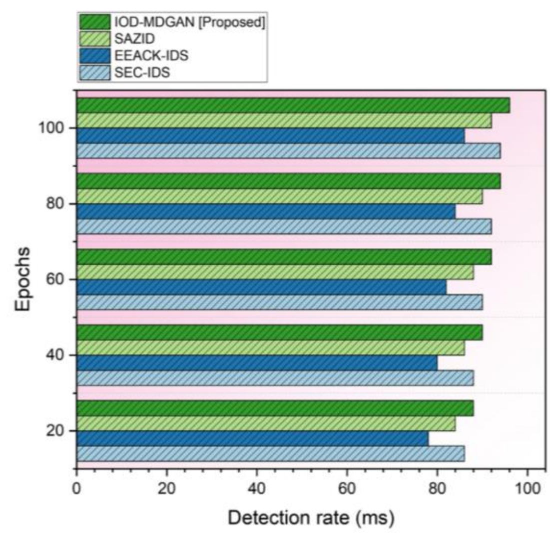

Fig. 5: Outcome of detection rate

Table 4: Value of throughput

Epochs	Throughput (Mbps)			
	SEC-IDS	EEACK-IDS	SAZID	IOD-MDGAN [Proposed]
20	450	532	684	742
40	452	534	686	744
60	454	536	688	746
80	458	538	690	748
100	460	540	692	750

Table 5: Value of detection rate

Epochs	Detection rate (ms)			
	SEC-IDS	EEACK-IDS	SAZID	IOD-MDGAN [Proposed]
20	86	78	84	88
40	88	80	86	90
60	90	82	88	92
80	92	84	90	94
100	94	86	92	96

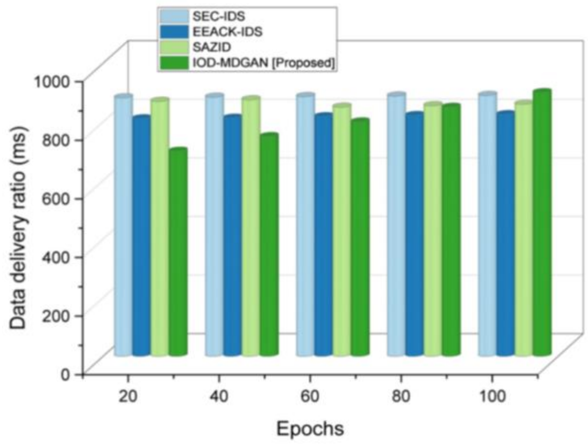

Fig. 6: Data delivery ratio

Table 6: Value of data delivery ratio

Epochs	Data delivery ratio (ms)			
	SEC-IDS	EEACK-IDS	SAZID	IOD-MDGAN [Proposed]
20	882	811	870	700
40	884	813	875	750
60	886	818	850	800
80	888	822	855	850
100	890	825	860	900

Table 7: Value of cost-effectiveness

Epochs	Cost Effectiveness			
	SEC-IDS	EEACK-IDS	SAZID	IOD-MDGAN [Proposed]
20	82	74	77	65
40	84	76	79	68
60	86	79	82	72
80	88	81	85	76
100	90	83	87	79

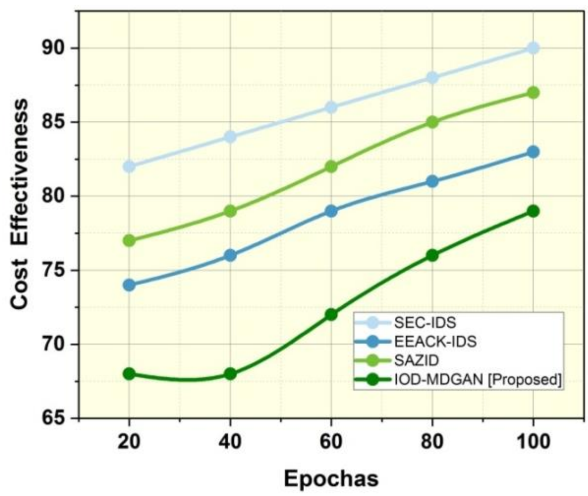

Fig. 7: Outcome of cost-effectiveness

Cost-Effectiveness

Cost-effectiveness in MEC evaluates the efficiency of obtaining desired objectives with minimal assets and costs. When comparing the suggested approach (IOD-MDGAN is attained 79) with the current approaches (SEC-IDS is attained 90, EEACK-IDS is attained 83 and SAZID is attained 87). Compared to the existing method, our suggested methodology is superior as shown in Fig. (7) and Table (7):

$$Cost\ effective = \frac{Benifit\ /output}{cost/input}$$

Discussion

Secured Edge Computing-Intrusion Detection System (SEC-IDS), Smart Ant Colony Zone-Intrusion Detection System (SAZID), and Enhanced Energy-Aware Clustering and Key Management-Intrusion Detection System (EEACK-IDS) each have specific limitations when applied in Mobile Edge Computing (MEC). SEC-IDS, while offering enhanced security, struggles with scalability and efficiency when faced with large volumes of edge devices, leading to potential delays in detection. SAZID, which leverages ant colony optimization, faces challenges with dynamic environments as its efficiency drops when the network topology changes frequently, limiting its real-time applicability. EEACK-IDS, though energy-efficient and scalable, tends to sacrifice detection accuracy under resource-constrained conditions, leading to a higher false-positive rate.

To overcome these limitations, the integration of Intelligent Outlier Detection using a Multidimensional Generative Adversarial Network (IOD-MDGAN) can provide a more robust solution. IOD-MDGAN can enhance detection accuracy by learning complex attack patterns in a multidimensional space, improving the system's adaptability to dynamic environments. Its ability to generate realistic outlier samples allows the IDS to detect anomalies more effectively, even in large-scale, resource-constrained MEC networks. Additionally, the generative capabilities of MDGAN enable the system to anticipate and mitigate emerging threats, providing a more scalable, real-time, and energy-efficient intrusion detection framework for mobile edge computing environments.

Conclusion

In conclusion, an extensive data processing framework for MEC can manage the growing amount and complexity of data in today's connected world. Data processing and edge computing can improve real-time decision-making, latency, and user experiences across sectors. MEC deliberately put computer resources at the network's edge to bypass cloud processing's latency and bandwidth constraints. Driverless cars, industrial automation, and augmented reality benefit from their proximity. Resources, edge devices, tasks, data privacy, and security must be considered in architecture. Due to edge device heterogeneity and processing power fluctuations, data processing efficiency needs adaptive algorithms, load balancing, and edge computing for smartphones' large-scale infrastructure for processing data. Adapting these features to specific use cases and technical advancements might boost the data processing efficiency of MEC. Implemented within the MEC framework, our suggested technique identifies IOD-MDGAN as the ideal option, demonstrating low latency (78 ms), high throughput (750 Mbps), efficient detection rate (96 ms), timely data delivery ratio (900 ms) and exceptional cost-effectiveness (79). This experimental assessment demonstrates the usefulness and scalability of our massive data processing framework designed for MEC scenarios. Furthermore, network latency and capacity limits might affect data transmission efficiency between edge devices and central processing units. Upcoming studies could concentrate on improving the IOD-MDGAN model's fault tolerance and scalability to handle the increasing amount and complexity of IoT data streams. To further increase the efficacy and efficiency of the suggested architecture, improvements for edge devices with limited resources should be investigated.

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Author’s Contributions

Anitha Premkumar and Sowmya Vemagal Lakshminarayana: All experiments coordination, data collection, implementation, analysis and results.

Shankar Rajagopal and Natesh Mahadev: Grammar and paper flow.

Rajesh Natarajan and Sujatha Krishna: Manuscript proof-reader, edited and correction.

Ethics

It should be noted that the authors have no conflict of interest. All co-authors have read and approved the manuscript and no competing financial interests exist. We confirm that the submission is not currently being considered for publication anywhere else.

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