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UGECGAD: EVALUATING THE EFFICACY OF UNSUPERVISED GAN ARCHITECTURES FOR ECG ANOMALY DETECTION

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ABSTRACT

Anomaly detection in Electrocardiogram (ECG) signals is critical for reliable diagnosis and continuous patient monitoring. Although traditional approaches are incapable of describing the rich nonlinear structure in ECG data, they are ineffective in detecting these abnormalities. Although Generative Adversarial Networks (GANs) has recently attracted increasing interest for ECG anomaly detection, research available currently does not provide a systematic evaluation of their advantages and disadvantages for practical situations. This paper addresses this gap by critically reviewing unsupervised GAN-based approaches, evaluating their ability to reconstruct normal ECG signals and accurately detect deviations. We introduce a rigorous empirical comparison of different GAN architectures and their adversarial variants, highlighting key challenges in their implementation. Our results show that the ECG-Adversarial Autoencoder (ECG-AAE) is superior to the other GAN-based approaches in terms of training anomaly, and provides the best performance in anomaly detection. This study contributes new insights into the robustness of ECG-AAE, establishing its potential for precise and reliable ECG anomaly detection in practical healthcare applications.

Keywords*: Generative Adversarial Networks, Deep Learning, Electrocardiogram, Anomaly Detection, Unsupervised Learning*

1. INTRODUCTION

The anomaly discovery (AD) issue remains a critical and enduring issue that seeks to identify a set of facts that differs from the predicted structure, i.e., misfits. This issue is present in numerous disciplines, including industrial fault diagnosis, intrusion detection, and biomedical signalling diagnosis. Biomedical signalling diagnostic refers to the procedure of extracting the appropriate illness from signs of the makeup and functioning of the human organisms inside processes and tissues. As a result, numerous investigators attempt to address the finding of anomalies problem by employing various approaches. In recent years, investigators discovered that GAN-based methods are ideal for addressing this issue. Prior research on GAN-based ECG anomaly detection has mostly examined individual GAN architectures, such as AnoGAN, BeatGAN, and ECG-ADGAN, frequently assessing them separately or without conducting thorough comparisons. These studies' practical applicability is limited because they ignore real-world issues like noise, inter-patient variability, and class imbalance. In contrast, our study systematically compares several unsupervised GAN-based techniques, highlighting their advantages and disadvantages while proving that ECG-AAE performs better. In contrast to earlier studies, we place a strong emphasis on robustness, dependability, and practical application, offering fresh perspectives on automated ECG monitoring for better clinical judgment. They achieved good results when applying anomaly detection to signal data, historical data, and related data from other fields. Conventional ECG anomaly detection techniques are limited in their adaptability by their reliance on handcrafted features and inability to handle nonlinear complexities. Despite the potential of GANs, the effectiveness and robustness of various architectures have not been thoroughly examined in previous research. Most ignore real-world issues like noise and variability or concentrate on just one variation. By methodically contrasting unsupervised GAN-based techniques, this study closes the gap and identifies the most successful one as ECG-Adversarial Autoencoder (ECG-AAE). Our research helps create automated, dependable ECG monitoring systems for better patient care and early diagnosis. In the following paragraphs, we will go over how the GAN-based techniques for Electrocardiogram detection of anomalies work and how we're employing them to address the AD challenge [1]. Amongst all of the methods used, Generative Adversarial Networks (GANs) have become known as an effective autonomous learning tool, able to encapsulating intricate patterns and frameworks found in diverse datasets. GAN-based unsupervised approaches show great promise in electrocardiogram (ECG) analysis, wherein the prompt identification of irregularities is crucial for prompt medical attention. The article investigates the use of GANs in the field of ECG detection of abnormalities, specifically their ability to acquire complex characteristics and depictions from typical cardiac rhythms and then detect oddities lacking requiring for training data that is labelled. In the present study, we employed the MIT-BIH a database to determine the efficacy of different approaches [2].

Generative Adversarial Networks (GANs) are a game-changing approach in computational intelligence, altering how systems synthesize as well as comprehend intricate information. GANs, invented by Ian Goodfellow and collaborators in 2014, offer an effective system for training generative algorithms using adversarial learning. The basic idea of GANs is the collaboration of 2 neuronal nets—the producer and the perception—in an ongoing antagonistic combat. The tool for generation seeks to generate information that is comparable from actual information, whereas the tool for discrimination tries to accurately distinguish among actual and produced examples [24]. As a consequence of this continuous anxiety, the machine's capacity to generate progressively accurate information is continuously enhanced. GANs are adaptable in an extensive variety of programs, including video and image synthesizing, stylistic move, and knowledge augmentation. This primer looks into the basic concepts, evolution, and multiple uses of GANs, emphasizing their revolutionary impact on the fields of AI and machine learning [3]. Equation 1 and Figure 1 depict the GAN model.

$$\min_G \max_D V(D,G)$$

$$),G) = \mathbb{E}_{x\sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z\sim p_z(z)}[\log(1 - D(G(z)))]$$

Eqn (1)

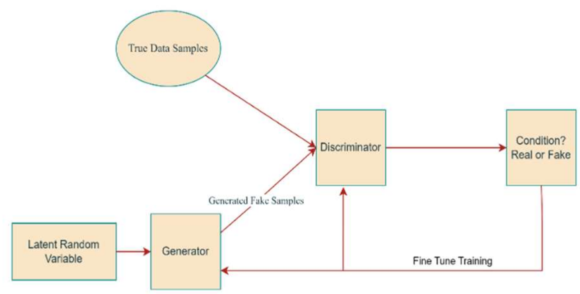

Figure 1: GAN construction and its parts.

I.

2. SUPERVISED AND UNSUPERVISED LEARNING STRATEGIES A. SUPERVISED LEARNING

Supervised training is a machine learning methodology for determining a structure's contribution and production connection based on an array of matched input and output training data. An source-output learning trial is too identified as branded exercise info or overseen facts since the production is supposed of to be the tag of the information that was provided or oversight. It is also known as Training with an Instructor, Learning from Annotated Information, or Inductive reasoning Machine Learning. Supervised instruction seeks to create a computer system capable of learning how to map between input and result and predicting its results given fresh inputs. If the result consists of a limited number of individual values representing the input's labeled classes, the acquired transfer results to the grouping of the provided information. If the result accepts constant values, the input undergoes regression[23]. Input and output information about relationships is often expressed using learning-model variables. When these variables are not readily accessible from samples used for training, the system for learning has to execute a method of estimation to get them. In contrast to Uncontrolled Development, supervising instruction data requires overseen or marked knowledge, whereas undetected learning instruction information is alone because they are not marked. Semi-supervised Understanding means a technique that uses both overseen and unattended data for training. Active Learning refers to incremental supervised instruction in which the algorithm proactively searches a user/teacher for declares throughout the learning procedure. Figure 2 depicts a block diagram for supervised learning.

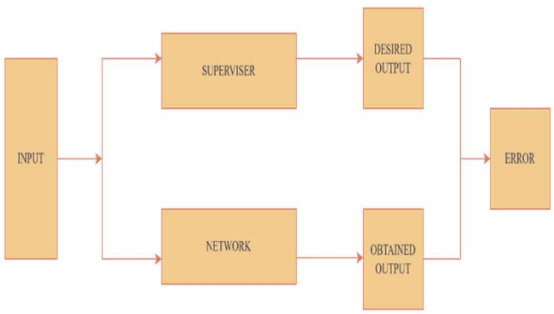

Figure 2: Block Schematic for Supervised Learning [2]

B. Unsupervised Learning

Unsupervised training refers to the methods an algorithm may investigate to signify certain contribution designs in a way that duplicates the logical layout of the whole set of effort layouts or trends [5]. It is an assignment for machine learning to predict a function that will define the unidentified pattern from unknown information. This is just the development of methods; there are no labels to oversee the education/training. The procedure receives an immense quantity of information and features for every observation as sources but not as the output that is wanted. Unsupervised learning is commonly used to divide pictures into two distinct groups or clusters according to basic features such as size, hue, and form. Figure 3 shows a block structure of autonomous learning. It is likewise mentioned to as an autonomous or self-learning process since there is no external foundation for providing knowledge to the network's members. This is dependent on regional circumstances and inner processes. At the input layer stage, the structure is given a usual of exercise patterns or facts; the system's connection heavy objects are tuned to some sort of competition between the final output nodes, with a node with the greatest score being the one that is chosen. Unsupervised data mining is best suited for linking and clustering computations [6].

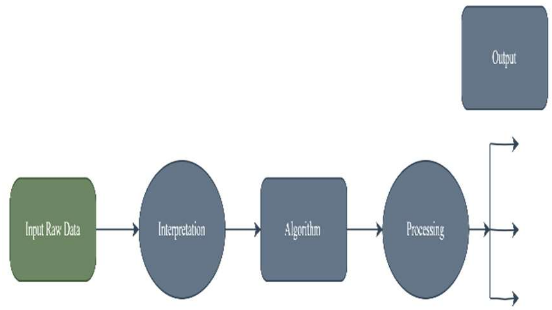

Figure 3: Block Diagram for Unsupervised Learning[3]

3. ANOMALY DISCOVERY AND SCORE IN ECG SIGNAL

A. Anomaly Detection

The goal of identifying abnormalities in electrocardiogram (ECG) signals is to identify abnormal beats, heart rate, and oscillations. To accomplish this objective, a system that detects anomalies needs to be able to detect them on all pulse cycles. Additionally, the device examines the whole record to identify any abnormal beat parts such as an uneven R-R intermission and ectopic beats. As a result, a system for detecting anomalies consists of five different components: removing noise, pulse identification, beat division, beat categorization, and rhythmic categorization. Figure 4 depicts a typical detection system for pulse abnormalities. The noise suppression technique aims to reduce the impact of signal processing caused by the device being recorded or movement of the patient [22]. The goal of pulse identification is to locate the cardiac rhythm and estimate the circulatory rate. The cardiac fragmentation method recovers the whole pulse based on a known heart position. The heart rate categorization detects anything aberrant pulse pattern on the Electrocardiogram facts. The beat that is irregular categorization corresponds to the pulse sorting, nonetheless in its place of scrutiny solitary single pulse form, it examines a dated sign on the Electrocardiogram data [7]. Figure 5 depicts a typical and atypical ECG signal from an individual.

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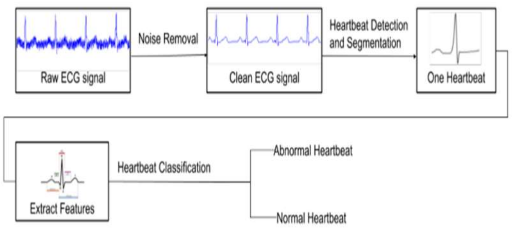

Figure 4: Heart Anomaly Detection[4]

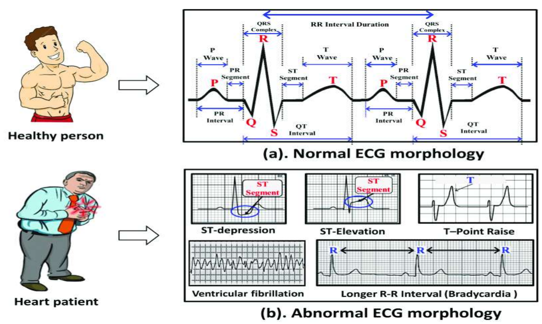

Fig Figure 5: Normal and abnormal ECG Signal[5]

B. Anomaly Score

An anomaly score indicates the distance an indicator departs from the usual course of action of an entire system or procedure. Anomaly scores may be employed to detect anomalies, mistakes, problems, or uncommon incidents in a variety of areas, including financial services, health care, and safety.

The identification of anomalies has uses in the analysis of ECG indications, which are data series capturing the electrical functions of the cardiac muscle. Anomaly detection in ECG signals can aid in determining the presence of unusual cardiac rhythms such as cardiac arrhythmia ischemia, or infarction of the myocardium, all of which can pose dangers to health. The subsequent calculations describe anomaly detection

Generator Loss: The producer (G) tries to harvest information (G(z)) that is vague since actual facts (x). The loss function for the producer is:

$LG=-Ez\sim pz(z)[logD(G(z))]$ Eqn (2)

where (D) is the discriminator, and (z) is the dormant vector.

Discriminator Loss: The discriminator (D) tries to differentiate amid actual information (x) and produced data (G(z)). The loss function for the discriminator is:

$LD=-Ex\sim pdata(x)[logD(x)]-Ez\sim pz(z)$
$[log(1-D(G(z)))]$ Eqn (3)

Reconstruction Loss: For anomaly detection, the reconstruction loss (R(x)) is crucial. It measures how well the generator can reconstruct the input data (x):

$R(x)=\|x-G(z*)\|2$ Eqn (4)

where (z^*) is the latent vector that minimizes the reconstruction error for (x).

Anomaly Score: The anomaly score (A(x)) combines the reconstruction loss and the discriminator's output:

$A(x)=\alpha R(x)+(1-\alpha)(1-D(G(z*)))$ Eqn (5)

Residual Loss = Actual Value - Predicted Value

Here are diverse approaches to compute the anomaly notch in ECG signals, depending on the type of model and the features used.

To determine an abnormality rating, we must establish an upper limit that distinguishes between typical and unusual signals based on the restoration deviation. The level of significance can be variable or fixed, based on the data features and the efficacy of the model. A common approach for determining the best threshold is to use the ROC, or headset working typical, curve, which conspiracies the true positive rate (TPR) towards the false positive rate (FPR) across dissimilar heights. The optimum limit is the one that optimizes the TPR while minimizing the FPR, or, correspondingly, optimizes the area under the curve (AUC) [19].

4 GAN METHODS FOR ANOMALY RECOGNITION IN ECG CLASSIFICATION FOUNDED ON UNSUPERVISED LEARNING

Generative Adversarial Networks (GANs) are successful instruments to identify deviations in categorization of ECG. By studying typical ECG readings, GANs can detect deviations from produced structures and recognize deviations. The unsupervised learning approach proves successful as it doesn't need marked asymmetry information. GANs improve the precision and dependability of ECG anomaly identification. The ones that follow are various GAN methods that utilize unsupervised machine learning to identify deviations in cardiac rhythm signals.

A. AnoGAN

AnoGAN is a neural network-based anomaly recognition system that identifies ECG abnormalities through autonomous learning. The Generative Adversarial Network (GAN) structure serves as the foundation for the model. When provided with an aberrant ECG signal, the model produces an artificial signal that is identical to the source pattern. Abnormalities are identified by calculating the distinction among the signal being input and produced frequencies [8].

At the point when learning in AnoGAN, the demise of the Creator cannot be reduced, but the lack of a the discriminator does. Even though both the Generator and Discriminant were intended to have the identical acquiring measure, the learning capacity of the Creator was found to be fewer. Multiple tests showed that the greatest reduction equilibrium was obtained when the initial measure of the Discriminant was 1 and that of the generator itself was 4. Another issue is that AnoGAN's choice boundaries is unreliable. As a result, additional tests using the F-measure are carried out in order to establish the choice border. For assessment of performance, the model's precision is assessed using Epoch, and its the goodness-of- is reviewed using AUC and the F-measure. Figure 6 demonstrates the AnoGAN system [9].

By using this method, achieved the following measures Acc, Precision, F1 Score, Recall and AUC is 92.7,87.3,91.43,80.5 and 89.4 respectively.

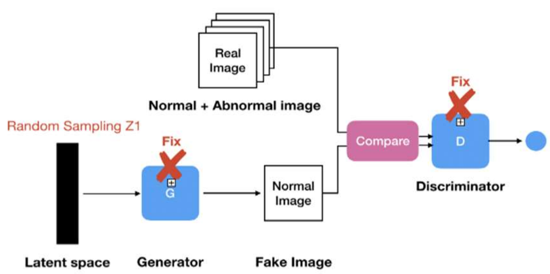

Figure 6: AnoGAN Architecture

B. BeatGAN

BeatGAN is an uninterrupted time period detection of anomalies technique that does not require any kind of oversight. BeatGAN provides understandable outcomes when evaluating a supplied beat's aberrant temporal ticks to adversarially created sounds. Its resilience is ensured by normalizing errors in reconstruction with an aggressive generating strategy, as well as adding information with data series distortion [10]. Figure 7 shows the component architecture of BeatGAN.

BeatGAN reliably recreates the information and uses an adversarial generation method to normalize it. To enhance its precision, a bending technique was developed to supplement data used for training with cyclic series of features. BeatGAN identifies abnormalities effectively in both Electrocardiogram statistics as of the MIT-BIH arrhythmia record then sensory period information from CMU Movement Take [11].

Through the implementation of this technique, obtained the following results Acc, Precision, F1 Score, Recall and AUC is 94.8, 95.3,92.9,90.7 and 94.3. Many Studies demonstrate that BeatGAN effectively and precisely recognizes unusual surpasses in ECG sequences and directs doctors' focus on abnormal moments ticks as well.

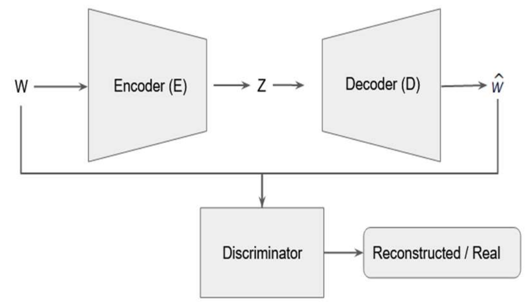

Figure 7: BeatGAN architecture[8]

C. ECG ADGAN

ECG-ADGAN is an innovative technique to identify ECG adversarial signals using conditional generative adversarial networks. The primary concept behind ECG-ADGAN is to use a conditional GAN to produce ECG signals for various groups while also identifying abnormalities in the heart. For producing genuine adversarial scenarios, the algorithm undergoes training utilizing class-specific ECG signals [12]. Through the implementation of this technique, obtained the following results Acc, Precision, F1 Score, Recall and AUC is 95.5, 96.9, 91.8, 94.3 and 95.9 respectively.

To synthesize ECG signals, encased a (Bi-LSTM) layer into a GAN construction then developed the discriminator using a small-scale discrimination approach. The technique creates specimens which correspond to the information's pattern of typical signals in the normal category, permitting an expanded asymmetry detection system to be constructed accurately. Figure 8 illustrates a schematic illustration of ECG ADGAN. Experimental findings indicate that this technique surpasses multiple innovative semi-supervised training-based Electrocardiogram algorithms for irregularity exposure and precisely recognizes an unidentified asymmetry the classroom in the MIT-BIH unrhythmic record [13].

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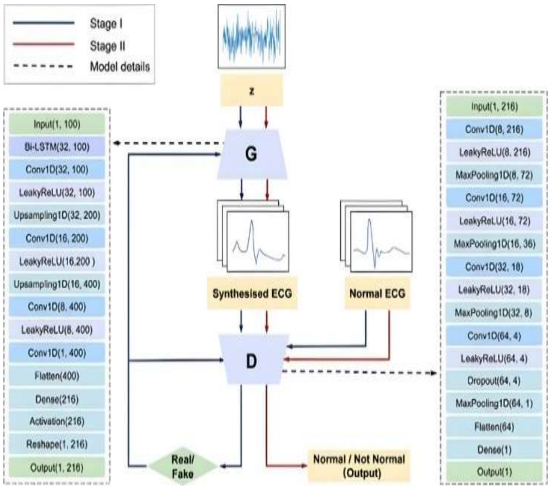

Figure 8: ECG-ADGAN Architecture

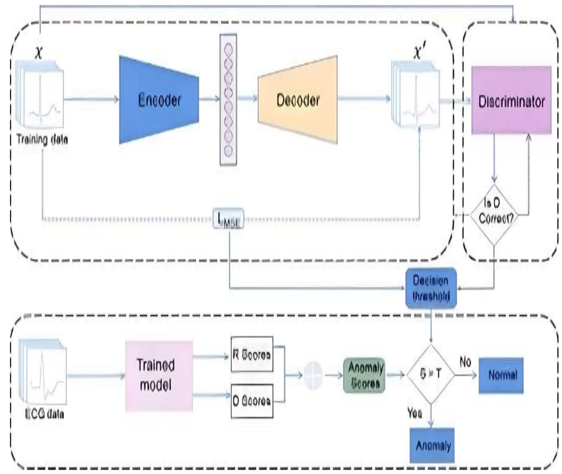

Figure 9: ECG-AAE Architecture[11]

D. ECG-AAE

ECG-AAE is an innovative technique to identify aberrant ECG occurrences that utilizes an adversarial automatic encoder and a temporal convolutional network (TCN). The ECG-AAE context has trio mechanisms: 1) an autoencoder, 2) a discriminator, and 3) an outlier detector, as depicted in Figure 9. To harvest Electrocardiogram signs that are identical to the source indications, the automatic encoder tries to decrease reconstructive defects.

The discriminator has been taught to differentiate among regular and recreated information using data coming from both sources. To enhance the autoencoder's reconstructive efficiency, both the automatic encoder and the discriminant undergo revisions at the same time. Lastly, the normal ECG is evaluated using an assortment of reconstructive faults and classifier values (the probability output of the discriminator). The test information is converted over into prospective distance, and the associated restoration gap is determined using the difference between recreated specimens for testing and real testing data [15]. Through the implementation of this technique, obtained the following results Acc, Precision, F1 Score, Recall and AUC is 96.73,98.54,96.66,94.86mand 96.72.

E. VAE GAN

The merging of models that generate has enabled fresh methods to AI, especially in the areas of autonomous learning and information era. Variational automatic encoders (VAEs) and Generative Adversarial Networks (GANs) are both separate yet mighty structures that have received considerable interest from students and professionals the same, as illustrated in Figure 10. VAEs thrive at collecting complicated hidden structures by creating a probabilistic framework that allows for both generation and inference. GANs, on the other hand, produce realistic data samples by utilizing a competitive architecture among an estimator and a device that discriminates. We cast-off a mini-batch discrimination exercise tactic and incorporated a Bi-LSTM layer into a GAN [16]

Through the implementation of this technique, obtained the following results Acc, Precision, F1 Score, Recall and AUC is 95.5, 71.96, 83.25, 98.74 and 95.90. [10]

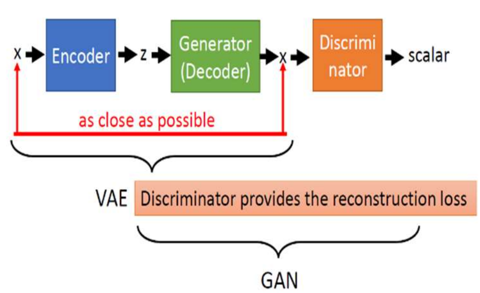

Figure 10: VAE GAN Architecture

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F. Transformer Based

A Transformer-based GAN for ECG uncovering of anomalies uses the transformative ability of the focus the processes in Transformers to analyze and produce electrocardiogram, or ECG, signals [17]. The new approach employs a generator network to create normal ECG patterns and the network of discriminators to differentiate between real and generated signals. The system of attention enables the algorithm to observe complicated relationships over time and subtle differences in ECG waves, thereby improving its ability to detect deviations [20]. Figure 11 depicts the classical construction, which contains of deuce portions: an embedding layer and a standard transformer encoder.

Through the implementation of this technique, obtained the following results Acc, Precision, F1 Score, Recall and AUC is 89.5, 87.1,92.3,98.2 and 93.0.

The generator strives to produce realistic ECG signals that can effectively deceive the discriminator using an antagonistic method of learning, while the distinction trains to correctly differentiate between regular and aberrant structures [21]. This Transformer-based GAN has an opportunity for enhancing the precision and durability of ECG detection of anomalies, resulting in improvements in detection and treatment for cardiac conditions [18].

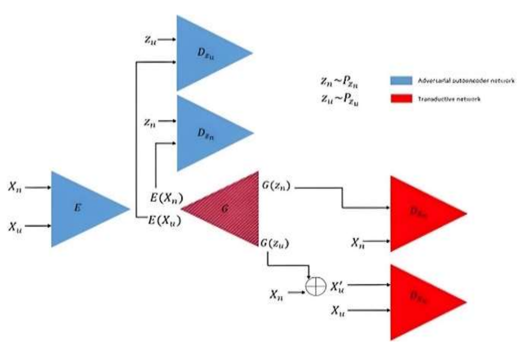

Figure 11: Transformer Based

5. RESULT AND ANALYSIS

In this part, we will conduct an in-depth evaluation of the findings acquired from various techniques, including an in-depth review of the information that was gathered and the results that were noticed. The main objective is to decode and analyse our results, putting light on the consequences and importance that they have inside the context of our goals. We hope to offer an understandable and insightful comprehension of the connections, trends, and patterns contained within the information by carefully analyzing it and applying mathematical methods.

In addition, this part will examine the results in relation to the original hypotheses or questions being investigated, providing an overview that spans the separation among actual data and a theoretical basis. The comprehensive examination not only exposes the complexities of the findings, but it also fosters a deeper comprehension of the topic, thereby directing the next phase of research and guiding use in practice.

Metrics for performance are crucial in artificial intelligence for determining the way an algorithm operates. They aid in gauging the precision, efficacy, and resilience of algorithms through contrasting forecasts to reality. distinct artificial intelligence assignments (such as regression, categorization, and grouping) need various metrics for assessment. Selecting an appropriate measurement is vital as it influences the choice of typical, parameter tuning, and the general comprehension of how the model operates. We established the subsequent indicators of recital.

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

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

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

F1 Score= 2*((Precision*Recall)/(Precision + Recall))

Where: **TP** (True Positives), **TN** (True Negatives)
FP (False Positives), **FN** (False Negatives)

The following are the Bar Graphs for performance metrics of the above discussed methods.

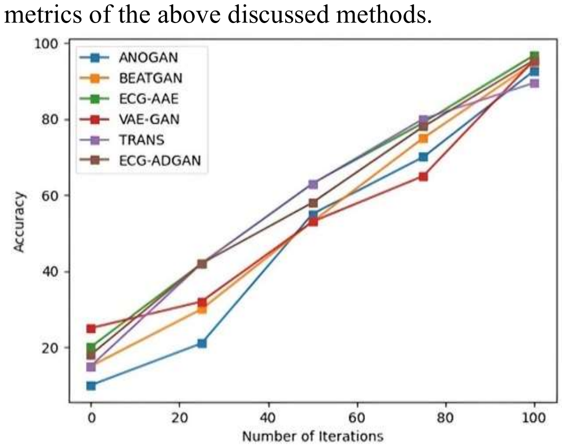

Figure 12: Bar Graph for Accuracy

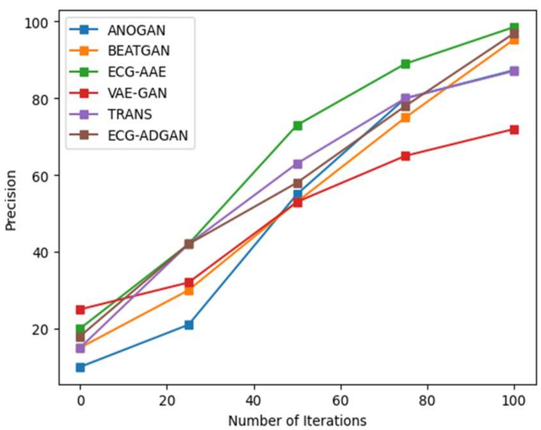

Figure 13: Bar Graph for Precision

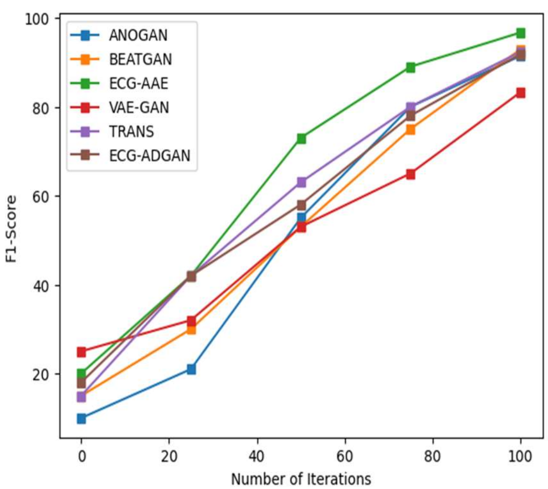

Figure 14: Bar Graph for F1-Score

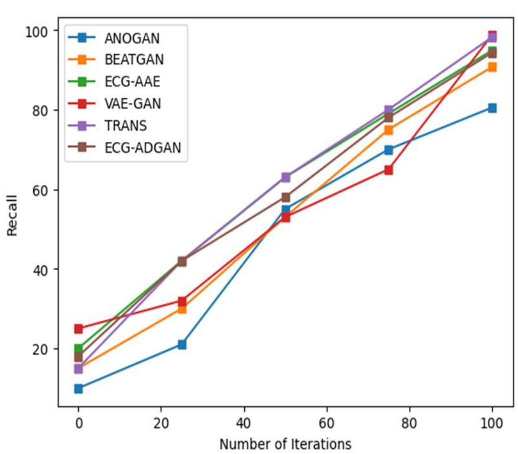

Figure 15: Bar Graph for Recall

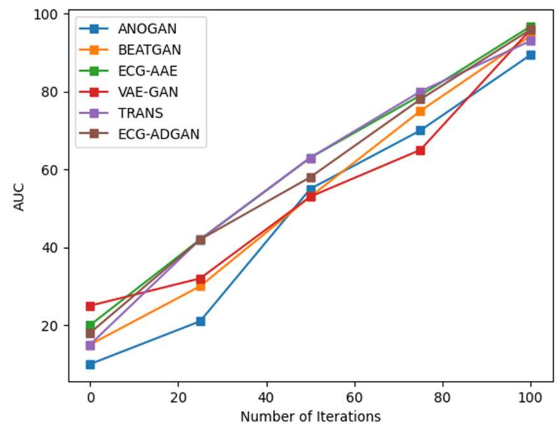

Figure 16: Bar Graph for AUC

Current research concentrates on individual GAN variations, lacks thorough comparisons, and ignores practical issues like noise and variability. In order to overcome the shortcomings of conventional techniques, our study thoroughly evaluates various GAN architectures in order to determine which one is best for precise and trustworthy anomaly detection. The study demonstrates the ECG-Adversarial Autoencoder's (ECG-AAE) superior performance and real-world application potential. This research advances the development of more reliable, automated ECG monitoring systems, enhancing early diagnosis and patient outcomes by addressing issues like noise, variability, and class imbalance.

6. CONCLUSION

This paper provides a comprehensive overview of unsupervised GAN-based approaches for ECG anomaly detection. We critically reviewed several GAN architectures and their adversarial counterparts and assessed their applicability for recovering normal ECG signals and robustly detecting abnormalities. Our strong empirical study confirmed that the ECG-Adversarial Autoencoder (ECG-AAE) significantly outperformed other GAN-based methods in terms of various performance measures. This study identifies ECG-AAE as the best method for ECG anomaly detection by presenting a methodical comparison of various GAN architectures, stressing their advantages and disadvantages. Our research offers fresh perspectives on enhancing the scalability, robustness, and dependability of unsupervised ECG monitoring systems. Because of the ECG-AAE's resilience in learning the distribution of normal ECG signals and identifying anomalies, it is a promising approach for making patient monitoring more dependable and efficient. By methodically contrasting unsupervised GAN-based techniques, this study improves ECG anomaly detection and finds that ECG-Adversarial Autoencoder (ECG-AAE) is the most successful. By offering a thorough empirical assessment and boosting the dependability of automated ECG monitoring for better healthcare outcomes, it closes research gaps. Real-world application of GAN-based ECG anomaly detection is hindered by noise, patient variability, and computational complexity. Clinical trust is hampered by explainability, and there is still work to be done on improving detection thresholds. Closing these gaps is essential to creating ECG detection systems that are dependable and comprehensible. In our future work, we will combine ECG-AAE with deep learning techniques to further enhance its performance in detecting ECG anomalies.

REFERENCES

[1]. Zenati, H., Foo, C., Lecouat, B., Manek, G., & Chandrasekhar, V.R. (2018). Efficient GAN-Based Anomaly Detection. ArXiv, abs/1802.06222.

[2]. Benti, D.M., Janbhasha, S., Desisa, E.G. (2023). Identification of Generative Adversarial Network Forms, Open Issues, and Future Study Areas: A Study. In: Fong, S., Dey, N., Joshi, A. (eds) ICT Analysis and Applications. Lecture Notes in Networks and Systems, vol 517. Springer,

[3]. F. Di Mattia, P. Galeone, M. De Simoni, and E. Ghelfi, “A Survey on GANs for Anomaly Detection,” Jun. 2019,

[4]. Q. Liu and Y. Wu, “Supervised Learning,” in *Encyclopedia of the Sciences of Learning*, Springer US, 2012, pp. 3243–3245.

[5]. H. U. Dike, Y. Zhou and Q. Wu, “Unsupervised Learning Based On Artificial Neural Network: A Review,” in *2018 IEEE International Conference on Cyborg and Bionic Systems, CBS 2018*, Institute of Electrical and Electronics Engineers Inc., Jul. 2019, pp. 322–327.

[6]. H. Zu Li and P. Boulanger, “A survey of heart anomaly detection using ambulatory electrocardiogram (ECG),” *Sensors (Switzerland)*, vol. 20, no. 5. MDPI AG, Mar. 01, 2020..

[7]. P. K. Sahoo, H. K. Thakkar, W. Y. Lin, P. C. Chang, and M. Y. Lee, “On the design of an efficient cardiac health monitoring system through combined analysis of ECG and SCG signals,” *Sensors (Switzerland)*, vol. 18, no. 2, Feb. 2018,.

[8]. D. H. Shin, R. C. Park, and K. Chung, “Decision Boundary-Based Anomaly Detection Model Using Improved AnoGAN from ECG Data,” *IEEE Access*, vol. 8, pp. 108664–108674, 2020, doi: 10.1109/ACCESS.2020.3000638.

[9]. Aditya, Singh., P., Niranjan, Reddy. 1. AnoGAN for Tabular Data: A Novel Approach to Anomaly Detection. (2024).

[10]. Miloš, Cekić. "5. Anomaly Detection in Medical Time Series with Generative Adversarial Networks: A Selective Review." Artificial intelligence, undefined (2023).

[11]. B. Zhou, S. Liu, B. Hooi, X. Cheng, and J. Ye, “BeatGAN: Anomalous Rhythm Detection using Adversarially Generated Time Series,” 2019.:

[12]. N. Mejri, L. Lopez-Fuentes, K. Roy, P. Chernakov, E. Ghorbel, and D. Aouada, “Unsupervised Anomaly Detection in Time-series: An Extensive Evaluation and Analysis of State-of-the-art Methods,” Dec. 2022,

[13]. K. F. Hossain *et al.*, “ECG-Adv-GAN: Detecting ECG Adversarial Examples with Conditional Generative Adversarial Networks,” Jul. 2021,

[14]. Alessio, Staffini., Thomas, Svensson., Ung-il, Chung., Akiko, Kishi, Svensson. "2. A Disentangled VAE-BiLSTM Model for Heart Rate Anomaly Detection." Bioengineering, undefined (2023).

[15]. J. Qin *et al.*, “A Novel Temporal Generative Adversarial Network for Electrocardiography Anomaly Detection.”

[16]. Dr., Seda, SAĞLAMYÜREK, TAŞDEMİR. "4. Unsupervised Transformer-Based Anomaly Detection in ECG Signals." Algorithms, undefined (2023).

[17]. L. Shan *et al.*, “Abnormal ECG detection based on an adversarial autoencoder,” *Front Physiol*, vol. 13, Sep. 202.

[18]. Lianfeng, Shan., Yu, Li., Hua, Jiang., Peng, Zhou., Jing, Niu., Ran, Liu., Yuanyuan, Wei.,

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Jiao, Peng., Huizhen, Yu., Xianzheng, Sha., Shijie, Chang. "11. Abnormal ECG detection based on an adversarial autoencoder." Frontiers in Physiology, undefined (2022). doi: 10.3389/fphys.2022.961724

[19]. D. Li, D. Chen, L. Shi, B. Jin, J. Goh, and S.-K. Ng, "MAD-GAN: Multivariate Anomaly Detection for Time Series Data with Generative Adversarial Networks," Jan. 2019,

[20]. Seong-Tae, Kim., Gyeong-Moon, Park. "3. Time Series Anomaly Detection using Transformer-based GAN with Two-Step Masking." IEEE Access, undefined (2023). doi: 10.1109/access.2023.3289921

[21]. A. Alamr and A. Artoli, "Unsupervised Transformer-Based Anomaly Detection in ECG Signals," *Algorithms*, vol. 16, no. 3, Mar. 2023, doi: 10.3390/a16030152.

[22]. Bagheri, F., Ghafarnia, N. and Bahrami, F. 2013. Electrocardiogram (ECG) Signal Modeling and Noise Reduction Using Hopfield Neural Networks. *Engineering, Technology & Applied Science Research*. 3, 1 (Feb. 2013), 345–348.

[23]. Hii, K.H., Narayanamurthy, V. and Samsuri, F. 2019. ECG Noise Reduction with the Use of the Ant Lion Optimizer Algorithm. *Engineering, Technology & Applied Science Research*. 9, 4 (Aug. 2019), 4525–4529

[24]. Mohguen, W. and Bouguezel, S. 2021. Denoising the ECG Signal Using Ensemble Empirical Mode Decomposition. *Engineering, Technology & Applied Science Research*. 11, 5 (Oct. 2021), 7536–7541.