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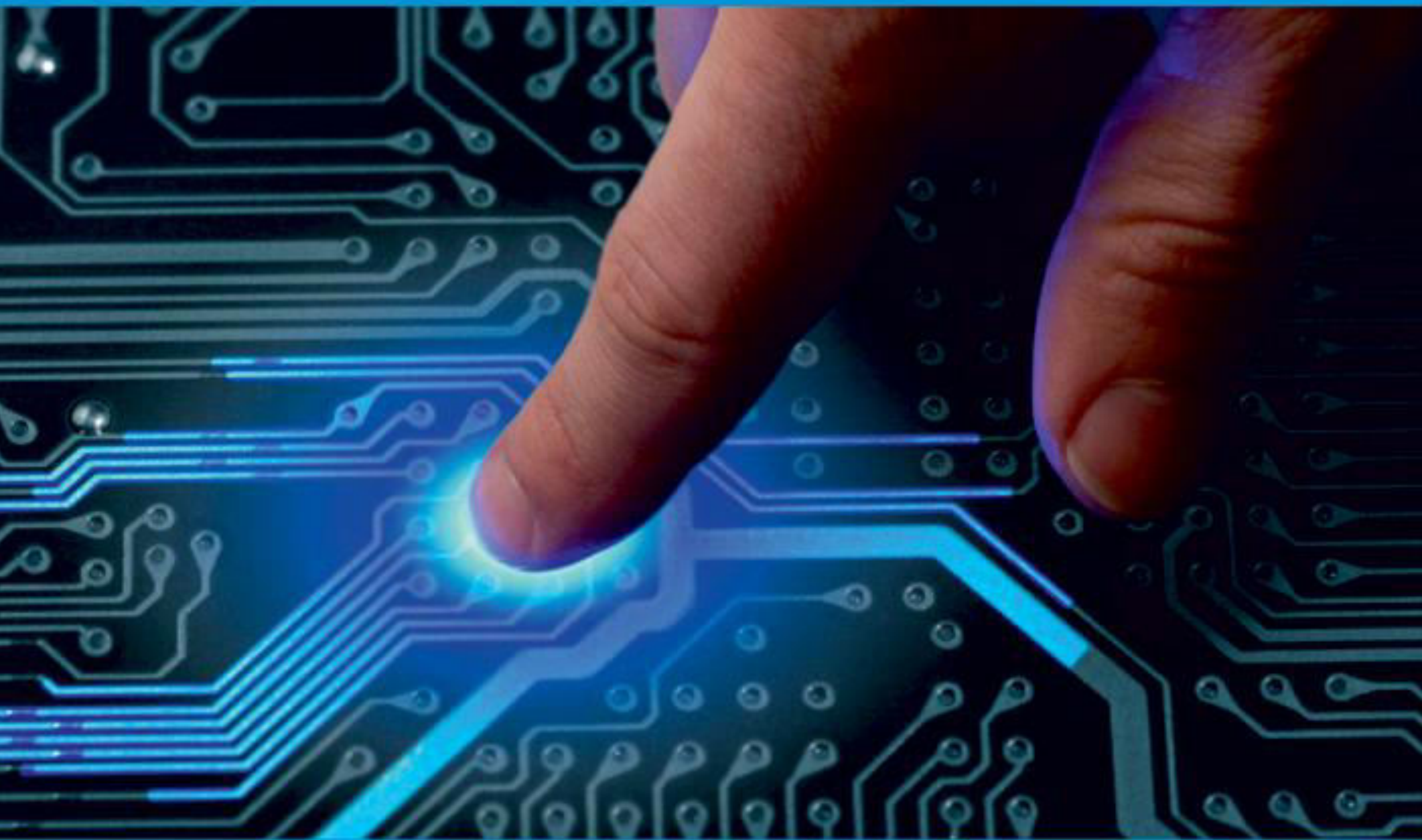

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Hyperparameter Tuning in ECG Image Classification in GAN Model using ADAM Optimization

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ABSTRACT: ECG (Electro Cardiogram) plays a significant role in the diagnosis of cardiovascular disease. An ECG record shows the abnormalities of the heartbeat and asses the heart function. The Generative Adversarial Network, inspired by creating the synthetic realistic images by two networks discriminator and generator is employed by a deep learning algorithm for ECG images. The tuning of hyperparameters in GAN models is complex. An important step in creating the Generative Adversarial Network is selecting the best hyperparameters. By tuning the model manually, different possible ranges of values are tried until the best fit is achieved. Machine learning algorithms such as stochastic optimization (ADAM) can provide an effective alternative to manual methods. Two phases of optimization are proposed in this paper for the GAN model. In the first phase, a Generative Adversarial Network is trained to create synthetic data over the different parameters to limit the duration of the training phase to optimize by using UCI repository ECG datasets with four classes Abnormal, Normal, History of Myocardial Infraction Patients and Myocardial Infraction. The second phase is hyperparameter optimization is made less using Linear Regression and comparing the existing algorithm Stochastic Optimization (ADAM) to achieve an optimal rate. With regression, ADAM achieves a 95.95% accuracy rate compared with existing optimization on the 10,000+ ECG images dataset.

KEYWORDS: GAN, Hyperparameter Optimization, ECG Images, Image Classification

I. INTRODUCTION

Cardiovascular disease, or CVD for short, is a group of conditions that affect the heart and blood arteries. These illnesses include, among others, coronary artery disease (CAD), heart failure, stroke, and peripheral arterial disease (PAD). People of all ages, genders, and races can be affected by CVD, which is one of the main causes of death and disability in the world. High blood pressure, elevated cholesterol, smoking, being obese, being physically inactive, and having a family history of the disease are some of the risk factors that can make CVD more likely to occur. Based on the kind and severity of the illness, CVD symptoms can change. Chest pain or discomfort, shortness of breath, exhaustion, vertigo, nausea, and perspiration are some typical symptoms that may occur. In addition to medication or medical procedures like angioplasty, stenting, or heart surgery, the treatment for CVD may also include lifestyle modifications including a healthy diet and frequent exercise.. Using Synthetic Minority Oversampling Technique (SMOTE), six ML classifiers, and Hyperparameter Optimization (HPO), this study carries an effective method. We built and tested the model using two public datasets. Based on the results, SMOTE and Extra Trees (ET) optimized with hyperband outperformed the state-of-the-art CVD detection models by 99.2% and 98.52%, respectively. Doctors can use the proposed model to determine a patient's heart disease status. The classification of Electrocardiogram (ECG) images is of prime importance in detecting diverse cardiac abnormalities. However, optimal performance in ECG image classification using a Generative Adversarial Network (GAN) model necessitates meticulous tuning of hyperparameters. The process of hyperparameter tuning refers to the selection of the most suitable values for the hyperparameters that govern the behavior and performance of the GAN model. The selection of the optimization algorithm employed during the training process is one of the crucial aspects of hyperparameter tuning in ECG image classification with GAN models. ADAM (Adaptive Moment Estimation) optimization is a popular choice due to its effective adaptability of learning rates for different parameters. ADAM algorithm combines the benefits of AdaGrad and RMSprop optimization algorithms, to ensure faster convergence and better generalization in deep learning models.

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The hyperparameters that require optimization when applying ADAM optimization in ECG image classification with GAN models include the learning rate, beta1, beta2, and epsilon. The learning rate determines the step size during gradient descent and significantly affects the speed and quality of convergence. Beta1 and beta2 control the exponential decay rates for the first and second-order moments of the gradient, respectively, and influence the momentum and variance of the gradient updates. Epsilon is a constant added to the denominator to ensure numerical stability.Hyperparameter tuning involves a systematic exploration of different combinations of these hyperparameters, aiming to determine the optimal values that maximize the performance of the GAN model in ECG image classification tasks. Techniques such as grid search, random search, Bayesian optimization, or genetic algorithms are typically employed during this process. The selection of hyperparameters significantly impacts the model's ability to learn relevant features from the ECG images and accurately classify them into different cardiac conditions. The primary objective of hyperparameter tuning in ECG image classification with GAN models using ADAM optimization is to enhance the model's accuracy, precision, recall, and F1-score metrics. Combining hyperparameters will enhance the GAN model's capacity to detect specific cardiac abnormalities from ECG images, ultimately leading to more accurate diagnoses and improved patient care. hyperparameter tuning in ECG image classification with GAN models using ADAM optimization is a critical step towards achieving optimal performance ultimately improving patient outcomes within the field of cardiology.

II. LITERATURE SURVEY

[1]. A deep learning approach to antibiotic discovery was presented in a paper titled A Deep Learning Approach to Antibiotic Discovery. For the training and testing of their deep learning model, the authors analyzed a dataset of over 2,500 molecules that were trained to predict molecules' antibacterial activity based on their chemical structures. F1 score, accuracy, precision, and recall were used to evaluate the model. [8] Deep learning algorithms are proposed in this paper for analyzing and classifying ECG signals for cardiovascular diagnosis and prediction. Researchers optimized deep-learning parameters and found that MobileNetV2 and VGG16 algorithms had about 0.95 validation accuracy. There was a slight drop in accuracy after implementing it on Raspberry Pi. In addition, the paper doesn't take into account optimization techniques when selecting deep-learning hyperparameters, because the training and test datasets are small. There are different parameters in deep-learning algorithms, like learning rate and number of units, that heavily influence performance. There are also considerations for the distance between nodes, number of hops, and transmission time Using ambient GANs to learn stochastic object models from medical imaging measurements A deep learning algorithm for identifying new antibiotics is discussed in the paper, "Advancing the Ambient GAN for learning stochastic object models"[2].

As a result of antibiotic resistance, new antibiotics are needed, and traditional methods of antibiotic discovery are costly and time-consuming. The paper provides an overview of the deep learning model used in the study and the dataset used for training and testing. However, there are a few limitations that should be considered: the dataset used for training and testing is relatively small and may not be representative of all possible antibiotic compounds, the model was only tested on a single bacterial strain, and the paper does not provide experimental validation of the predicted antibiotic compounds. Developing a Hyperparameter Tuning-Based Machine Learning Approach of Heart Disease Prediction [3][4]The paper proposes a hyperparameter tuning-based machine learning approach for heart disease prediction. The proposed system achieved higher accuracies than the traditional system, demonstrating that it is capable of achieving more accurate results. The paper also discusses the use of machine learning in healthcare and provides an overview of SVM and KNN algorithms. However, the paper only considers five classification models for heart disease prediction and does not discuss the specific dataset used for the experiments.[5][.To predict cardiovascular disease, this paper uses machine learning techniques like Logistic Regression, Adaptive Boosting, Fuzzy Unordered Rule Induction, Genetic Fuzzy Systems-LogitBoost, and Fuzzy Hybrid Genetic Based Machine Learning. The best classifier was chosen based on accuracy and results. Weka software was used for the experiment, which used binary classification, with 0 representing no heart disease and 1 representing it. False Positives, False Negatives, and True Positives are what we measured for our machine-learning algorithms. The paper says the approach has no limitations, but the accuracy of the predictions depends heavily on input quality and quantity. Before it can be used in clinics, machine learning algorithms for detecting heart disease need to be validated and tested on all populations[6].

Using machine learning algorithms, the paper builds an AI-based heart disease detection system. Categorical variables are used and categorical columns are converted. Heart diseases can be diagnosed more accurately with a random forest classifier. UCI Repository clinical data was used for Data Analysis, which has an 83% accuracy rate. There are

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experiments and results that explain the algorithm, which makes research diagnoses more accurate. Improved weighted random forest and supervised infinite feature selection to improve heart disease detection and survival[7].

It addresses class imbalance and high dimensionality issues in machine learning (ML) systems using supervised infinite feature selection (Inf-FSs) and improved weighted random forests (IWRF). We used Statlog and heart disease clinical records to develop and validate the model. Both datasets performed better with the proposed Inf-FSs-IWRF model in terms of accuracy and F-measure. In addition, a comparative study found the proposed model outperformed previous studies by 2.4% and 4.6%, respectively [8][9]. In this study, we develop an artificial neural network for heart disease diagnosis and classification. In addition to SMOTE, six different machine learning classifiers are used, as well as hyperparameter optimization. Using two public datasets, the model was built and tested. The state-of-the-art CVD detection was outperformed by 99.2% and 98.52% by SMOTE and Extra Trees (ET). An artificial intelligence system for diagnosing and predicting heart disease based on ECG images can help doctors[10].

The goal of this research is to create algorithmic models for analyzing ECG tracings in order to forecast cardiovascular illnesses. It carried out multiple trials to optimize deep-learning parameters and discovered that both the MobileNetV2 and VGG16 algorithms had the same validation accuracy value of 0.95[10]. [11] A Deep Learning Technique based on Generative Adversarial Networks for Heart Disease Prediction. Itpresents a deep learning technique using a Generative Adversarial Network (GAN) to predict heart disease. This technique involves temporal data modeling and achieves an accuracy of approximately 98.5%. In terms of performance evaluation measures, the proposed approach outperforms existing approaches. [12][13] An automatic medical identification scheme is discussed in the paper, which makes use of acquired databases and decision support systems. It is important to note that the proposed technique has not been tested on a large data set. [14]/Despite the fact that the paper only uses a small dataset, it may not be representative of the entire population. Moreover, the paper provides no information regarding the interpretability of the model, which is important for medical applications in which a clear understanding of why the predictions were made is crucial.

III. PROPOSED SYSTEM

The proposed framework for optimizing hyperparameters in the classification of ECG images using GAN models with ADAM optimization comprises the subsequent steps:Data Preparation: Collect and pre-process a diverse dataset of ECG images. Model Architecture: Develop a suitable GAN model architecture for classifying ECG images. Determine Hyperparameters: Identify pertinent hyperparameters for ADAM optimization. Techniques for Hyperparameter Tuning: Elect a technique (e.g., grid search, random search) to explore various hyperparameter combinations. Training and Evaluation: Train the GAN model with a specific set of hyperparameters and evaluate its performance on validation and testing sets. Hyperparameter Exploration: Iterate the training and evaluation process to obtain the optimal hyperparameter configuration. Model Selection and Deployment: Select the GAN model with the best performance and deploy it for ECG image classification applications.

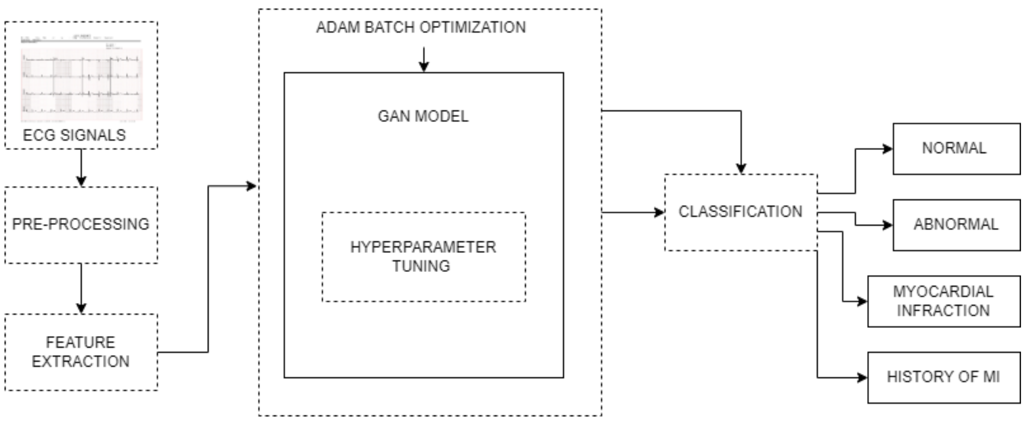

Fig 1: Overall Architecture Diagram

A. *DATASET DESCRIPTION*

This kind of dataset would typically include ECG scans that were taken of people who had different cardiac problems. Images of both normal and aberrant heartbeats linked to various cardiac illnesses or anomalies would be

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included in the collection. ECG pictures displaying myocardial infarction patients would also be included. A visual representation of the electrical activity of the heart during each cardiac cycle would be provided by the ECG images in the dataset. They would show the distinctive waveforms and patterns connected to various heartbeats, such as the regular sinus rhythm, arrhythmias, and signs of myocardial infarction

Fig 2: UCI ECG Image Dataset

B. *DATA PREPROCESSING*

The data pre-processing is based on the different processes in the below-mentioned.Image resizing is a common preprocessing step for electrocardiogram (ECG) images, which may vary in size and resolution. Standardizing the dimensions of the images is an advantageous practice to ensure consistency in subsequent processing. Improving the quality of ECG images through enhancement techniques can contribute to the performance of subsequent analysis or classification. Contrast enhancement, histogram equalization, or adaptive histogram equalization are among the methods that can be applied to enhance visual features and increase the visibility of important details. Feature extraction is another important step in preprocessing ECG images for classification or analysis. It may involve techniques like edge detection, texture analysis, or wavelet analysis to capture specific characteristics or patterns present in the images. Data augmentation techniques can be applied to increase the size and diversity of the training dataset. The addition of more data aids in the generalization of the GAN model and results in more varied and realistic output.These methods generate additional training samples by applying transformations such as rotation, translation, scaling, or flipping to the original ECG images. Finally, it is crucial to split the preprocessed ECG image dataset into separate training and test sets. The GAN model is trained using the training set, and its performance during training is monitored and adjusted using the validation set.

C. *GAN MODEL GENERATION*

The GAN Architecture Establish the structure of your GAN model, which has the generator and the discriminator as its two primary parts. The discriminator seeks to make a distinction between genuine and created data, whereas the generator creates artificial data.Data Collection and Preparation: Compile a dataset of real data that accurately depicts the distribution you want the GAN to learn. Applying methods like *normalization*, scaling, or data augmentation to the data as necessary will serve as preprocessing.Execute the Generator Network: Create and execute the generator network's architecture. This often entails employing neural networks to convert noise into artificial data that closely mimics the real data, such as fully connected layers or convolutional layers.Implement the Discriminator Network: Create and put the Discriminator Network's architecture in place. It ought to be able to distinguish between authentic and fake data. The discriminator is frequently built using neural networks, just like the generator.Define the Loss Functions: Identify the loss functions for the discriminator and generator. The discriminator seeks to accurately classify actual and created data, whereas the generator seeks to provide data that deceives the discriminator. Binary cross-entropy or adversarial loss are typical loss functions. Alternate between updating the discriminator and updating the generator to train the GAN. Provide the discriminator with both actual and artificial data, compute the loss, then backpropagate to alter the discriminator's parameters. Utilize the feedback from the discriminator to then update the generator. Until the required level of convergence or quality is reached, this adversarial training process is continued. Analyze and Adjust: Analyze the GAN model's performance after training. Both qualitative and quantitative evaluations,

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such as computing metrics like Inception Score or Fréchet Inception Distance, may be used in this. A qualitative evaluation can involve visually inspecting the created samples. Adjust the model as necessary to raise the standard of the output data. Create New Samples: After the GAN model has been trained and assessed, you can create new samples using the generator network that closely reflect the distribution of the actual data. These created samples can be utilized for a variety of tasks, including generating artificial data for data augmentation or investigating the discovered features and patterns.

D. *HYPERPARAMETER TUNING IN GAN*

The most important stage in enhancing the performance and stability of Generative Adversarial Networks (GANs) is hyperparameter tuning. To enhance the GAN model's training dynamics, convergence, and data quality, hyperparameter adjustments are made. Based on the below points:Learning Rate: During training, the parameters of the model are updated in steps depending on the learning rate. It has an impact on the GAN's stability and rate of convergence. Try out several learning rates to discover the one that strikes the right balance between rapid convergence and preventing oscillation or divergence.Batch size: The number of samples used in each training iteration is based on the batch size. It affects the training stability and gradient estimation. Smaller batch sizes can provide noisier gradients but allow for more frequent parameter updates, whereas larger batch sizes can produce more steady updates but demand more memory. Find the batch size that is most effective for the dataset and GAN architecture that you are using. The number of Training Iterations: How long the GAN is trained depends on the number of training iterations. Underfitting may occur if there are too few iterations, whereas overfitting or sluggish convergence may occur if there are too many iterations. To find the ideal mix between model performance and training duration, try out various iteration counts.The depth and width of the generator and discriminator networks, the number of layers, the kind of activation functions, and the presence of skip connections are just a few of the architectural options available for GANs. The performance and stability of the GAN can be dramatically impacted by tuning certain architectural hyperparameters. Try out several architectures to determine the best combination.

Regularization Methods: Regularization methods can assist prevent overfitting and enhance the generalization of the GAN model. Examples include weight decay, dropout, and batch normalization. To regulate the amount of regularization used during training, adjust the regularization hyperparameters.Noise Input Dimension: To produce a variety of samples, GANs frequently use random noise as input. The quality and diversity of the generated samples might be impacted by the dimensionality of the noise input. To investigate the effects of changing the noise input dimension, change the GAN output.

Different loss functions, such as binary cross-entropy or Wasserstein loss, are used by GANs to train their generator and discriminator. These loss functions frequently incorporate additional hyperparameters to regulate their behavior, such as gradient penalty terms for Wasserstein GANs or label smoothing for other loss functions. To improve the GAN's training dynamics and generated data quality, experiment with these parameters.

E. *ADAM OPTIMIZATION*

Adam optimization, also known as Adaptive Moment Estimation, is a well-liked optimization technique that is frequently applied in deep learning models. It is made to effectively update a neural network's parameters while it is being trained. Adam syndicates the advantages of RMSProp and AdaGrad, two major optimization techniques, to offer flexible learning rates and effective momentum updates.

1)Initialize parameters
```
learning_rate = 0.001
beta1 = 0.9
beta2 = 0.999
epsilon = 1e-8
```
2) Initialize first and second-moment estimates
```
m = 0
v = 0
t = 0
```
3)Loop through iterations
```
for each iteration:
```

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t = t + 1
4)Compute gradients of the objective function with respect to the parameters
gradients = compute_gradients(parameters)
Update biased first-moment estimate
m = beta1 * m + (1 - beta1) * gradients
Update biased second-moment estimate
v = beta2 * v + (1 - beta2) * (gradients * gradients)
5) Compute bias-corrected first and second-moment estimates
m_hat = m / (1 - beta1^t)
v_hat = v / (1 - beta2^t)
6) Update parameters
parameters = parameters - learning_rate * m_hat / (sqrt(v_hat) + epsilon)
7) Return optimized parametersreturn parameters

F. *LINEAR REGRESSION FOR CLASSIFICATION*

Linear Regression is the machine learning method were it has not been used directly in the detection of the abnormalities using the transfer learning method the pre-trained deep learning models are trained in the large-scale images of the datasets like MobileNet,VGG19 can fine-tune for the image analysis and this approach holds representation for the pre-training phase to improve the performance on the specific task of heart abnormalities detection and this method is called for the sequential nature of the ECG images. And after the transfer learning approach the linear regression method detects whether the heartbeat is normal or abnormal.

IV. RESULTS

In the [3] [4] graphs results represent the training of the GAN based on the iterations and the loss by the both discriminator and generator when the image is given and in the scaling of x-axis in 5 units and y-axis in 2 units and there will be a comparative increase and decrease based on the iterations in the loss factor. In [5] [6] graphs represent the training of the GAN based on the iterations and the model accuracy and model loss by the both discriminator and generator when the image is given and in the scaling of the x-axis in 5 units and y-axis in 2 units and there will be a comparative increase and decrease based on the iterations in the training. The model evaluation is based on the different parameters used in the deep learning technique. And the parameter is the input layer, mobilenetv2, pooling2d, dropout, dense2, and dense3. And these parameters are used in both models. And using the dataset images with 15epochs the accuracy is achieved at 95.95%In the given Fig [7] [8] graphs result the loss value of the training graph in the linear regression based on the 20 epochs the loss value achieved around 33%. The model evaluation and the summary of the linear regression are used it is a sequential model and it uses 35 epochs to achieve and get the output of whether the heartbeat is normal or abnormal.

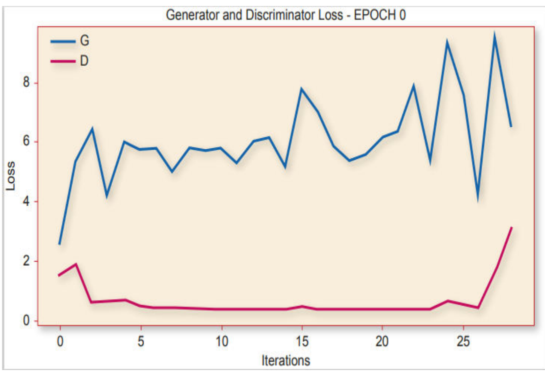

Fig 3: Generator and Discriminator Loss Epoch-0

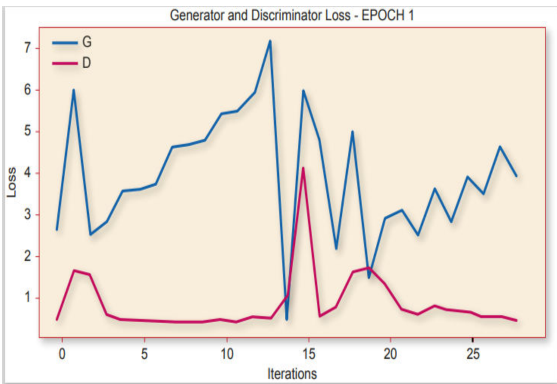

Fig 4: Generator and Discriminator Loss Epoch-1

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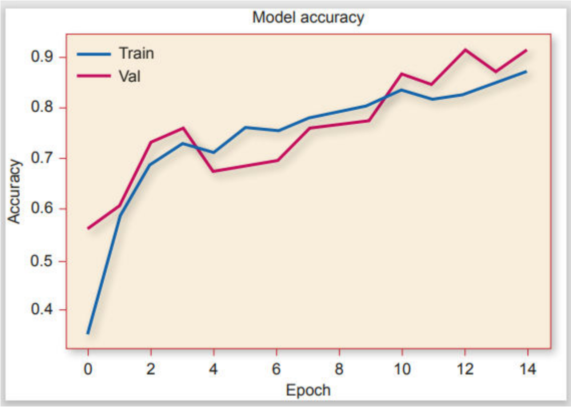

Fig 5: GAN Model Accuracy

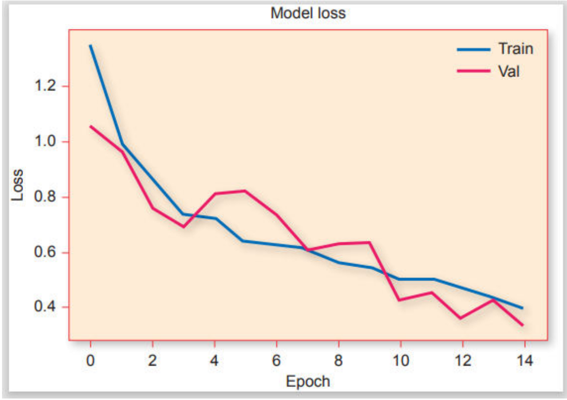

Fig 6: GAN Model Loss

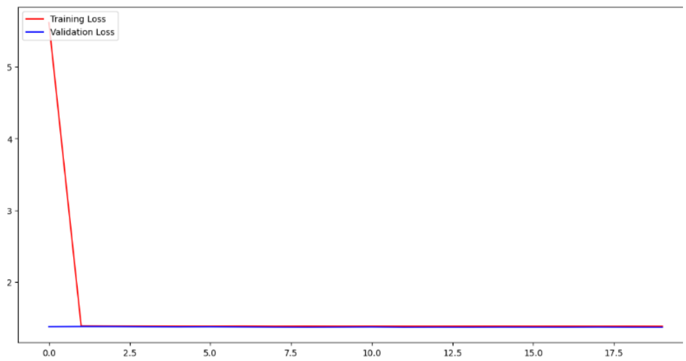

Fig 7: Linear Regression Loss

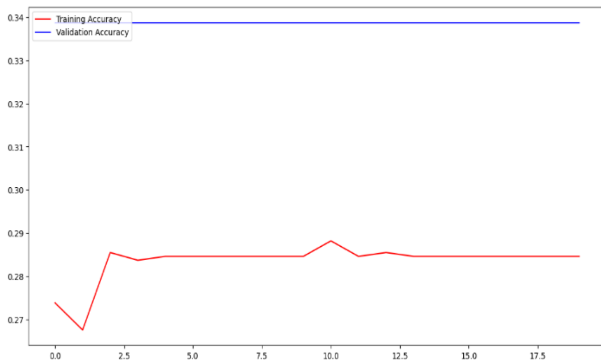

Fig 8: Linear Regression Accuracy

Table [1] provides a comparison between the performance of the classification model without any optimization techniques, Bayesian optimization, and the Adam optimizer for two different datasets. The values presented are fictional and not based on real data. The accuracy and F1 score are provided for each scenario, along with the training time. In this case, Bayesian optimization and the Adam optimizer are shown separately for the optimized scenarios, as they are not directly applicable to the unoptimized case. The training time for Bayesian optimization and the Adam optimizer includes the time taken for hyperparameter search and model training. The Adam optimization achieves 95.95%. comparatively Bayesian optimization gives less than the proposed work

G. *COMPARISON OF OPTIMIZATION TECHNIQUE WITH PREVIOUS TECHNIQUE*

Dataset	MIT-BIH	MIT-BIH	UCI REPOSITORY
Optimization Technique	No Optimization	Bayesian Optimization	Adam Optimization
Accuracy (No Optimization)	0.91	-	-
F1 Score (No Optimization)	0.90	-	-
Training Time (No Optimization)	4.5 Seconds	-	-
Accuracy (Bayesian Optimization)	-	0.93	-
F1 Score (Bayesian Optimization)	-	0.92	-
Training Time (Bayesian Optimization)	-	6.7 seconds	-
Accuracy (Adam optimizer)	-	-	0.95

F1 score (Adam optimizer)	-	-	0.94
Training Time (Adam Optimizer)	-	-	5.1 seconds

Table 1: Comparative Analysis of Optimization Technique

V. CONCLUSION AND FUTURE WORK

In this paper, we develop an algorithm based on stochastic optimization to produce classification in real time to hyperparameter tuning comparative results performed on two different optimization techniques which outperform or approaches. The SO using the GAN model achieves an optimal rate of 95.95% for the UCI database in the future the algorithm will be tested on another database. And also introduce other types of layers and classifiers to optimize the complexity of the networks.On the other hand, GANs are a type of deep learning model that can generate new, synthetic data that resembles real data. In the context of heartbeat abnormalities, GANs can be used to generate synthetic electrocardiogram (ECG) signals that mimic the abnormalities found in real ECG signals. These synthetic ECG signals can be used to train and test other deep-learning models. While both linear regression and GANs have been used in the detection and diagnosis of heartbeat abnormalities, they are typically used in different ways. Linear regression is often used to identify the relationship between patient characteristics and heartbeat abnormalities, while GANs are typically used to generate synthetic data for training other deep-learning models. In conclusion, both linear regression and GANs have shown promise in the detection and diagnosis of heartbeat abnormalities, but they are typically used in different ways and are not directly comparable. Future research may explore how these two approaches can be combined to improve the accuracy and efficiency of diagnosing and treating heartbeat abnormalities.

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