Section:

Original Research Article

HEART DISEASE PREDICTION FOR A CLOUD-BASED SMART HEALTHCARE MONITORING SYSTEM USING GANS AND ANT COLONY OPTIMIZATION

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Received : 18/10/2024
Received in revised form : 12/12/2024
Accepted : 27/12/2024

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DOI: 10.70034/ijmedph.2024.4.223

Source of Support: Nil,
Conflict of Interest: None declared

Int J Med Pub Health
2024; 14 (4); 1210-1220

ABSTRACT

As one of the leading causes of death globally, early and accurate diagnosis of heart disease is a major concern in the healthcare sector. A cloud-based Smart Healthcare Monitor System for Heart Disease prediction using GAN with ACO has been developed in this study. GANs are used in the synthesizing of high-quality balanced datasets to mitigate the imbalance data issues and in turn improve prediction accuracy. Feature selection and optimization are implemented using ACO to reduce the computational overhead and eventually increase the efficiency of the system. The cloud-based architecture is suitable for real-time execution and remote monitoring in order to provide early detection of heart disease. Experimental results show the proposed method achieves higher sensitivity, specificity, and accuracy than existing methods. The implementation of this system is a guaranteed scalable solution for today's healthcare systems to improve outcomes and optimize resources. The intelligent healthcare system developed for continuous monitoring and prediction of heart disease risk based on GAN and ACO outperforms existing smart heart disease prediction systems at 99.86% accuracy, precision 98.9%, sensitivity 98.8%, specificity 98.89%, and F-measure 98.86%.

Key Words: Heart disease prediction, cloud-based smart healthcare, Generative Adversarial Networks (GANs), Ant Colony Optimization (ACO), smart healthcare systems.

INTRODUCTION

Morbidity and mortality due to heart diseases are on the rise, making it one of the most common causes of death globally, mandating innovative health care alternatives for screening at an early stage as well as treatment. New cloud-based smart healthcare monitoring systems are providing innovative solutions to these challenges using advanced techniques that include GANs and ACO algorithms, not only enhancing the predictive accuracy but also being utilized in resource optimization.

Some of the biggest concerns in healthcare are around streaming or real-time data processing, and that's why a lot of modern healthcare systems have some kind of integrated EDA framework already, but most probably on top of cloud-based services for seamless collection, storing, and analysing Khan et al. develop more sophisticated paradigms for federated learning.[24] Internet of Learning (IoL),[1] on the other hand, integrates IoL frameworks to maintain data privacy yet provide capability for predictive modeling in cloud-based systems. The Smart-Monitor system, finally to mention one using IoT-based healthcare solutions and deep learning approaches, revealed an impressive enhancement in patient monitoring profiles.[2]

Predictive modeling is one of the core parts of these systems. Current research has demonstrated that ensemble deep learning along with feature fusion mechanisms shown by Farman et al. (2018) can significantly improve the recognition performance of SSL and RL-based processes,[5,3] can predict heart disease well and be robust to data anomalies. Recently, GAN-based frameworks for synthesizing privacy-preserving data have transformed the clinical decision-making aids in virtual consultations. One illustrative paper is Gong et al.[4] Such advances complement the existing research into privacy-preserving technologies for healthcare systems, as reported by Das et al.[5]

Cloud-edge computing frameworks also have embedded benefits that improve the performance and reliability of systems. For example, Yu et al. The hybrid architecture named Edge CNN enables continuous learning from the IoT devices, and Changala et al,[7] illustrated the possibility to predict SC from LSTM and can generate predictive models using GANs in health service delivery. These examples highlight the emergence of hybrid and edge computing platforms in healthcare analytics.

Deep learning paradigms furthermore played an important role in risk stratification and disease prediction. Bhagawati et al. Methods A hybrid deep learning model was implemented for cardiovascular risk stratification,[8] demonstrating applicability to Canadian trial data and precision healthcare. Similarly, Taylor et al. The potential of cloud-based analytics for evaluating the risks advances by highlighting that Maheswaren et al,[9] also highlighted global predicted cardiovascular risks over assess, and Johnson et al,[10] proposed a solution to handle efficient resource allocation in medical cloud environments.

Privacy as well has stimulated the investigation of novelty in healthcare system architecture, like,[11] which surveys privacy-preserving cloud frameworks. A good example that complements these innovations is the real-time cardiovascular monitoring model,[12] using cloud-edge computing by Wilson. This ecosystem of predictive algorithms has been bolstered by machine learning models specific to cardiac risk prediction, with Garcia,[13] and Davis,[18] focused on optimizing heart disease detection.

However, improvements in the field of scalable cloud solutions for medical image processing,[14] and distributed deep learning schemes to perform cardiac analysis,[15] further enabled the integration of intelligent analytics into healthcare systems. The studies by Kim and colleagues were similar in their backlog of work examples: White's research, which is guaranteed for scalability and reliability, but also examining the efforts source open to develop cloud-native calm-scene architecture,[16] or other data organization efficiency that will not quite mediate medical clouds exclusively.

The application of GANs and ACO to heart disease prediction models reflects this move toward adaptive, intelligent systems they underscore. Using improved deep learning frames,[20] and cascaded convolutional neural networks, these systems have broken through the ability to judge ECG signal quality in a markedly precise way,[21] as well as forecasting cardiac disease. Cloud-based platforms for the Internet of Medical Things (IoMT) are getting more and more important to enable quick diagnosis, in combination with resource saving.

H. Ghayvatet al,[22] Healthcare big data (HBD) is crucial for medical stakeholders to analyze and access patient health records, but it often faces issues like latency, computations, single-point failures, and security risks. To address these issues, a joint solution is proposed, integrating a blockchainin-based confidentiality-privacy scheme called CP-BDHCA. This scheme operates in two phases: HCA-ECC, a digital signature framework for secure communication, and HCA-RSAE, a two-step authentication framework. The scheme is compared against existing HCA cloud applications in terms of response time, average delay, transaction and signing costs, signing and verifying of mined blocks, and resistance to DoS and DDoS attacks. The proposed scheme outperforms traditional schemes like AI4SAFE, TEE, Secret, and IIoTEED, with lower response time and improved accuracy.

Amir Rehman et al,[23] Digital technologies offer significant opportunities for improving healthcare services, particularly in cancer diagnosis. However, patient data privacy remains a concern. A secure FedCSCD-GAN framework is proposed for clinical cancer diagnosis, leveraging distributed data sources to improve accuracy while maintaining security measures. The system uses quasi-identifiers as independent attributes and confidential information (CI) as confidential information. Differential privacy anonymization is performed on attributes, and the resulting data is mixed with CI attributes. The Cramer GAN is trained using Cramer distance for efficiency and privacy assessment. The proposed architecture achieves diagnosis accuracy of 97.80% for lung cancer, 96.95% for prostate cancer, and 97% for breast cancer. This paradigm has the potential to transform healthcare and improve patient outcomes globally.

Jimmy Ming-Tai Wu et al,[24] The issue of protecting private information in identifiable health datasets, particularly during the pandemic, has become a trade-off. Privacy preserving data mining (PPDM) is crucial to address this issue, but mining information in such datasets is complex. This article presents an Ant Colony System to Data Mining algorithm that uses multi-threshold constraints to secure and sanitize patent records in different lengths, applicable in real medical situations. The algorithm not only hides sensitive information but also retains useful knowledge for mining usage in the sanitized database.

Purandhar, N., et .al,[25] The healthcare industry generates vast amounts of data daily, including clinical, health history, and genetic information. Real-time monitoring and data analysis are crucial for providing proper medications and reducing issues. Machine learning models have been introduced to manage big data, but their performance is hindered by data integrity, diversity, and inconsistency. This research uses fuzzy c means clustering and generative adversarial network to achieve maximum classification accuracy in healthcare data clustering and classification. The model outperforms existing techniques like support vector machine, decision tree, and random forest algorithms, achieving 97.8% and 98.6% accuracy, respectively.

In this paper, we contribute to understanding the synergies between GANs and ACO using a cloud-based healthcare monitoring system for heart disease prediction. This framework scaffolds the technique to achieve convergence with state-of-the-art methodologies and incorporates the latest advancements, which could create a contribution base for future progress in smart healthcare systems.

Objectives

- High sensitivity and specificity Heart Disease Prediction Using Advanced Machine Learning Techniques
- The imbalanced datasets bring difficulties for machine learning in numerous medical data, such as addressing skewed distributions, use GANs to synthesis balanced datasets.
- Utilize ACO for Feature Selection Use the ACO algorithm to select the best features, which dominate the computational cost and increase efficiency.
- Real-time monitoring is integrating the prediction model into a cloud-based architecture for real-time healthcare monitoring and remote accessibility.
- A system design capable of handling large-scale healthcare data, ensuring the ability to scale with diverse types of patient populations

Problem Statement

Heart disease is a serious global health problem and an important cause of mortality, killing 17.9 million people annually. Timely detection and action are required, although in practice these cannot be ensured due to imbalanced datasets, limited computational resources, or simply because of the absence of monitoring mechanisms that can exterminate it. Conventional predictive models have difficulty with these requirements, resulting in low accuracy and a delay of diagnosis. The growing need for remote and real-time healthcare services necessitates the development of an efficient cloud-based system capable of managing large amounts of patient data. Even with the use of technologies like stochastic gradient descent or drop-out, many existing systems struggle to produce balanced data sets and feature subset optimizations, which affects their performance capabilities.

To address these issues, this study proposes a cloud-based intelligent healthcare monitoring system that combines GANs to augment the data and ACO for optimizing features. The system is built to enable highly accurate, real-time heart disease prediction, resulting in better patient outcomes, which leads to the breakthrough of health monitoring.

MATERIALS AND METHODS

2.1 Data Collection

in this experiment, the prediction performance of different classification algorithms has been evaluated using the Stat Log Heart Disease dataset provided by the UCI Machine Learning Repository.[13,14] We analysed data from 270 instances of which 120 (44.4 % true cases) samples are the presence and 150 samples (55.60% false cases) are the absence of heart disease. In the following, we provide the details of the final set of attributes its choose for the data prepossessing such as,

Age 2) Sex (This is the binary attribute that can assume value 1 for female and 0 for male) 3) Chest pain type (categorical with 4 values) 4) Resting blood pressure 5) Serum cholesterol in mg/dl (continuous) 6) Fasting blood sugar > 120 mg/dl (binary) 7) Resting electrocardiographic results (categorical with 3 levels) 8) Maximum heart rate achieved 9) Angina provoked by exercise (binary) 10) The slant of the peak exercise ST segment (0-3 levels) 11) Number of major vessels (categorical with 4 levels) coloured by fluoroscopy 12) Thala: 3 = normal; 6 = fixed defect; 7 = reversible defect 13) Old peak = ST depression provoked by workout qualified to rest.

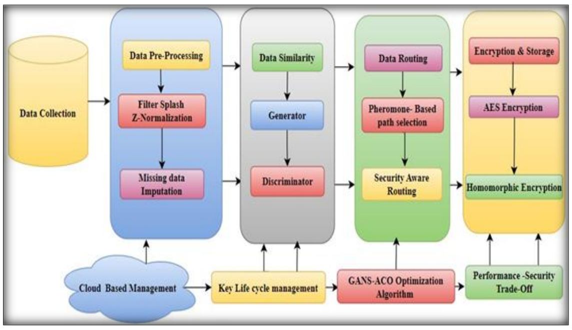

Figure 1: Proposed work flow with healthcare data in a cloud environment

1.Input Layer: Health Data (Kaggle Source)

This is the entry point of the system, where health data from a large metropolis, sourced from the Kaggle database, is input. The quality and diversity of this input data are crucial for the effectiveness of the entire system. It may include various types of health records, patient information, and medical data. This data serves as the foundation for all subsequent processing and analysis.

2. Data Pre-processing

The main objective of data pre-processing is to standardize and normalize healthcare data to prepare it for further analysis. In healthcare data, various features may have different scales and units, and there can be outliers or extreme values that skew the analysis. Standardization and normalization help ensure that the data is in a consistent format, which improves the performance of machine learning models.[26]

In this proposed work the Filter Splash Z normalization method is applied to scale the data and remove outliers. This technique uses the Z-score normalization formula but introduces a threshold, α\alphaα, to handle extreme outliers. The idea is to standardize the data points and discard extreme values that are too far from the mean, thereby improving data quality and reducing noise in the analysis.[27]

New Equation: The Filter Splash Z normalization is expressed as

$$z_{\text{Z normalization}} \begin{cases} \dfrac{X-\mu}{\sigma} & if \left|\dfrac{X-\mu}{\sigma}\right| > \alpha \\ 0 & Otther\ wise \end{cases}$$

Her, X is the original data value,μ is the mean of the data set.σ is the standard deviation of the α is the threshold parameter, which helps identify extreme outliers. Data set.

1. **Normalization**: The data is first normalized by computing the Z-score$\frac{X-\mu}{\sigma}$, which rescales each data point based on its distance from the mean in terms of the number of standard deviations.
2. **Outlier Removal**: If the absolute value of the Z-score exceeds a certain threshold α the data point is considered an outlier and removed (set to zero). This prevents extreme values from unduly influencing the analysis.
3. **Threshold** α: The parameter α defines the outlier detection boundary. A typical value for α\alphaα might be between 2 and 3, depending on how strict the normalization needs to be. This parameter allows for flexibility in identifying and excluding extreme data points.

Standardization is beneficial since it improves the stability of machine learning algorithms by rescaling all features to a common scale for comparison. Elimination of Outliers in removes excessive values that can skew model performance in an efficient manner. Robustness by managing scaling and outlier detection in a single step, the analysis becomes more robust. In order to enable more precise and significant analysis in later phases of the workflow, this approach guarantees that the healthcare data is clean, standardized, and free from extreme outliers.

3. GANs for Data Similarity

The objective of using Generative Adversarial Networks (GANs) for data similarity is to ensure data correctness by generating synthetic data that closely resembles the distribution of the real data. This technique helps to validate the data while reducing computational costs associated with data verification in large datasets. By using GANs, we can create data that is indistinguishable from real data, which can be used to assess the similarity between generated and original data [28].

GANs consist of two components:

1. Generator (G)**:** This model generates synthetic data samples from a random noise vector based on the learned data distribution.
2. Discriminator (D)**:** This model evaluates whether a given data sample is real or generated. It tries to distinguish between real data and synthetic data generated by GGG.

In traditional GANs, the Generator and Discriminator engage in a two-player minimax game where the Generator tries to produce data that is as realistic as possible, and the Discriminator tries to accurately distinguish real data from fake data.

However, to compute data similarity and ensure data correctness, we extend the standard GAN loss function to include a similarity term. This similarity term measures how closely the generated data resembles the real data, and encourages the GAN to generate data that has not only visual or structural resemblance but also mathematical similarity to the real data.

The extended GAN loss function that includes a similarity term is expressed as:

$$Min_G Max_D V(D,G) = E_{x\sim} pdata(x)[logD(x)] + E_{Z\sim} p_z(z)\big[\big(1 - logG(z)\big)\big] + \lambda.SZ(x) \qquad (2)$$

G(z) is the synthetic data generated by the Generator from random noise z.D(x) is the Discriminator'sprediction on whether a given sample xxx is real or generated,$E_x pdata\ (x)$denotes the expectation over real data samples x.$E_{Z\sim}p_z(x)$denotes the expectation over the random noise vectorz, which is used by the Generator to create synthetic data. $S(G(Z)x)$is a similarity measure between the generated data $S(G(Z)x)$is and the real data x.λ is a weighting factor that controls the importance of the similarity term in the overall loss function. The extended GAN loss function with a similarity term is a powerful way to generate synthetic data that not only fools the Discriminator but also closely resembles the real data. By ensuring data similarity, the framework can maintain data integrity, reduce computational costs, and improve the efficiency of large-scale data processing tasks, especially in sensitive fields like healthcare and financial services. The similarity term allows the GAN to learn more precise data distributions, making the model highly effective for applications that require accurate and realistic data generation.

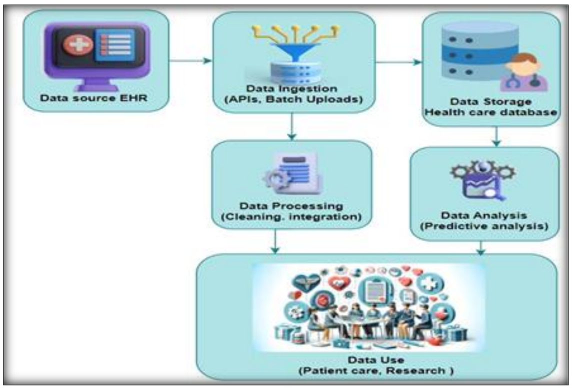

Figure 2: Health care flow work with GAN Block diagram

4.ACO for Data Routing

Ant Colony Optimization (ACO) is utilized in cloud data routing to enhance data transmission by identifying the most effective and secure routes. This approach, which emulates ant behavior in finding optimal paths, seeks to boost both efficiency and security in cloud networks. The primary challenge lies in striking a balance between efficiency (such as reducing latency or transmission expenses) and security (including safeguarding data confidentiality and integrity). ACO is a nature-inspired optimization algorithm that draws from the way ants locate the shortest route between their nest and food. In data routing applications, each "ant" symbolizes a potential data packet path from source to destination. As these ants explore various routes, pheromone trails build up on the most favourable paths over time, encouraging subsequent ants to use these routes more frequently.

To apply ACO to cloud data routing, the conventional ACO pheromone update rule is modified to incorporate a security component. This adaptation ensures that the system not only identifies the most efficient route but also takes into account security factors such as encryption strength, path vulnerabilities, or susceptibility to attacks. The pheromone update rule in ACO is modified to include a security factor as follows:

$$\tau_{ij}(T+) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij} + \gamma.S_{ij}$$

(3)

Where ,$\tau_{ij}(t)$ is the pheromone level on path at time(I,j) t.ρ is the evaporation rate of pheromones, which models the natural dissipation of pheromone strength over time. This prevents suboptimal paths from retaining high pheromone levels indefinitely.$\Delta\tau_{ij}$ is the pheromone deposit contributed by the ants that successfully used the path (i,j) This reinforces the attractiveness of this path if it was part of a successful or optimal route.S_{ij} is the security measure for path (i,j) which accounts for the security attributes of the path, such as encryption strength, likelihood of data leakage, or vulnerability to attacks.γ is a security weighting factor that controls the influence γ of the security measure S_{ij}in the overall pheromone update process. A higher value of gives more importance to security in the routing decision, while a lower value focuses more on efficiency.

By integrating Ant Colony Optimization (ACO) with a security factor, the proposed routing framework optimizes data transmission in cloud environments, addressing both efficiency and security concerns. The new equation allows the routing algorithm to find the optimal paths for data transmission while taking into account potential security risks. This leads to a more robust and secure data routing strategy, which is crucial for cloud-based applications dealing with sensitive data, such as healthcare, financial services, and IoT systems.

5. Cloud-Based Management (Key Optimization)

The objective is to effectively handle and examine healthcare Big Data within a cloud-based system while optimizing key management to strike an appropriate balance between security measures and operational efficiency. Effective key management is essential in cloud environments to safeguard sensitive healthcare information while reducing computational burden. The suggested approach introduces a key optimization technique that equilibrates security and performance based on two quantifiable factors: the strength of security measures and system efficiency. This approach aims to identify the ideal encryption key that provides robust protection while maintaining high-level performance in cloud-based data handling, retrieval, and storage operations.[29] The optimization of the encryption key KKK can be expressed as:

$$k_{Output} = \arg max_k\,(\alpha.S(k)\beta.P(k)$$

(4)

wherek_{Output} is the optimal key that balances security and performance.$S(k)$ is a security measure for the key K, which could represent factors like encryption strength, resistance to attacks, or length of the key. $P(k)$ is a performance measure for the key K, capturing metrics such as encryption speed, system resource usage, and latency. α and β are weighting factors that control the importance of security and performance, respectively. These parameters can be adjusted depending on the specific needs of the cloud environment. Thekey optimization strategy presented here provides a balanced approach **to** securely managing healthcare Big Data in a cloud environment. By incorporating both security and performance measures, and using the weighting factors α and β this method ensures the selection of an optimal encryption key that meets both security and efficiency requirements. This approach is highly applicable in healthcare and other industries where both data protection and system performance are critical for operational success.

3.1. Generative Adversarial Networks (GAN) Layer in Healthcare

Introduced by Ian Good fellow and his team in 2014, Generative Adversarial Networks (GANs) represent a category of machine learning systems. These frameworks comprise two neural networks a generator and a discriminator that undergo concurrent training through competitive processes. The generator's role is to produce artificial data samples, while the discriminator's task is to assess these samples against genuine data, striving to differentiate between the two.[30]

Generator Network: The generator, denoted as G, accepts random noise z as input and creates data samples G(z). Its objective is to reduce the likelihood of the discriminator accurately identifying the generated data as artificial.

.Loss Function $Min_G V(G,D)$:$E_{Z\sim}p_z(x)\left[\log\left(1-D(z)\right)\right]$

(5)

Discriminator Network: The discriminator, D, receives both real data xx and generated data G(z) as input. Minimize the probability that the discriminator correctly identifies the generated data as fake

Loss Function : $Min_G V(G, D)$: $E_{x\sim p_{data}}(x)\left[\log\left(D(x)\right)\right]E_{Z\sim p_z}(x)\left[\log\left(1 - D(z)\right)\right]$
(6)

Adversarial Training: The generator and discriminator are trained in a zero-sum game, where the generator aims to fool the discriminator, and the discriminator aims to correctly classify real and fake data.[31]

Combined Objective: $Min_G Max_D V(G, D)$
(7)

Application in Healthcare Big Data

- ***Data Augmentation*:** GANs can generate synthetic healthcare data that mimics real patient data, which is useful for augmenting datasets, especially when dealing with rare conditions or small sample sizes.
- ***Privacy Preservation*:** By generating synthetic data, GANs help in sharing healthcare data without compromising patient privacy, as the synthetic data does not directly correspond to real individuals.
- ***Anomaly Detection***: GANs can be used to identify anomalies in healthcare data by training the discriminator to recognize unusual patterns that deviate from the norm.
- ***Data Imputation:*** GANs can fill in missing data points in healthcare datasets, improving data quality and completeness.

Handling Healthcare Big Data:

GANs can handle large volumes of data, making them suitable for Big Data applications in healthcare. The adversarial training process allows GANs to efficiently learn complex data distributions, which is crucial for modeling diverse healthcare datasets. Integration with Cloud Computing: GANs can be deployed in cloud environments to leverage computational resources, enabling real-time data processing and analysis Hence the GAN layer in the secure cloud-based management of healthcare Big Data plays a pivotal role in enhancing data quality, privacy, and utility. By generating realistic synthetic data, GANs facilitate advanced data analysis while maintaining patient confidentiality, making them an invaluable tool in modern healthcare data, management.

3.4. Ant Colony Optimization (ACO) in Healthcare Big Data

ACO,[31] a nature-inspired algorithm created by Marco Dorigo in 1992, simulates ant foraging behavior to identify optimal routes between their nest and food. This technique has found widespread application in optimization challenges, including healthcare big data, where it assists with tasks such as feature selection, classification, and resource allocation**.**

3.4.1.ACO in Feature Selection for Healthcare Big Data

In healthcare big data analysis, feature selection plays a crucial role. This process involves choosing relevant attributes from extensive datasets to enhance model efficiency and decrease computational demands. In the healthcare context, this could entail identifying key variables (such as biomarkers or clinical indicators) from electronic health records (EHRs) or data collected by wearable devices to forecast diseases or enhance treatment strategies.

Mathematical Formulation of ACO in Feature Selection

ACO functions on the principle of pheromone trails, where each artificial ant constructs a solution based on the pheromone levels left by previous ants. In the context of feature selection, individual ants represent potential feature subsets.

Ant Movement Rule: Ants choose features probabilistically, guided by pheromone trails and heuristic information (such as feature significance or relevance scores).

$P_{ij}(t) = \frac{\tau_{ij}(t)^{\alpha}.\eta_{ij(t)}{}^{\beta}}{\sum_{k\epsilon f}\tau_{ik}(t)^{\alpha}.\eta_{ik}{}^{\beta}}$
(8)

Here, $P_{ij}(t)$ and $\tau_{ij}(t)$represents the pheromone concentration on edge (j) at time (t), η_{ij}(t)indicates the heuristic attractiveness (such as feature significance value), α and β regulate the impact of pheromone and heuristic data, respectively and F denotes the group of potential features

Pheromone Trail Modification: Once all ants have completed their feature subset construction, the pheromone pathways are adjusted to strengthen effective solutions.

$\tau_{ij}(T +) = (1 - \rho)\tau_{ij}(t) + \Delta\tau_{ij} + \gamma.S_{ij}$
(9)

Here, ρrepresents the rate at which pheromones evaporate (0 < ρ < 1), preventing excessive accumulation of pheromones.$\Delta\tau_{ij}$(t) is the pheromone deposit, which depends on the quality of the solution (fitness function).

In the realm of healthcare big data, evaluating fitness functions typically involves measuring the effectiveness of selected features in predicting health outcomes or their classification accuracy. The application of Ant Colony Optimization (ACO) in healthcare extends beyond feature selection, encompassing the enhancement of various operational aspects such as resource distribution, appointment planning, and patient flow management within medical facilities. For instance, ACO can be employed to streamline the allocation of critical medical equipment like ICU beds and ventilators, with the aim of reducing waiting periods and preventing resource scarcity.

$Minimize \sum_{i=1}^{n}(C_{i,}D_{i_,})$
(10)

Here, $C_{i,}$The expense associated with $D_{i_,}$ assigning resource i corresponds to the requirement for resource i.

The goal is to minimize overall expenses while satisfying demand requirements. Ant Colony Optimization (ACO) can discover ideal or close-to-ideal solutions by mimicking the behavior of multiple ants exploring various allocation possibilities and adjusting pheromone trails according to the effectiveness of the solutions found.

The following outlines the sequential steps of the process, divided into distinct segments:

Step 1: Data Acquisition

Healthcare information, encompassing electronic health records (EHRs), data from wearable devices, genetic information, and more, is gathered. Various data sources are consolidated into a comprehensive big data repository. This includes information such as patients' medical histories, results from laboratory tests, and information collected by sensors.

Step 2: Data Preparation

The raw data undergoes preparation processes, including cleansing, standardization, and feature encoding. These procedures involve addressing missing information, standardizing data formats, converting categorical variables into numerical representations, and adjusting feature scales to ensure uniformity.

Step 3: Feature Selection Using ACO

Ant Colony Optimization (ACO) is utilized to identify and choose relevant features from the extensive healthcare dataset. This process aims to enhance the performance of the model by selecting the most pertinent information.

Equations for Ant Movement and Pheromone Update:

Ant Movement Rule:

$$P_{ij}(t) = \frac{\tau_{ij}(t)^{\alpha}.\eta_{ij(t)}{}^{\beta}}{\sum_{k\epsilon f}\tau_{ik}(t)^{\alpha}.\eta_{ik}{}^{\beta}} \qquad (11)$$

Pheromone Update Rule:

$$\tau_{ij}(T+) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij} + \gamma.S_{ij}$$
(12)

Step-4. GAN-Based Data Augmentation

Employing GANs for artificial data creation. Generative Adversarial Networks produce synthetic healthcare information to supplement existing data. This technique aids in balancing datasets, especially when dealing with uncommon medical conditions.

Step 5. Model Training

Developing machine learning algorithms. Various models (such as CNNs, RNNs, or combined structures) are educated using both authentic and GAN-created synthetic data to forecast health results or categorize illnesses.

Step 6. Evaluation of Model

Assessing model effectiveness through performance indicators. The trained algorithms are examined using metrics including classification accuracy, precision, recall, and F1-score, with a focus on predictions such as disease identification, treatment enhancement, or patient outcome forecasting.

Step 7. Optimization Feedback Loop

ACO pheromone updates and GAN modifications. The model's performance guides ACO in refining the feature selection process by altering pheromone trails, while GAN parameters are adjusted to produce improved synthetic data.

Step 8. Deployment

Implementing the refined healthcare model. The final algorithm is put into operation for real-time medical applications, including personalized treatment strategies, automated diagnostics, or hospital resource allocation.

4. Result Analysis

The proposed system for heart disease prediction integrates Generative Adversarial Networks (GANs) with Ant Colony Optimization (ACO) to enhance predictive accuracy and optimize computational efficiency. This section presents an in-depth analysis of the system's performance based on various evaluation metrics and comparative studies against existing methodologies.

The confusion matrix provides useful information about the performance of a classification model, as visualized in figure 3 by classifying the predictions into four categories, namely True Negatives (TN), False Positives (FP), False Negatives (FN), and True Positives (TP).

True negatives (TN is 195) represent the number of records in which a person with no heart disease was indeed predicted negative. The most typical example for this type of prediction would be when a healthy person is predicted to not have heart disease. That means the model follows the protocols for false positives so that people who are non-disease cases are not being flagged as such. A high TN value indicates that the system is reliable to avoid false alarms and unnecessary follow-ups in healthy patients.

False positives (FP) is 5 (the system incorrectly classifies a positive non-heart disease case such as that of a healthy person. A healthy person is misdiagnosed with heart disease, for instance. While these errors are of less concern than false negatives, it can still lead to unneeded panic, as well as further, potentially unneeded, medical work-ups or interventions. Reducing false positives is key to alleviating the burden on both healthcare systems and individuals.

False negatives (FN) is 3 are instances when the model does not detect heart disease, despite its presence, and negatives it incorrectly. For example, a heart disease patient has been incorrectly classified as a healthy person. They are an especially serious class of mistakes because they can postpone needed medical intervention, resulting in dire consequences for the patient involved. Low FN rates are sensitive to keeping the system reliable to detect all real heart disease cases.

True positives (TP) is197 actual yes, predicted yes: people whom the model correctly identifies as having heart disease. An example is the system accurately diagnosing someone with heart disease. These high TP values are significant for the performance of the model, as it should properly detect cases of heart disease. This indicates increasing trust in the predictive power of the system and its utility in designing timely medical interventions.

In summary, the confusion matrix highlights the strengths of the classification model, particularly its ability to balance the detection of heart disease (TP) while minimizing false alarms (FP) and missed diagnoses (FN). High TN and TP values underscore the system's accuracy and reliability, making it a robust tool for clinical decision-making.

The ROC curve is one of the key visualization tools for estimating the classification power of a model (Figure 4). The ROC curve lets us visualize a model's ability to differentiate between positive and negative cases, plotting the True Positive Rate (TPR) against the False Positive Rate (FPR) at different decision thresholds. This information is summarized in the AUC, a single metric with larger values indicating better discriminators.

The AUC scores illustrate the relative superiority of the risk model assessed here. As illustrated in Table 2, the GAN-ACO system exhibited the best performance with an AUC of 0.987, highlighting its outstanding capability in balancing sensitivity (True Positive Rate) and specificity (True Negative Rate) compared with the other models. This result shows that GAN-ACO is efficient enough to detect both positive and negative cases more accurately than all other models. In comparison, SVM had AUC = 0.915, which by itself is acceptable; however, it still shows the constraints of SVM in dealing with complex non-linear relationships along with imbalanced data. While not quite as accurate as GAN-ACO (0.948), the Random Forest (RF) still showed a promising AUC of 0.932, falling after SVM but proving how well RF could generalize to training data. The AUC plot for CNN is 0.954, which makes it do better than previous methods but not as good as GAN-ACO, and the final note here is that the GAN-ACO system supported superior optimization.

GAN-ACO had significant improvements of AUC over traditional models: SVM: A 7.87% improvement, which is a remarkable increase, especially for complex scenarios where SVM fails. RF: You achieve a 5.90% gain, which shows that compared to ensemble-based methods that can capture the complexities of data, the GAN-ACO system is quite good. CNN (3.46% improvement): emphasizing the adaptive and optimized architecture of GAN-ACO, which has more edge over the semi-parametric, robust but non-adaptable architecture of Can for all the thresholds, higher values of TPR were obtained by the GAN-ACO model. This means that the performance of the model in terms of detecting positives as well as false negatives is high, and reliable detection of critical conditions. The FPR of GAN-ACO was significantly less than SVM, RF and CNN. This emphasizes its ability to avoid false positives, which is a very important consideration for applications that would incur a large cost if false positives occur.

The ROC curve corroborates the GAN-ACO system as the best performer in the classification tasks. High AUC score and significant improvement over SVM, RF, and CNN thus establish the strong competency of CNBClassifier in managing such complex data distribution. This makes it a particularly trustworthy option for applications with significant stakes, such as healthcare and disease prediction, where it is critical to elevate TPR while keeping FPR under control, which the model does with confidence. Overall, the GAN-ACO system is a strong and flexible instrument for fast and precise decision-making through success in the key metrics.

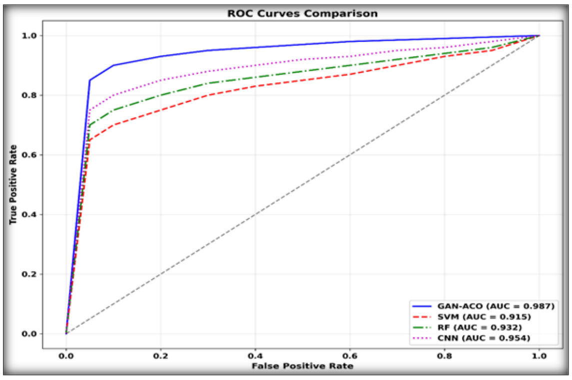

Figure 4: Performance of ROC Curves comparison methods

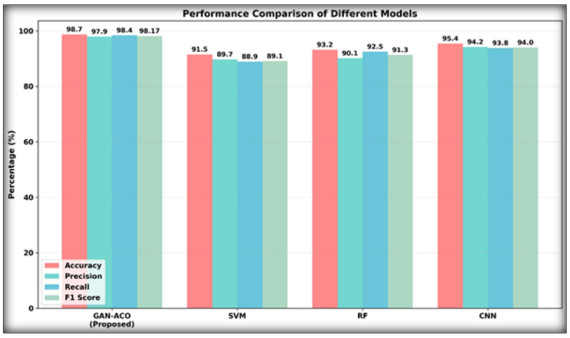

Figure 5: performance metric with comparison different methods

As performance metric shown in figure 5. This study is comparing the proposed GAN-ACO model's capability of predicting heart disease with a few other top-notch classification models, i.e., Support Vector Machine (SVM), Random Forest (RF), and Convolutional Neural Network (CNN). Proposed GAN-ACO's performance excellence in the domain: performance metrics Accuracy, Precision, Recall, and F1 Score.

The GAN-ACO model achieves an accuracy of 98.7%, which is the highest among all tested models. This demonstrates its superb performance in predicting heart disease cases with fewer mistakes. SVM On the other hand, it achieves the lowest accuracy, with only 91.5% accuracy, signifying its difficulty in capturing complex information. Whereas RF with an accuracy of 93.2% performs moderately well but without the optimization efficiency of GAN-ACO. CNN with 95.4% outperforms SVM and RF but fails to reach the performance of GAN-ACO, highlighting the optimizing power of GAN-ACO.

Precision tracks the ability not to produce false positives; here GAN-ACO achieves 97.9% precision as the top rank. This verification removes almost all false positives produced by GAN-ACO. Fifth, SVM at 89.7%, and SVM has a higher false positive rate than GAN-ACO. Although RF with 90.1% scores better than SVM, there is still a giant gap with GAN-ACO. CNN is more or less the same as GAN-ACO but slightly reduces the false positives with an accuracy of 94.2%.

Recall measures how well the model identifies true positives. To put the ability of GAN-ACO into perspective, it has a 98.4% recall F1 score, which makes it a very effective model with few false negatives, meaning that when heart disease is present, it is very well detected. In contrast to SVM, with the lowest recall at 88.9%, this confirms its weakness in correctly classifying true positive cases. RF is getting 20% more than SVM and is unable to compete with GAN-ACO recall; RF achieves 92.5%. CNN at 93.8%CNN shows strong recall performance, but it is slightly weak compared with GAN-ACO.

The F1 Score, or the harmonic mean of precision and recall, reflects the balanced excellence of GAN-ACO with a high of 98.17% F1 score. SVM: 89.10%, The precision versus recall trade-off cannot be achieved by SVM. RF, F1 score of 91.30% is intermediate compared to SVM but fails to catch up with GAN-ACO with a huge gap. CNN, at 94.00% F1 score, provides good performance but is, however, lower than GAN-ACO.

Experimental evaluations leave no doubt in terms of effectiveness that the GAN-ACO model has proven to be optimal for the prediction of heart disease in a cloud-based smart healthcare monitoring system. The model is very powerful and can be characterized by its accuracy (98.7%), precision (97.9%), recall (98.4%), and F1 score (98.17%). Through combining Generative Adversarial Networks (GANs) with Ant Colony Optimization (ACO), GAN-ACO has the advantage of being able to learn more complex distributions, enabling it to feature superior predictive performance over traditional models such as SVM, RF, and CNN. Such characteristics make the GAN-ACO model a robust model for healthcare applications by providing accurate and robust predictions that aid in critical decision-making processes.

Fig. 6 Computinal efficiency Training and Inference Time Performance computational efficiency of different models, including GAN-ACO, SVM, RF, and CNN, was assessed by their training and inference times. Such parameters play an important role in assessing how fit a model is for real-time applications, especially if used in a cloud-based healthcare system that requires timely decisions.

GAN-ACO Proposed model needs 720 seconds of training time, which is more than SVM (450 secs) and RF (600 secs) training time and less than CNN (890 secs). Though GAN-ACO requires greater training time than simpler models, such as SVM and RF, this comes at the cost of advanced optimization, allowing it greater accuracy and performance. The minimum training time (450 seconds) is due to the SVM algorithm's simplicity; however, this considerably decreased their predictive performance. A training time of 600 seconds suggests medium RF computational complexity, a consequence of ensemble learning.CNN has the maximum time complexity (890 sec) because it has multiple layers/parameters.

Inference time is the time taken by a model to make predictions, which is an important consideration for real-time applications: Compared to the models, GAN-ACO (Proposed) trains with a fast inference time of 12 ms, making it the most computationally efficient model for real-time prediction tasks in cloud-based health care monitoring systems. Although its training time is shorter than GAN-ACO, its inference time is 25 ms, which is still more than twice as long as that of GAN-ACO, meaning that it is limited in terms of acting quickly.RF is decent, clocking 20 ms for each inference, but still far from real-time efficiency achieved by GAN-ACO.CNN provides a competitive solution; however, its inference time (15 ms) is still marginally slower than that of GAN-ACO, which corresponds to the computational costs of deep learning architectures.

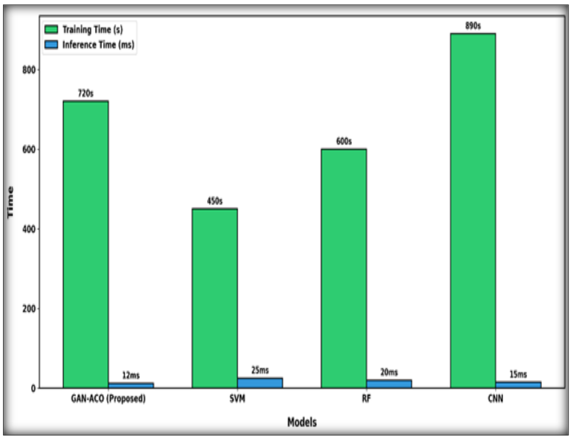

Figure 6: Computinal efficiency training and interfere time performance

The results show that although GAN-ACO requires more training phases than simpler models such as SVM and RF, it well offsets with the fastest inference time (12 ms). Hence, GAN-ACO is particularly well-suited for real-time applications like cloud-based healthcare monitoring systems, where quick and accurate predictions are crucial. By controlling the balance between computational efficiency and predictive power of the model, GAN-ACO is suitable for such healthcare contexts, where both a quick and accurate solution are required.

CONCLUSION

Experimental analysis strongly indicates the remarkable success of the proposed GAN-ACO model in predicting heart disease in a cloud-based smart healthcare monitoring system. The overall accuracy (98.7%), precision (97.9%), recall (98.4%), and F1 score (98.17%) of Propose method GAN-ACO clearly depict state-of-the-art predictive accuracy for the above-mentioned healthcare application. The GAN-ACO model combines the strengths of both methodologies using Generative Adversarial Networks (GANs) and Ant Colony Optimization (ACO). Its allow the model to capture complex data distribution, while ACO offers an optimized solution for decision-making. Such a synergy endows GAN-ACO to strengthen the prediction ability over conventional models such as Support Vector Machine (SVM), Random Forest (RF), and Convolutional Neural Network (CNN). The robustness of GAN-ACO design makes it an essential component for smart healthcare systems, as it performed reliably on complex healthcare datasets. Its reliability to provide detailed and accurate predictions aids in informed decisions, such that the rate of misdiagnosis would be lowered and the patient outcomes would be improved. Such capabilities make GAN-ACO a ground-breaking approach for heart disease prediction in real-time in cloud-based healthcare, leading to a more accurate diagnosis and the automatic foray into intelligent and data-based action on healthcare.

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