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Heart disease detection with trust-based authentication framework in Edge-cloud-IoMT using Adaptive Aggregation Multi-scale Fusion Network

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Abstract

Heart disease is a vital problem of death across the globe. An earlier identification through continuous monitoring can considerably enhance patient outcomes. Incorporating data within edge-cloud Internet of Medical Things (IoMT) frameworks provides promising avenues for disease diagnosis. However, conventional approaches struggle with resource constraints at edge, thereby affecting scalability. In this research, Adaptive Aggregation Multi-scale Fusion Network (AAMF-Net) is introduced to detect heart disease in edge-cloud-IoMT. Initially, IoMT is simulated, wherein involved entities are cloud, edge as well as IoMT. Here, various steps are conducted for authentication and Deep High-order Attention Neural Network (DHA-Net) is utilized for key generation. The data secured at cloud is employed to detect heart disease. An input data obtained from cloud is pre-processed based on outlier removal, missing value handling and categorical encoding. Thereafter, equalized feature contribution is obtained utilizing Variable Stability Scaling (VSS). Afterwards, features are selected by Supervised Infinite Feature Selection (Inf-FSS) and then, synthetic data is generated employing Finite Elements-Synthetic Minority Oversampling Technique (FE-SMOTE). Lastly, AAMF-Net is used to diagnose heart disease and AAMF-Net is devised by incorporating Adaptive Aggregation with Self-Attention Network (AASAN) with Edge-guided Multi-scale Attention Fusion Network (EdgeMAF-Net). AAMF-Net performed better than other existing models by acquiring 96.37% of accuracy as well as 97.13% of detection rate.

Keywords: Internet of Medical Things, Key generation. Heart disease, Adaptive Aggregation with Self-Attention Network, Edge-guided Multi-scale Attention Fusion Network.

1. Introduction

IoMT is the developing trend in offering solutions to several healthcare issues. Also, it provides the chance for technological progressions in healthcare to succeed. Moreover, it enables a solution to stay relevant with current trends. In today's worldwide society, a dynamism in healthcare sector mostly depends on the data produced by an implementation of IoMT. However, an effective utilization of these data remains a trouble in clinical domain. IoMT offers a promise of having accessibility to large amount of clinical data that can be extracted or harnessed in resolving health-based problems . IoT-cloud-enabled healthcare systems have diverse benefits,

like effectual patient monitoring, enhanced management of patient's information, cost-effective and easier access to patient's data. Furthermore, it confronts numerous problems such as scalability, privacy, security and patient safety. Also, it facilitates electronic clinical systems for sharing data corresponding to modern technology by connecting applications, services and devices. An edge computing is stated as the extended type of a cloud computing, wherein data is evaluated nearer to edge of a network from data generation region. The edge computation is regarded as local processing that minimizes common data traffic, latency and distance. The clinical information is gathered by IoMT and thereafter, transferred to an edge computing for primary analysis. If a clinical data is irregular, it is transmitted to the fog computing for decision-making. According to data communication process, the clinical experts can be quickly informed of medical information for providing earlier warning as well as prompt treatment for elder persons.

An edge computing is exploited for pre-processing data and making quick preliminary diagnosis in order to determine whether clinical data is abnormal or normal. The edge computing only transfers abnormal clinical information to fog computing for diagnosing diseases. Therefore, an efficient process is necessary for protecting every information from unauthorized access and keep it private. A major essential security feature necessary is authentication process by privacy , Although positive characteristics of IoMT are well studied in diverse researches, an implementation of IoMT faces various challenges. One amongst the biggest challenges is privacy and security of IoMT. Certainly, the clinical data are frequently considered as highly invasive and sensitive. Patients may frequently unlike the leakage of their clinical or health-related data. Thus, an accountability to secure such information is massive. An unintentional presence of a malevolent device or devices run by rogue entities could be sufficient for violating strict necessity of patient's data confidentiality. The consideration of IoMT trust, security and privacy is emerging quickly. Recently, trust, security as well as privacy have gained much attention amongst researcher society . Heart disease, encompassing problems such as heart failure and arrhythmias, continues to be one amongst main causes of mortalities across the globe. An earlier identification and accurate diagnosis of heart disease enhance patient outcomes and decrease death rate by providing timely interference as well as care. It allows healthcare providers to overcome risk factors, improve longer-term disease management and tailor treatment plans.

Additionally, it is cost-efficient and has positive effect on public health by minimizing overall problem of heart disease mortality and morbidity.

Heart disease identification from various symptoms or factors is the multilayered trouble, frequently prone to inaccuracies and unpredictable resultants. With a complication of data accessible from healthcare area, the human intelligence is not only adequate for ascertaining accurate diagnosis. The issues related with people involved in detection can be widely considered as low accuracy during decision-making, lack of proficiency, complexities in skill upgrade and time-dependable performance. The preliminary phase is authentication of patient data, encryption and classifying heart disease based on collected data. An enhanced encryption standard technique acquires data encryption. If an alert is generated for clinician and the patient is predicted with heart disease, they will be notified immediately. During recent times, various techniques are developed for heart disease detection. Long Short-Term Memory (LSTM) is accountable to sort the heart disease. Deep Learning (DL) methods with the cloud computing, IoT as well as big data to offer modern e-health systems that leverage development of online connections for clinical conditions. DL refers to the Machine Learning (ML) framework that utilizes multilayered networks, whereupon initial layer extracts data and consequent layers assess as well as categorize patterns. Deep Belief Network (DBN), Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) are the instances of deep discriminatory frameworks for diagnosing heart disease. DL networks are fundamental to identify heart diseases from patient data. Current progressions for heart disease identification have integrated various DL methods, tackling problems including imbalanced data and enhancing model effectiveness ,

The significant aim is to introduce AAMF-Net for detecting heart disease in edge-cloud-IoMT. Heart disease is the crucial global health concern, requiring accurate diagnostic techniques for early prevention and detection. In this research, IoMT is initially simulated and the involved entities are cloud, edge as well as IoMT. Various steps are conducted for authentication and key is generated employing DHA-Net. An authentication technique is based on several security operations, such as DES encryption, hashing function, X-OR functions, OTP, and so on. For trust-based authentication, direct trust, identity trust, indirect trust, mediation trust, and attestation trust are considered. Herein, data secured at cloud and an input data is acquired from cloud. Then, data is pre-processed based on outlier removal, missing value handling and

categorical encoding. Afterwards, equalized feature contribution is obtained employing VSS. Thereafter, features are selected employing Inf-FSs and next, synthetic data is generated using FE-SMOTE. Finally, heart disease is diagnosed utilizing AAMF-Net, which is derived by incorporating AASAN with EdgeMAF-Net.

The major contribution is presented as follows.

- ❖ **AAMF-Net to detect heart disease in edge-cloud-IoMT:** A quick progression of IoMT-cloud-edge has modernized remote healthcare monitoring, facilitating heart disease detection and patient care. This research proposes AAMF-Net to detect heart disease in edge-cloud-IoMT. Moreover, AASAN with EdgeMAF-Net are incorporated to design AAMF-Net.

The other sections are organized as follows: Section 2 describes literature overview of traditional approaches and their limitations, section 3 interprets system model of edge-cloud-IoMT, section 4 describes methodology of AAMF-Net, section 5 discusses experimental outcomes of AAMF-Net and lastly, section 6 illustrates conclusion of AAMF-Net.

2. Motivation

An incorporation of IoMT, cloud, and edge computing has enabled intellectual healthcare systems capable of accurate heart disease analysis and improved security in management of clinical data. Many classical approaches struggle with incomplete or noisy data, leading to decreased accuracy. Considering this fact as motivation, this research proposes an efficient DL model for identifying heart disease detection. This section elaborates literature review and disadvantages of conventional methods for heart disease detection.

2.1 Literature Survey

A. Pati., *et al.* developed Fog-empowered framework for real-time analysis in heart patients using Ensemble Deep learning (FRIEND) to diagnose heart disease. It effectively provided affordable and improved heart diagnostics, but this method exhibited high cost and failed to employ edge computing concept to boost heart disease identification. W. Almuselem., presented Dynamic Hash-based Message Authentication Code (D-HMAC) for cloud-edge

computing-based healthcare. This scheme established the secure network environment by implementing Zero Trust Architecture (ZTA) within cloud-edge healthcare application in detecting heart disease. However, it was not extended to digitally sensitive patient information, thereby maintaining applications with maximum interoperable data sharing. M. A. Umar., *et al.* designed Explainable-Internet of Things (IoT) framework for predicting and monitoring heart disease. It facilitated proactive management as well as informed decisions, though this technique did not concentrate on the user training, scalability and security across other healthcare areas for refining a model. Also, this method was failed to assure its wide-ranging applicability and reliability in various healthcare environments. R. Javed., *et al.* introduced CNN for accurate prediction of chronic heart disease. This approach efficiently distinguished normal and pathological cardiac states with high accuracy. Nevertheless, it did not enhance an interpretability of model utilizing sophisticated techniques or feature significance assessment, which could enable adoption by clinical experts.

T. Ding, *et al.* devised LSTM for categorizing and detecting heart problems. It accurately classified various cardiovascular issues, even though it was not able to assist highly responsive and combined healthcare solutions. M. A. Jan, *et al.* developed Hybrid mutual authentication approach to improve patient's health outcomes. This scheme facilitated protected communication among servers and wearable devices. Nevertheless, it did not improve an authentication process by implementing highly effective security algorithms and multi-factor authentication methods. G. Zheng, *et al.* introduced dual-cryptography mechanism for multi-user oriented data sharing. It ensured recoverability from the server failures, but this technique did not establish a unified key management framework and faced numerous challenges while implementing in distributed healthcare scenarios. L. Hak and S. Fugkeaw., presented Secure, Scalable, and Lightweight Cross-Domain IoMT Sharing (SSL-XIoMT) for enabling effective, privacy preserving authentication. It provided scalable and secure solution for the cross domain IoMT data as well as reduced computational overhead. However, it did not include searchable encryption for private queries.

2.2 Challenges

The challenges faced by conventional approaches to detect heart disease are interpreted below.

- The technique designed in enabled data recovery during server failures and prevented single points of failure. However, this model was not appropriate for high-frequency IoMT data updates.
- An explainable-IoT framework presented in to monitor and predict heart diseases handled features with larger value range. Nevertheless, it did not capture temporal patterns in data.
- In , CNN was introduced for classifying various heart conditions. This model mitigated overfitting issues and strengthened patient outcomes in handling chronic heart diseases, even though it was failed to overcome class imbalance problems.
- An authentication approach developed in imitated an actual environment of the smart hospitals, but still, it required mutual authentication for each section, leading to enhanced latency.
- Detecting heart disease in edge-cloud-IoMT based systems confronts challenges like limited incorporation of diverse data, noise in data and lack transparency in predictions, which can lessen user confidence and treatment efficiency. Hence, an effective hybrid model is required to ensure reliability and interpretability for clinical decision-making.

3. System model of edge-cloud-IoMT

Figure 1 delineates the system model of edge-cloud-IoMT. IoMT devices gather vast quantity of medical data and healthcare that acquires computational resources as well as time for processing centralized systems utilizing cloud computing. Edge computing transfers most meaningful and relevant information to cloud. It massively lessens workload of cloud computing resources and data centers besides improving operation effectiveness. In an edge computing, data pre-processing has revealed as a crucial part in identifying and catching outliers or any abnormalities of IoMT data. In an edge computing, patient's information gathered by IoMT is transferred to edge layer for diagnosing diseases with DL. Ultimately, diagnosis reports obtained from DL techniques at edges are transferred to cloud server for the hospital database, patients and healthcare institutions. Furthermore, edge computing is utilized for IoMT systems for achieving smaller-scale computing and larger storage ability while assuring minimum latency and optimum IoMT resource utilization.

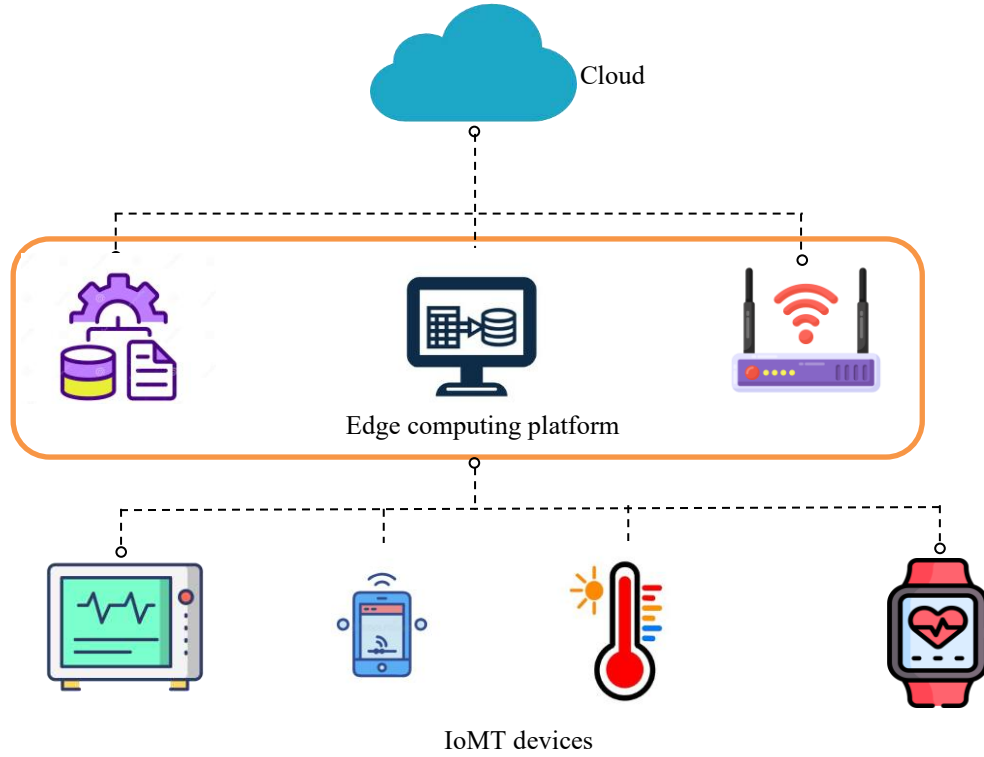


Figure 1. System model of edge-cloud-IoMT

4. Adaptive Aggregation Multi-scale Fusion Network to detect heart disease in edge-cloud-IoMT

Leveraging IoMT, cloud and edge devices supports scalable and real-time monitoring for the remote patient management. Several approaches employ either edge or cloud processing exclusively, leading to delays or limited computational capacity. Here, AAMF-Net is presented for heart disease detection in edge-cloud-IoMT. Firstly, IoMT is simulated and the entities involved are cloud, edge as well as IoMT. Various steps carried out are initialization, data access control, registration, authorization, data protection, trust-based authentication and key generation, which is carried out by DHA-Net. The considered security operations are DES encryption, hashing function, X-OR functions, OTP, and so on. The data secured at cloud is employed for diagnosing heart disease. Initially, an input data is pre-processed based on outlier removal, missing value handling and categorical encoding. Thereafter, equalized feature contribution is acquired employing VSS. Afterwards, feature dimensionality reduction is done

using Inf-FSSs and then, FE-SMOTE is utilized to generate synthetic data. Lastly, heart disease is detected utilizing AAMF-Net and it is devised by joining AASAN with EdgeMAF-Net. Figure 2 demonstrates visual depiction of AAMF-Net for diagnosing heart disease in edge-cloud-IoMT.

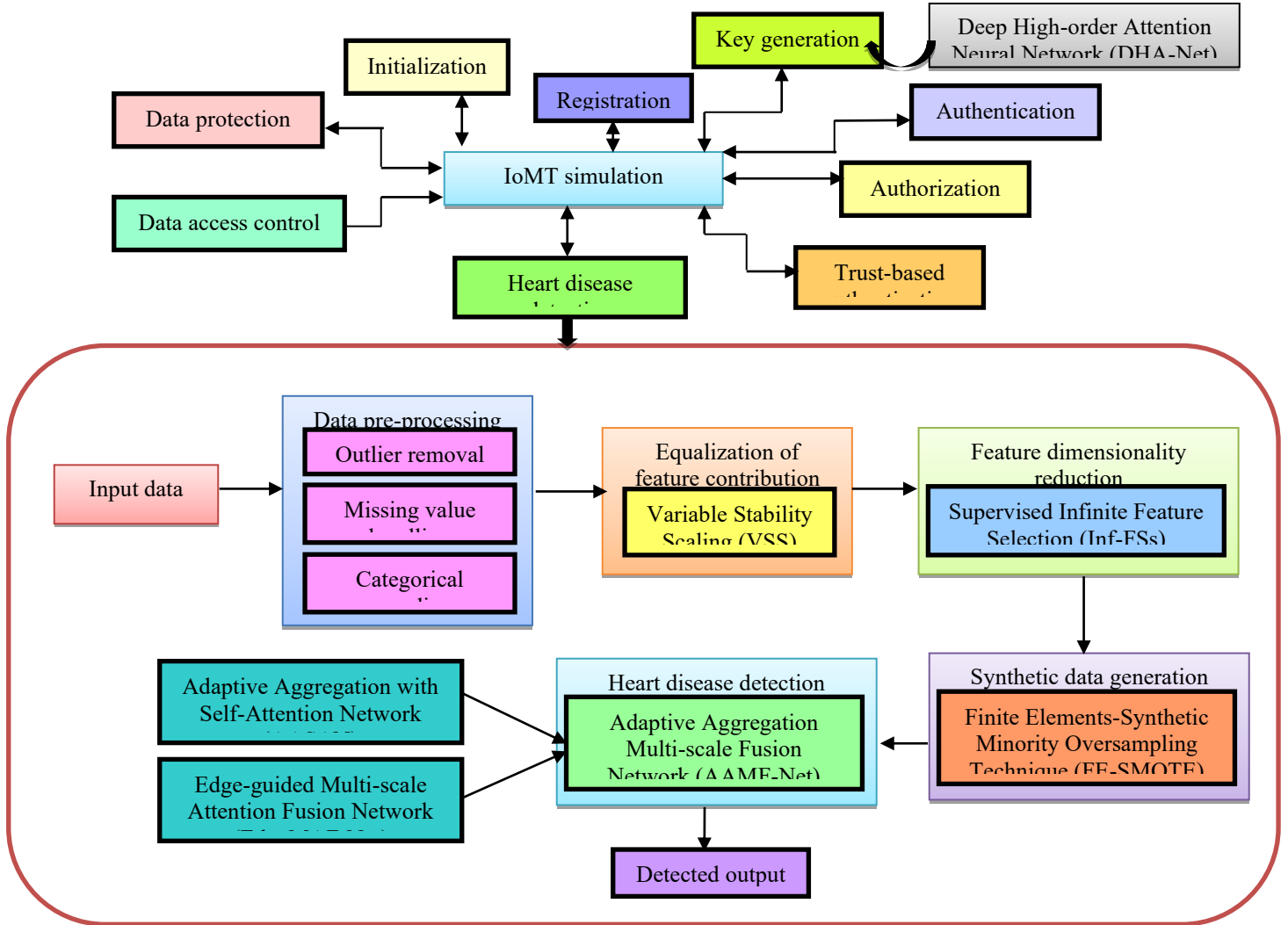


Figure 2. Visual representation of AAMF-Net for heart disease detection in edge-cloud-IoMT

4.1 Initialization

During this phase, public key PK , hash function HF , security parameters in, up and cq as well as random numbers xb, ql, mj, lt, hz and ga are initialized.

4.2 Registration

In registration phase, the process is conducted between cloud, IoT and edge. During registration between edge and cloud, edge ID ED_{id} as well as edge password ED_{pwd} are stored in cloud as

ED_{id}^* and ED_{pwd}^* . Thus, message MS_1 is generated in cloud, which is stored in edge as MS_1^* . Again MS_1^* is stored in cloud as MS_1^{**} and thus, edge is registered with the cloud. During registration between IoT and edge, ID and password of IoT specified as IT_{id} and IT_{pwd} are stored in edge as IT_{id}^* and IT_{pwd}^* . Thus, the message MS_2 is generated that is again stored in IoT as MS_2^* . Then, MS_2^* is stored in edge as MS_2^{**} and therefore, IoT is registered with the edge. In registration between IoT and cloud, IT_{ip} comprising IT_{id} and IT_{pwd} is stored in edge as IT_{ip}^* . It is again stored in cloud as IT_{ip}^{**} and the cloud sends OTP to IoT and it is stored as OTP^* . Then, OTP^* is stored in cloud as OTP^{**} and thus, IoT is registered with the cloud.

4.3 Key generation

At cloud, private key VK is generated employing DHA-Net and then, it is stored as VK^* in edge. DHA-Net is a modern Neural Network (NN) structure developed to improve key generation processes in the edge-cloud-IoT environments. It exploits DL models integrated with high-order attention mechanisms to efficiently capture complicated, multi-level feature interactions within data, thereby enhancing security, efficiency and robustness of key generation.

4.4 Authentication

During this phase, an authentication message AM_1 is generated and stored in edge as AM_1^* . In edge, the message MG_1 is generated and it is stored in cloud as MG_1^* . Then, verification message mg_1 is sent by cloud and it is stored in IoT as mg_1^* . After storing a message, IoT is authenticated by the cloud.

4.5 Authorization

In authorization phase, a request AM_2 is given to edge and it is stored as AM_2^* . The request from edge is again stored in cloud as AM_2^{**} . Thereafter, an authorization message MG_2 is generated by

cloud and sends to edge, which is stored as MG_2^* . An edge sends verification message VE_1 to cloud and it is stored as VE_1^* . Afterwards, decrypted data to the IoT is sent by cloud.

4.6 Access control

For accessing data, IoT sends IT_{id} and IT_{pwd} to cloud, wherein password and ID are stored in cloud as IT_{id}^* and IT_{pwd}^* . After that, session password SE_{pwd} is generated by cloud and sends to IoT, which is stored as SE_{pwd}^* . Here, indirect trust, direct trust, mediation trust and attestation trust manage the access control. Thereafter, authorization message MG_4^* is generated and then, cloud accepts an access control from the IoT. Finally, IoT as well as cloud accept the information T as true.

4.7 Data protection

During data protection stage, encryption process and decryption process are conducted. Initially, encrypted data EN and KY send from edge is stored in cloud as EN^* and KY^* . Finally, data is decrypted and the decrypted data is illustrated as DY .

4.8 Heart disease detection

In this section, steps such as data acquisition, pre-processing, equalization of feature contribution, feature dimensionality reduction and synthetic data generation to detect heart disease are explained.

4.8.1 Acquisition of data

To carry out heart disease detection, an input data is taken from UCI Heart Disease Data and Cardiovascular_Disease_Dataset. It can be illustrated by,

$$D = \{D_1, D_2, \dots, D_h, \dots, D_l\} \quad (1)$$

$$Z = \{Z_1, Z_2, \dots, Z_h, \dots, Z_l\} \quad (2)$$

Here, D_h signifies h^{th} data, D_l implies total data in dataset D whereas Z_l depicts overall data and Z_h denotes h^{th} data in dataset Z . UCI Heart Disease Data contains 14 attributes, one file and 16 columns available in .csv format. Cardiovascular_Disease_Dataset includes 1000 subjects with about 12 features and the size files is 42.6 KB available in csv format.

4.8.2 Data pre-processing

Data pre-processing involves various steps for cleaning, transforming and preparing actual clinical data for efficient modelling and analysis. Here, input data D_h is pre-processed based on outlier removal, missing value handling and categorical encoding.

a) Missing value handling

Missing value handling is a step to manage and process incomplete data entries within database utilized for detecting heart disease. Here, median imputation is useful for the numerical features as well as mode imputation is employed for categorical features in order to maintain distributional properties. A missing value handling performed in input data D_h can be computed by,

$$MV_h = \begin{cases} Median(D_h), & \text{if } D_h \in \mathbb{N} \\ Mode(D_h), & \text{if } D_h \in \text{Categorical} \end{cases} \quad (3)$$

Here, $\mathbb{N}$ implies set of numbers whereas MV_h illustrates imputed data.

b) Outlier removal

Outlier removal process identifies and eliminates data points that considerably vary from other observations in database related to heart health conditions. Here, outliers are identified utilizing Z-score technique and eliminated from the continuous features. An outlier is removed on imputed data MV_h that can be modelled by,

$$OR_h = \frac{MV_h - Me}{SD} \quad (4)$$

Here, MV_h represents imputed data, Me depicts mean, SD reveals standard deviation and OR_h denotes outlier removed data.

c) Categorical encoding

Categorical encoding process transforms non-numeric variables into numerical formats that the system can process and interpret efficiently. An input subjected to categorical encoding process is outlier removed data OR_h . The categorical variables namely sex, thal, cp, cholesterol and so on are converted utilizing two methods as follows.

(i) *Learned embedding encoding*

A learned embedding encoding is appropriate for the high-cardinality features, wherein embedding layer maps categorization indices into dense vector, which is given by,

$$EM_{cat} = Embed(OR_{hcat}, \dim) \quad (5)$$

Here, D_{hcat} implies categorical index whereas $\dim$ signifies embedding size.

(ii) *One-hot encoding*

A one-hot encoding technique is applied, wherein categorical features have ≤ 5 distinctive values. A pre-processed data obtained after applying the above steps is indicated as O_h with dimension $[O \times V]$.

4.8.3 Equalization of feature contribution using VSS

An equalization of feature contribution step assures that an importance or influence of every feature in the predictive model is standardized or balanced. Here, VSS is employed for conducting equalization of feature contribution in O_h with $[O \times V]$ dimension.

VSS is the method employed in feature selection for enhancing interpretability and stability of feature contributions. It adjusts every feature's weight based on its consistency across diverse samples or conditions, promoting equalization of feature contribution. VSS expands a use of Z-score approach by including coefficient of variation (CV) as scaling factor, which can be given by,

$$V_h = \frac{O_h - Me(O_h)}{SD(O_h)} \cdot \frac{Me(O_h)}{SD(O_h)} \quad (6)$$

Here, O_h denotes input, Me and SD signifies mean as well as standard deviation whereas V_h implies equalized feature contribution with $[o \times v]$ dimension.

4.8.4 Feature dimensionality reduction using Inf-FSs

Feature dimensionality reduction step simplifies a database by lessening count of input features or variables while maintaining essential information. Herein, feature dimensionality reduction is carried out utilizing Inf-FSs by acquiring equalized feature contribution V_h with $[o \times v]$ dimension as an input.

a) Inf-FSs

Inf-FSs refers to graph-based feature filtering that provides ranking according to each possible subsets of features accomplish in supervised as well as unsupervised form. This technique is modelled based on fully-connected (FC) weighted undirected graph $DH = (fu, eg)$. Here, nodes fu indicate each feature as well as edges eg reflect pairwise links amid them. Consider DH as adjacency matrix JX , whereupon each components $zu_{rb,nc}$ ($1 \leq V_h, nc \leq qa$) depicts level of confidence, in which $\vec{\xi}_{rb}$ and $\vec{\xi}_{nc}$ nodes are both probable candidates for selection conducted with following weight operation.

$$JX(V_h, nc) = \varepsilon(\vec{\xi}_{rb}, \vec{\xi}_{nc}) \quad (7)$$

Herein, ε denotes weight operation. The weight operation $\varepsilon(\vec{\xi}_{rb}, \vec{\xi}_{nc})$ is produced by factors, like normalized standard deviation(dv_{rb}), fisher criteria(sr_{rb}) and normalized mutual information (nm_{rb}). The expressions of factors are specified as follows.

$$sr_{rb} = \frac{|\text{ME}_{rb,1} - \text{ME}_{rb,2}|^2}{dv_{rb,1}^2 + dv_{rb,2}^2} \quad (8)$$

$$nm_{rb} = \sum_{px \in SL} \sum_{gk \in fc_{rb}} ob(gk, px) \log \left(\frac{ob(gk, px)}{ob(gk)ob(px)} \right) \quad (9)$$

where, $dv_{rb,nh}$ indicates standard deviation and $\text{ME}_{rb,nh}$ illustrates mean for rb^{th} feature based on nh^{th} class instances, SL denotes class labels and $ob(gk, px)$ mentions joint probability distribution. Normally, mi_{lq} depicts measure of overall feature vector's information. Also, standard deviation (dv_{rb}) normalizes amongst 0 and 1 by high standard features (TU). Finally, three-elements are weighted linearly by,

$$wl_{rb} - sr_{rb}\varphi_1 + nm_{rb}\varphi_2 + dv_{rb}\varphi_3 \quad (10)$$

The parameters φ_x refers to mixing coefficient, wherein φ_x lies between $[0,1]$, $\sum_x \varphi_x = 1$. A score wl_{rb} interprets total features. Finally, matrix JX 's weights are constructed by linking corresponding sc as follows.

$$JX(rb, nc) = \varepsilon(\vec{\xi}_{rb}, \vec{\xi}_{nc}) = wl_{rb}wl_{nc} \quad (11)$$

After constructing adjacency matrix, a ranking is performed while evaluating feature redundancy. The selected features obtained from Inf-FSSs are represented as I_h with $[O \times i]$ dimension, where $i < V$.

4.8.5 Synthetic data generation using FE-SMOTE

An aim of synthetic data generation is to augment current data, improve model training, and overcome problems such as data scarcity, ultimately enhancing robustness and accuracy of heart disease identification models. Here, selected features I_h with $[O \times i]$ dimension is fed as input to generate synthetic data employing FE-SMOTE.

a) FE-SMOTE

FE-SMOTE technique constructs simplex within actual space for every positive sample and its neighborhood points. This technique assures that generated newer samples occupy boundary as well as interior areas of triangulation, with their mathematical expectancy similar to triangle's fundamental unit center. This arrangement adopts closest fit to local density distribution of positive samples.

(i) Building base unit

Consider unbalanced binary dataset as $N = \left\{ (C_\eta, \beta_\eta) \mid C_\eta \in HY^{ds}, \beta_\eta \in \{1, -1\}, \eta = 1, \dots, t \right\}$, β_η refers to label related to sample C_η . Assume $N^+ = \left\{ (c_\eta)_{\eta=1}^{t_1} \right\}$ and $N^- = \left\{ (c_\eta)_{\eta=1}^{t_2} \right\}$ are sample group of minority as well as majority classes, wherein $t_1 = |N^+|$ and $t_2 = |N^-|$, The fundamental unit is developed for every positive sample c_η , in accordance to nearest neighbor method, it is comprised of c_η and ds neighborhoods $NB_\eta = \left\{ c_\eta^{ra} \right\}_{ra=1}^{ds}$ closer to c_η , wherein c_η^{ra} indicates ra sample closer to c_η .

(ii) Triangulation of $(DS + 1)$ -sided polyhedron

For individual positive sample c_η , its $(ds+1)$ -sided polyhedron is triangulated with center q_k and Q . If center of polyhedron as well as two vertices of $ds+1$ edges are randomly integrated to form K_{ds+1}^2 triangles, individual triangle is triangulation.

$$Q = NB_\eta \cup \{c_\eta\} = \{q_{ws}\}_{ws=1}^{ds+1} \quad (12)$$

$$q_k = \left(\sum_{ws=1}^{ds+1} q_{ws} \right) / (ds+1) \quad (13)$$

(iii) Determination of total samples generated on triangular unit

Let DS_{lp} signifies sum of distance amongst two vertices of lp^{th} triangle as well as central vertex and employ it for measuring size of triangle component, then,

$$DS_{lp} = \frac{1}{2} \left(\|q_1^\eta - q_k^{lp}\|_2 + \|q_2^\eta - q_k^{lp}\|_2 \right) \quad (14)$$

Here, q_1^η, q_2^η and q_k^{lp} depicts three vertices of lp^{th} triangular component. Compute overall newer samples num_{lp} as follows.

$$MG = \left\{ e^{1-DS_{lp}} \right\}_{lp=1}^{K_{ds+1}^2 * t_1} \quad (15)$$

$$\overline{MG} = \left\{ \frac{e^{1-DS_{lp}}}{\sum_{lp} e^{1-DS_{lp}}} \right\}_{lp=1}^{K_{ds+1}^2 * t_1} = \{mg_{lp}\}_{lp=1}^{K_{ds+1}^2 * t_1} \quad (16)$$

$$num_{lp} = \lceil (t_2 - t_1) * mg_{lp} \rceil \quad (17)$$

(iv) Synthesize newer sample

In lp^{th} triangular component after splitting, the newer sample is generated based on below expressions.

$$q_{mid} = hy_1 q_1^{lp} + (1 - hy_2) q_2^{lp} \quad (18)$$

$$c' = hy_0 q_k^{lp} + (1 - hy_0) q_{mid} \quad (19)$$

$$c' = hy_0 q_k^{lp} + (1 - hy_0) (hy_1 q_1^{lp} + (1 - hy_2) q_2^{lp}) \quad (20)$$

Here, hy_0 and hy_1 follow uniform distribution between 0 and 1. The generated synthetic data is denoted as S_h with $[z \times i]$ dimension, where $z > o$.

4.8.6 Detection of heart disease using AAMF-Net

The detection of heart disease involves identification of heart-related health problems by assessing diverse data sources. Herein, heart disease detection is accomplished using AAMF-Net, which is designed by incorporating AASAN with EdgeMAF-Net based on Taylor concept. Additionally, AAMF-Net is tuned optimally using Adam optimizer .

Figure 3 interprets general outline of AAMF-Net for detecting heart disease. Initially, generated synthetic data S_h is multiplied with β_1 weight and hence, $\sum \beta_1 \times S_h$ is acquired. Simultaneously, generated synthetic data S_h is given to AASAN and an outcome K is obtained. An acquired output is multiplied with $\sum \beta_1 \times S_h$ to attain AASAN's outcome A_h . On the other hand, generated synthetic data S_h is passed to EdgeMAF-Net to obtain an output M . The attained resultant is multiplied with β_2 weight and AASAN's outcome to acquire EdgeMAF-Net's output G_h . Finally, Taylor concept is applied to AASAN's resultant A_h and EdgeMAF-Net's outcome G_h for attaining heart disease detected output R_h .

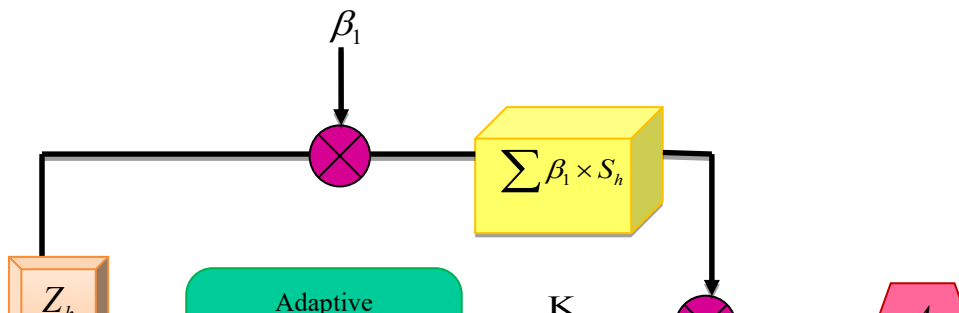


Figure 3. General structure of AAMF-Net for detecting heart disease

a) AASAN

AASAN refers to specialized DL developed to enhance interpretability and accuracy of heart disease diagnosis by efficiently combining various sources of data. Figure 4 illustrates architectural model of AASAN and generated synthetic data S_h is subjected as input.

At first, input S_h is fed to global branch, whereupon ResNet is employed as backbone network. Additionally, the network contains Self-Attention with Relative Position Encoding (SA-RPE) for highlighting longer-term dependencies. Global branch generates TransBlock resultant feature map FM_{ζ} , which is averaged employing channel to acquire attention map $\mathbf{X}$. Afterwards, threshold γ is fed to produce the binary mask $\mathbf{A}$. The γ value is modified and an expression of attention maps can be modelled by,

$$\mathbf{X} = \frac{1}{N} \sum_{n=1}^N |FM_{\zeta}^n(\alpha, \varpi)|, N = 2048 \quad (21)$$

$$\mathbf{A} = \begin{cases} 1, & \mathbf{X}(\alpha, \varpi) > \gamma \\ 0, & otherwise \end{cases} \quad (22)$$

where, n and (α, ϖ) mention n^{th} channel as well as spatial location of resulting feature map FM_{φ} . Then, section of interest denoted by P_H is generated by multiplying input S_h and mask A . When comparing with an input S_h , redundant background noises are suppressed to specific extent by the focal part of P_H . The produced attention map denoted by X covers overall data. Considering P_H as an input, local branch generates local feature map FM_H . By Adaptive Aggregation Feature (AAF) component, an ultimate outcome is attained by integrating depth features.

(i) SA-RPE component

SA-RPE captures longer-term dependencies by locational encoding and contextual data. Based on previous residual block, an input feature map $B \in \mathbb{R}^{\partial \times M \times J}$ is attained. Firstly, B is transformed into feature representation employing 1×1 convolution (conv) for acquiring Qu and Ky . Herein, Qu implies query encoding whereas Ky indicates key encoding. It is signified as $Qu = BM_{Qu}, Ky = BM_{Ky}$, wherein $Qu, Ky \in \mathbb{R}^{\partial \times M \times J}$. The relative locational encoding in a transformer presents $\square_{\partial} \in \mathbb{R}^{\partial \times 1 \times J}$ and $\square_M \in \mathbb{R}^{1 \times M \times J}$ illustrates width and height encoding. Also, the normal distribution generates $\square_{\partial}$ and $\square_M$. Here, $\square_{\partial}$ and $\square_M$ are summed and generalized to obtain relative locational encoding matrix Z , whereupon $Z \in \mathbb{R}^{\partial \times M \times J}$. A universal attention procedure observes the association amongst Qu and Ky . Moreover, Qu and Ky are multiplied to achieve targeted-content encoding matrix.

$$At(Qu, Ky) = QuKy^T \quad (23)$$

Here, $QuKy^T \in \mathbb{R}^{\partial \times M \times \partial \times M}$ and each pixel relation amongst Qu and Ky is acquired. Hence, two diverse but same features indicate maximum connection in $At(Qu, Ky)$. During this time, targeted-locational encoding matrix can be formulated by,

$$At(Qu, Z) = QuZ^T \quad (24)$$

wherein, $QuZ^T \in \mathbb{R}^{\hat{d} \times M \times \hat{d} \times M}$, a per-pixel link amongst Qu and Z is obtained. $At(Qu, Z)$ considers contextual as well as relative locational data of individual pixel. Finally, SA-RPE element's outcome $O(B)$ is represented by,

$$O(B) = \text{softmax}(QuZ^T \oplus QuKy^T)B \quad (25)$$

Here, $\oplus$ denotes element-wise addition. After that, softmax operation standardizes targeted positional as well as contextual encoding matrices. Thereafter, matrix B is multiplied and an outcome of SA-RPE is manifested as $O(\tau) \in \mathbb{R}^{\hat{d} \times M \times J}$.

A relative positional encoding introduced in SA-RPE element is similar to two trainable vectors of vertical as well as horizontal dimension $\square_{\hat{d}}$ and $\square_M$ to comprehend spatial attention. $At(Qu, Z)$ is obtained by multiplying Z and Qu . The spatially sensible similarity features are acquired by summing targeted positional matrix and contextual encoding matrix. SA-RPE concentrates on definite region and simple convergence.

(ii) AAF component

To incorporate unreliable features semantically, AAF is developed. A feature map generated by global as well as local branches are initially added element-wise for obtaining integrated matrix $\tau \in \mathbb{R}^{J \times \hat{d} \times M}$ to merge both feature maps. Afterwards, channel attention weight is presented by,

$$\hat{\lambda}(\tau) = \text{Conv}_{1d}(T(\tau)) \quad (26)$$

where, $\hat{\lambda}(\tau) \in \mathbb{R}^{J \times 1 \times 1}$, T interprets Global Average Pooling (GAP), Conv_{1d} indicates one-dimensional (1D) conv and τ depicts feature map.

Consider 1D conv operation's kernel's size as ϕ . The uncertain proportion link amongst ϕ and total channels J are regarded as linear mapping that illustrates $J = d \times \phi - a$. It can be given by,

$$J = 2^{(d \times \phi - a)} \quad (27)$$

When channel dimension J is given, ϕ of 1D conv is represented by,

$$\phi = \Phi(J) = \left\lfloor \frac{\log_2(J)}{d} + \frac{a}{d} \right\rfloor_{odd} \quad (28)$$

Here, $\lfloor \cdot \rfloor_{odd}$ obtains neighboring odd number whereas d and a refer to hyperparameters. Simultaneously, content attention weight $s(\tau)$ is attained through local feature aggregation branch, whereupon $s(\tau) \in \mathbb{R}^{J \times \partial \times M}$, $s(\tau)$ has equal scale as incorporated feature map τ , hence $s(\tau)$ highlights feature map information effectively.

$$s(\tau) = BN\left(M_2 ReLU\left(BN\left(M_1 \tau\right)\right)\right) \quad (29)$$

Here, $M_1 \in \mathbb{R}^{\frac{J}{\Psi} \times J \times 1 \times 1}$ and $M_2 \in \mathbb{R}^{J \times \frac{J}{\Psi} \times 1 \times 1}$ signifies parameters of conv kernel, BN denotes batch normalization whereas $ReLU$ specifies Rectified Linear Unit. A hyperparameter $\Psi = 2^o$ describes channel attenuation rate, in which $o \in \{2, 3, \dots, 10\}$. An ultimate attention weight V is acquired by combining $s(\tau)$ and $\lambda(\tau)$ as follows.

$$M = \sigma(\lambda(\tau) \oplus s(\tau)) \quad (30)$$

where, σ reveals sigmoid operation and AASAN's outcome can be expressed by,

$$A_h = \left[(S_h \otimes M) \oplus (S_h \otimes (1 - M)) \right] \times \left(\sum \beta_1 \times S_h \right) \quad (31)$$

Here, S_h depicts generated synthetic data, A_h mentions outcome from AASAN, $\otimes$ denotes product operation, $\oplus$ reveals element-wise addition whereas M signifies attention weight.

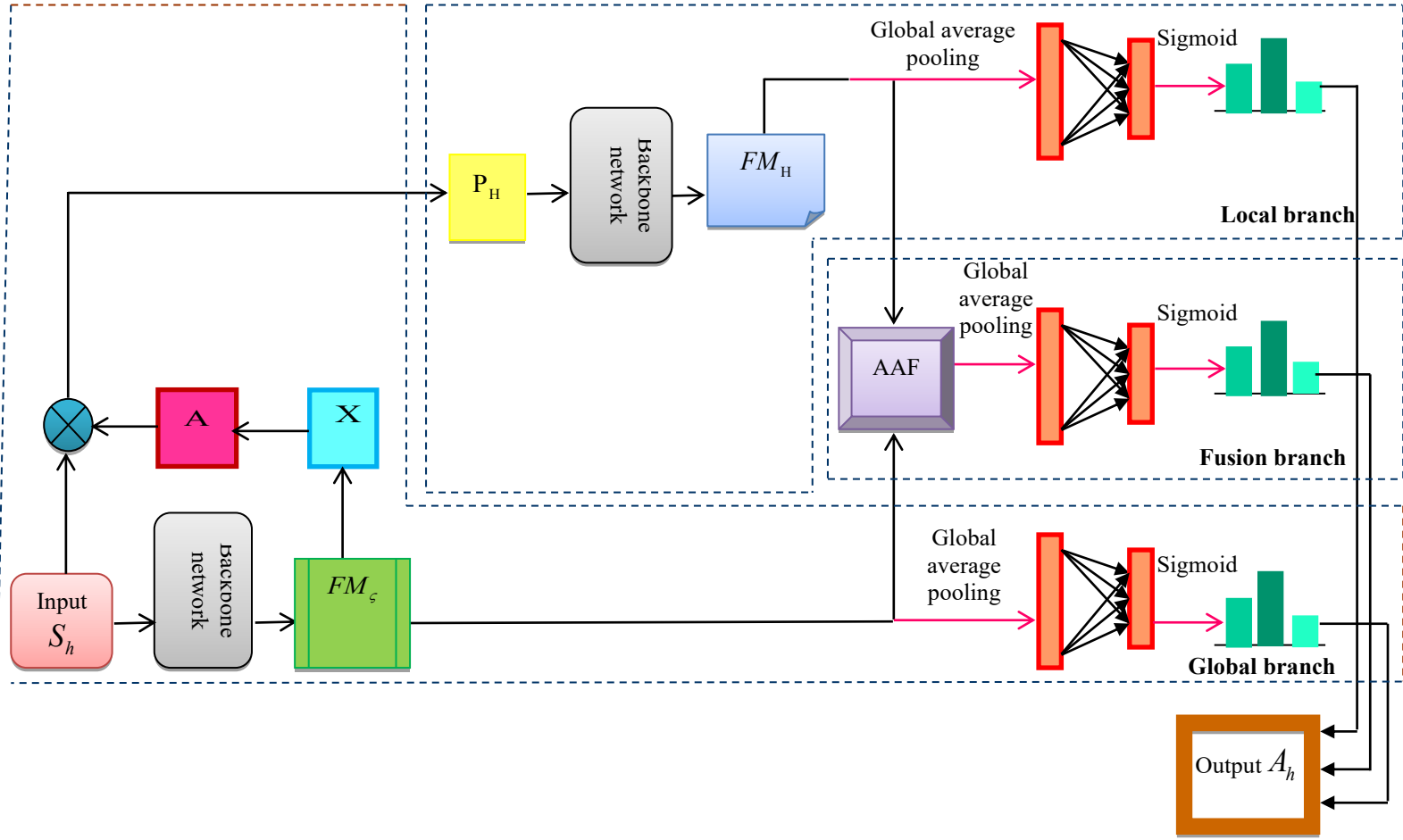


Figure 4. Architectural model of AASAN

b) EdgeMAF-Net

EdgeMAF-Net intends to improve an accuracy of heart disease identification by exploiting multiscale features and edge information, assuring complex and subtle cardiac irregularities are efficiently distinguished and captured. Here, S_h is fed as the input and figure 5 demonstrates structural representation of EdgeMAF-Net.

Firstly, considered input is passed to a stem element for extracting features and transforming dimension, thereby generating feature $Y_{P,0}^{W,0}$. Afterwards, $Y_{P,0}^{W,0}$ is passed to Cross-stage Partial Fusion Module (CSPFM) employ attention-guided process and Multi-scale Edge Attention Calibration Module (MSEACM) utilizes multi-scale improvement to capture suitable features.

Finally, resulting features $Y_{P,r}^{W,r}$ are subjected to classification head. In order to attain hierarchical representations, a network is classified into four stages, with an individual stage containing two developed elements.

(i) CSPFB

In particular, CSPFB allots feature extracting branches utilizing Transformer Channel Ratio (TCR) and leverages high-frequency attenuation transformer on relative channels. Moreover, Adaptive Noise Suppression (ANS) layer is developed for modifying filter power of every channel. Here, feature $Y_{P,0}^{W,0}$ is categorized into three parts as follows,

$$(\nu_0, \nu_{\zeta,0}^h, \nu_{\zeta,0}^\mu) = Split(Con_{1 \times 1}(Y_{P,0}^{W,0})) \quad (32)$$

Herein, ν_0 indicates features fed to following stage by skip connections, $Con_{1 \times 1}$ depicts 1×1 conv, $\nu_{\zeta,0}^h$ represents features subjected to CNN and $\nu_{\zeta,0}^\mu$ implies features passed to transformer branches in primary stage phase.

A local feature extraction is enhanced by CNN branch through two-layered bottleneck model. ANS adjusts filter parameters with regard to local feature. Here, 3×3 conv is employed to capture local features and Rectified Linear Unit (ReLU) is utilized to enhance them. After adaptive average pooling (pool) as well as FC, a weight vector is obtained for adjusting each channel's filter strength. It effectively suppresses high-frequency noises without affecting crucial edges as well as information in specific image, which is specified as,

$$ANS(\nu_{\zeta,0}^h) = \nu_{\zeta,0}^h \times se\left(FC\left(AAP\left(\square\left(Con_{3 \times 3}(\nu_{\zeta,0}^h)\right)\right)\right)\right) \quad (33)$$

Here, $se(.)$ indicates size expanding operation, $AAP(.)$ signifies adaptive average pool layer and $FC(.)$ mentions FC layer.

In high-frequency attenuation component, features perform 2D Fourier transform. Consequently, frequency parameters and their relative distances are calculated. Then, Gaussian attenuation

mask is applied to eliminate higher-frequency mechanisms efficiently. An attenuation mask process can be constructed by,

$$W'(m, j) = e^{-\frac{dt(m, j)^2}{2\sigma^2}} \odot (1 - \psi) + \psi \quad (34)$$

where, $W'(m, j)$ denotes high-frequency attenuation block, $\odot$ mentions dot product and ψ illustrates low attenuation. A high-frequency attenuation layer is presented as,

$$HFA(v_{\zeta,0}^r) = \text{Re} \left\{ \chi^{-1} \left[\chi(v_{\zeta,0}^\mu) \odot W' \right] \right\} \quad (35)$$

$$\chi(m, j) = \sum_{g=0}^{L-1} \sum_{y=0}^{B-1} \omega(g, y) e^{-\jmath 2\pi \left(\frac{mg}{L} + \frac{jy}{B} \right)} \quad (36)$$

$$dt(m, j) = \sqrt{\left(\frac{m-L/2}{L} \right)^2 + \left(\frac{j-L/2}{B} \right)^2} \quad (37)$$

$$\chi^{-1}(g, y) = \frac{1}{LB} \sum_{m=0}^{L-1} \sum_{j=0}^{B-1} \chi(m, j) e^{-\jmath 2\pi \left(\frac{mg}{L} + \frac{jy}{B} \right)} \quad (38)$$

Here, $\chi(\cdot)$ implies 2D Fourier transform, $HFA(v_{\zeta,0}^r)$ reveals features after high-frequency attenuation and $\chi^{-1}(\cdot)$ reveals inverse Fourier transform.

In addition, Swin-HFA block acquires the features managed by HFA and next, global features are extracted that can be computed by,

$$\hat{E}^w = B - MSA \left(LN \left(HFA(E^{w-1}) \right) \right) + HFA(E^{w-1}) \quad (39)$$

$$E^w = MLP \left(LN \left(\hat{E}^w \right) \right) + \hat{E}^w \quad (40)$$

$$\hat{E}^{w+1} = SW - MSA \left(LN(E^w) \right) + E^w \quad (41)$$

$$E^{w+1} = MLP\left(LN\left(\hat{E}^{w+1}\right)\right) + \hat{E}^{w+1} \quad (42)$$

where, E^w and $\hat{E}^w$ denotes resulting features from multi-layer perceptron (MLP) component and S-MSA layer of w^{th} block. In the primary block, S-MSA's input feature E^{w+1} is specified as $\nu_{\zeta,0}^\mu$, $LN(.)$ mentions layer normalization and $MLP(.)$ reveals Feed-Forward Network (FFN) operation. Generally, CSPFB effectively suppresses high-frequency noises and assists a model to extract important features.

(ii) MSEACM

MSEACM consists of Adaptive Gating Fusion Block (AGFB), Feature Enhancement Attention Block (FEAB) and Multi-scale Edge Enhancement Block (MSEEB). Particularly, information from S_h and ν_{out}^μ at various levels are captured by FEAB to produce multiscale feature representation $\square$. MSEEB combines edge enhancement techniques and multiscale pool to generate feature map I . Lastly, AGFB incorporates and recomputes S_h considering data in I by means of gating procedure.

1. FEAB

FEAB utilizes Local Global Attention Layer (LGAL) with various parameters in order to capture extensive and local context data. Firstly, LGAL reshapes $\nu_{out}^s \in L' \times B' \times H'$ and then it is divided into patches with dimension $\left(\frac{L'}{v} \times \frac{B'}{v}\right) \times (v \times v \times H')$. Next, average is identified for every patch, thereby resulting feature map of size $\left(\frac{L'}{v} \times \frac{B'}{v}\right) \times (v \times v)$. Then, FFN conducts linear conversion on a feature map. Thereafter, softmax operation computes linearly-converted feature's distribution over spatial dimension to modify weights.

Additionally, task embedding vector $\gamma \in \mathbb{R}^{H'}$ as well as patch feature vector $\mu_r \in \mathbb{R}^{dt}$ having $dt = \frac{L' \times B'}{v \times v}$ are supposed. Here, $\text{sim}(\mu_r, \gamma) \in [0, 1]$ denotes cosine similarity amid feature vector of each patch and an embedding vector. The weight $\hat{\mu}_r$ is calculated as,

$$\hat{\mu}_r = \rho \cdot \text{sim}(\mu_r, \gamma) \cdot \mu_r \quad (43)$$

where, $v \in \mathbb{R}^{H' \times H'}$ refers to learnable linear conversion matrix. Each $\hat{\mu}_r$ is multiplied with conversion matrix v to choose and rearrange channel. Then, feature matrix is passed back to original size using bilinear interpolation for acquiring enhanced features. The enhanced patches are concatenated by LGAL, which can be given as,

$$\mathcal{G}\beta_r(v_{out}^{\mathbb{N}}) = \text{Concat} \left[\underbrace{LG\left(\text{Con}(v_{out}^{\mathbb{N}}), 2\right)}_{\substack{\text{Local Context Extraction} \\ r \in \{1, 2\}, \mathbb{N} \in \{\zeta, out\}}}, \overbrace{LG\left(\text{Con}(v_{out}^{\mathbb{N}}), 4\right)}^{\text{Global Context Extraction}} \right] \quad (44)$$

where, $LGAB(., v)$ indicates LGAL with v adjusting captured data, $\text{Con}(\cdot)$ represents 1×1 conv to modify channel and $\text{Concat}(\cdot)$ illustrates feature concatenation along channel dimension.

An enhanced data from transformer and CNN branches are incorporated utilizing 3×3 grouped conv, which is formulated by,

$$\mathfrak{Z}(S_h, v_{out}^{\mu}) = \text{Con}_{3 \times 3} \left(\text{Con}_{1 \times 1}(S_h) + \text{Con}_{1 \times 1}(v_{out}^{\mu}) \right) \quad (45)$$

where, $\text{Con}_{3 \times 3}(\cdot)$ reveals 3×3 grouped conv to fuse features. Lastly, FEAB is illustrated by,

$$\square = \text{Concat} \left(\mathcal{G}\beta_1(S_h), \mathcal{G}\beta_2(v_{out}^{\mu}), \mathfrak{Z}(S_h, S_h) \right) \quad (46)$$

2. MSEEB

MSEEB helps a model to observe multiscale features and boundaries in images, containing core branch as well as diverse parallel sub-branches. The local features are captured by a core branch while managing spatial dimensions. The multiscale contextual data are extracted by each parallel sub-branch through adaptive pool operation with pool scale pl . Afterwards, channel number is modified by 1×1 conv layer, which is followed by 3×3 depthwise separable conv layer. The edge

gradients are computed employing Sobel operator. The edge enhancement function $SEE(.)$ dynamically elects critical boundary regions by sigmoid activation operation. The results of individual sub-branch are reinstated to original size $L \times B$ through bilinear interpolation and merged them. To end, Dual-domain Selection procedure optimizes features and incorporates them using 1×1 conv layer.

$$SEE(\omega_r) = \omega_r + \sigma \left(\text{Con} \left(\sqrt{(\omega_r - AVP(\omega_r))^2 + (SF_\omega * \omega_r)^2 + (SF_v * \omega_r)^2} \right) \right) \quad (47)$$

$$\delta_1(\square) = \text{Inter} \left(SEE \left(DWCon \left(\text{Con} \left(AVP(\square) \right) \right) \right) \right), r = \{3, 6, 9, 12\}. \quad (48)$$

$$I = \text{Con}_{final} \left(DSM \left(\text{concat} \left([\text{Con}(\square), \delta_3(\square), \delta_6(\square), \delta_9(\square), \delta_{12}(\square)] \right) \right) \right) \quad (49)$$

where, $DSM(.)$ signifies dual-domain selection process, $\text{Inter}(.)$ depicts bilinear interpolation function, $SEE(.)$ signifies edge enhancement operation, $\sigma(.)$ reveals sigmoid function, $*$ denotes 2D conv operation that utilizes Sobel operator in order to convolve feature map ω_r .

3. AGFB

AGFB recalibrates and selectively fuses data in I in accordance to S_h . Firstly, this element projects S_h to align channel dimensions of I , resulting in merged features using additive fusion techniques. Next, merged features are employed to develop gating weights to adjust data in S_h . Finally, optimized resultant features are developed through pointwise conv as well as batch normalization. An expression of EdgeMAF-Net outcome is given by,

$$G_h = \text{softmax} \left(\text{Con}_{1 \times 1} \left(\sigma \left(\text{Con}_{1 \times 1} \left(\text{Con}_{1 \times 1} (S_h) + I \right) \right) \right) \right) \times \beta_2 \times \left[(S_h \otimes M) \oplus (S_h \otimes (1 - M)) \right] \times \left(\sum \beta_1 \times S_h \right) \quad (50)$$

Here, G_h illustrates EdgeMAF-Net's outcome, $\text{Con}_{1 \times 1}$ depicts 1×1 conv, S_h signifies generated synthetic data, β_1 and β_2 specifies weight whereas I interprets semantically dependable combined feature, $\otimes$ implies product operation, M describes attention weight and $\oplus$ denotes element-wise addition.

(iii) Loss function

A class imbalance problem and sample category complications are effectively addressed by focal loss through dynamic modification of each sample's weight during training process. The loss function can be estimated by,

$$FL(v_\mu) = -x_\mu (1 - v_\mu)^\gamma \log(v_\mu) \quad (51)$$

where, x_μ implies class weight factor, denotes learnable focusing parameter and v_μ depicts estimated probability for definite class.

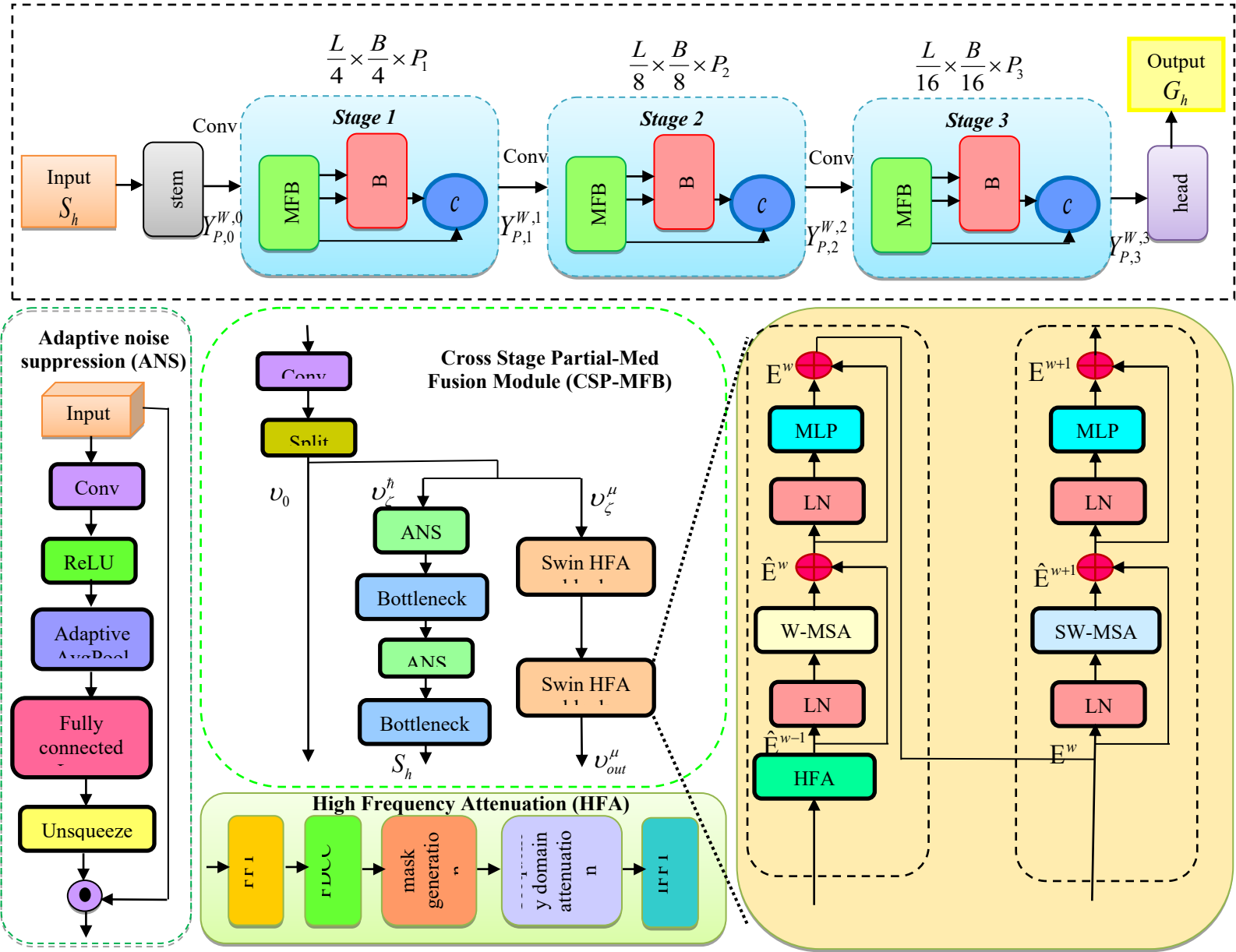


Figure 5. Structural representation of EdgeMAF-Net

c) Applying Taylor concept

Taylor concept refers to an application of Taylor series expansion methods to develop computational algorithms or models intended at diagnosing heart conditions. Particularly, it involves approximating complicated biological signals or mathematical functions corresponding to heart function, by stating them as infinite sum of polynomial terms centered across certain point. Herein, Taylor concept is applied to AASAN and EdgeMAF-Net's output such as A_h and G_h . An equation of Taylor concept is specified as,

$$p(b+1) = p(b) + \frac{p'(b)}{1!} \quad (52)$$

$$p'(b) = \frac{p(b) - p(b-\lambda)}{\lambda} \quad (53)$$

Assume $\lambda = 1$ and substitute in aforementioned expression and it is modelled by,

$$p'(b) = p(b) - p(b-1) \quad (54)$$

Substitute Eq. (54) in Eq. (52) and it is represented as,

$$p(b+1) = p(b) + p(b) - p(b-1) \quad (55)$$

$$p(b+1) = 2p(b) - p(b-1) \quad (56)$$

Let us consider,

$$p(b) = A_h \quad (57)$$

$$p(b-1) = G_h \quad (58)$$

$$p(b+1) = R_h \quad (59)$$

Substitute Eq. (57), Eq. (58) and Eq. (59) in Eq. (56), which is formulated as,

$$R_h = 2A_h - G_h \quad (60)$$

Substitute Eq. (31) and Eq. (50) in Eq. (60), which can be given by,

$$R_h = 2 \left[\left[(S_h \otimes M) \oplus (S_h \otimes (1-M)) \right] \times \left(\sum \beta_1 \times S_h \right) \right] - \left[softmax \left(Con_{1 \times 1} \left(\sigma \left(Con_{1 \times 1} \left(Con_{1 \times 1} (S_h) + I \right) \right) \right) \times \beta_2 \times \left[(S_h \otimes M) \oplus (S_h \otimes (1-M)) \right] \times \left(\sum \beta_1 \times S_h \right) \right] \right] \quad (61)$$

$$R_h = \left[\left[(S_h \otimes M) \oplus (S_h \otimes (1-M)) \right] \times \left(\sum \beta_1 \times S_h \right) \right] \left[2 - \left[softmax \left(Con_{1 \times 1} \left(\sigma \left(Con_{1 \times 1} \left(Con_{1 \times 1} (S_h) + I \right) \right) \right) \times \beta_2 \right) \right] \right] \quad (62)$$

Here, R_h indicates heart disease detected output, S_h specifies generated synthetic data, β_1 and β_2 reveals weight, $Con_{1 \times 1}$ illustrates 1×1 conv, M mentions attention weight, I depicts semantically dependable combined feature, $\otimes$ denotes product operation, and $\oplus$ implies element-wise addition.

5. Results and discussion

The evaluations and results of AAMF-Net for detecting heart disease are briefly elaborated in below subsections.

5.1 Experiment setup

The implementation of AAMF-Net is conducted in PYTHON tool and the experimental parameters of AAMF-Net are interpreted in table 1.

Table 1. Experimental parameters of AAMF-Net

Parameters	Description
Feature Pyramid Levels	4
Activation Function	ReLU
Optimizer	Adam
Batch Size	32

Weight Decay	1×10^{-4}
Learning Rate Scheduler	Cosine Annealing
Weight Initialization	He Normal
Number of Attention Heads	8
Kernel Size	3×3
Normalization	Batch Normalization
Learning Rate	1×10^{-4}
Number of Epochs	100
Dropout Rate	0.30
Early Stopping Patience	10
Random Seed	42

5.2 Dataset description

Cardiovascular_Disease_Dataset and UCI Heart Disease Data are the two datasets considered in this research.

5.2.1 UCI Heart Disease Data

UCI Heart Disease Data comprises of 14 attributes such as age, chest pain type, sex, resting blood pressure, fasting blood sugar, serum cholesterol, resting electrocardiographic outcomes, exercise-induced angina, high heart rate attained and so on. This dataset includes single file with 16 columns. The dataset size is 79.35 kB and overall files are available in .csv format.

5.2.2 Cardiovascular_Disease_Dataset

Cardiovascular_Disease_Dataset consists of 1000 subjects with about 12 features. This dataset includes diverse attributes like Oldpeak=ST, gender, chest pain type, number of major vessels, serum cholesterol, age, resting electrocardiogram results and so on. Moreover, it offers comprehensive interpretation of unit, data type and assigned code for individual attribute. The files are offered in csv format and their size is 42.6 KB.

5.3 Evaluation metrics

To estimate the performance of AAMF-Net, two evaluation measures namely accuracy and detection rate are employed.

5.3.1 Accuracy

Accuracy is stated as a proportion of exactly detected cases out of overall evaluated cases and it can be formulated by,

$$Acc = \frac{e + E}{e + E + f + F} \quad (63)$$

Here, e and E signifies true negative as well as true positive whereas f and F reveals false negative and false positive.

5.3.2 Detection rate

Detection rate refers to a proportion of actual heart disease cases, which are accurately identified by the model.

$$DR = \frac{E}{E + f} * 100 \quad (64)$$

5.4 Experimental outcomes

Figure 6 illustrates density plot for two considered datasets. Figure 6 a) and 6 b) shows density plot for UCI Heart Disease Data and density plot for Cardiovascular_Disease_Dataset. In both plots, red curve indicates normal samples and pink curve denotes abnormal samples. The separate peaks represent diverse value distributions for two classes, revealing that feature has better discriminative power. Although small overlap occurs in few intervals, an overall separation interprets that feature contributes efficiently to distinguish normal as well as abnormal heart conditions.

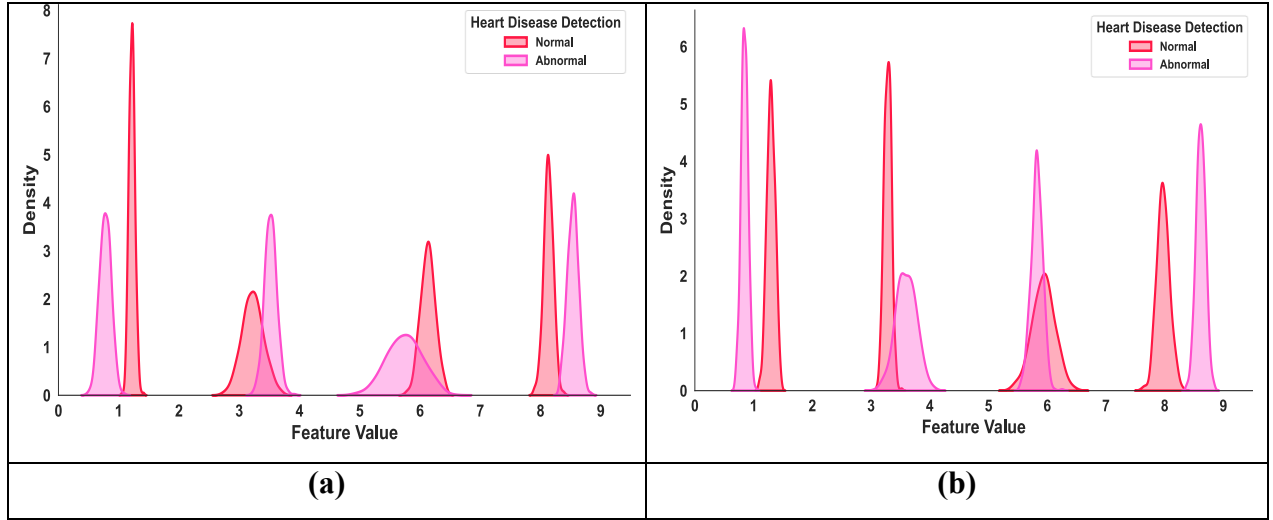


Figure 6. Density plot, a) UCI Heart Disease Data, b) Cardiovascular_Disease_Dataset

The deviation graphs for both datasets are depicted in figure 7. Figure 7 a) and 7 b) reveals deviation graph for UCI Heart Disease Data and deviation graph for Cardiovascular_Disease_Dataset. A deviation graph describes the prediction error for individual sample. Most of the samples have 0 deviation, representing accurate detection. Furthermore, small count of samples demonstrates +1 or -1 deviations, indicating underpredictions or overpredictions. An absence of any noticeable patterns in deviations mentions that prediction errors are randomly distributed and thus, AAMF-Net attains maximum accuracy. Also, random distribution of these deviations across datasets interprets stable model performance with minimum error rate.

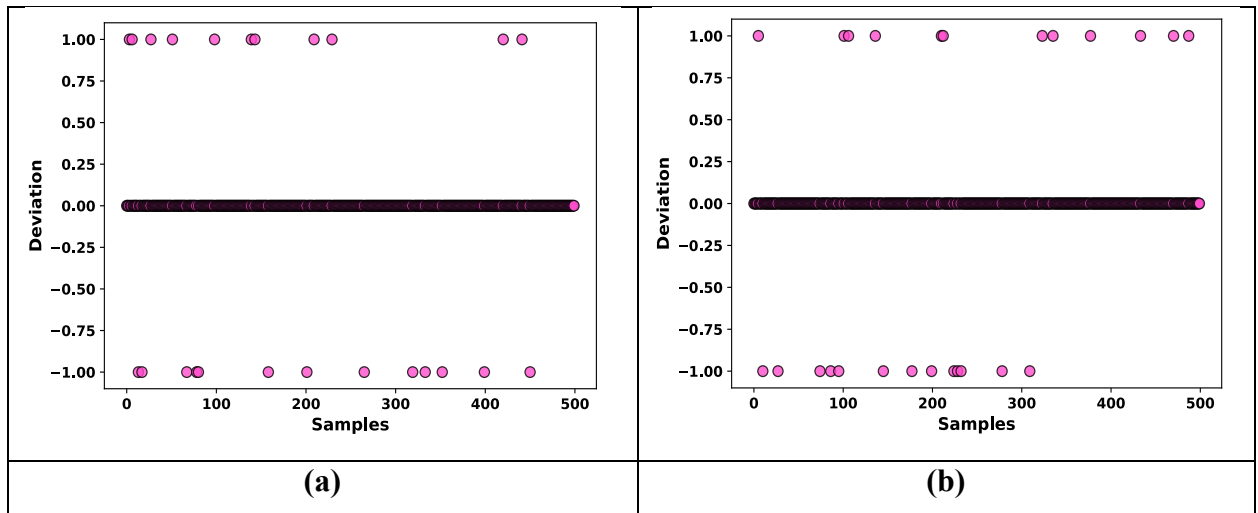


Figure 7. Deviation graphs, a) UCI Heart Disease Data, b) Cardiovascular_Disease_Dataset

5.5 Explainability analysis based on SHapley Additive exPlanations (SHAP)

Figure 8 delineates explainability assessment of AAMF-Net based on SHAP for UCI Heart Disease Data. Figure 8 a) shows multi-group decomposition plot, wherein Oldpeak, ca, thalch and sex are the most important features based on four groups. Figure 8 b) and 8 c) specified SHAP summary plot and waterfall plot. Age and chol are significant features based on summary plot as well as waterfall plot. These features are clinically important and highly suitable to interpret model's predictions.

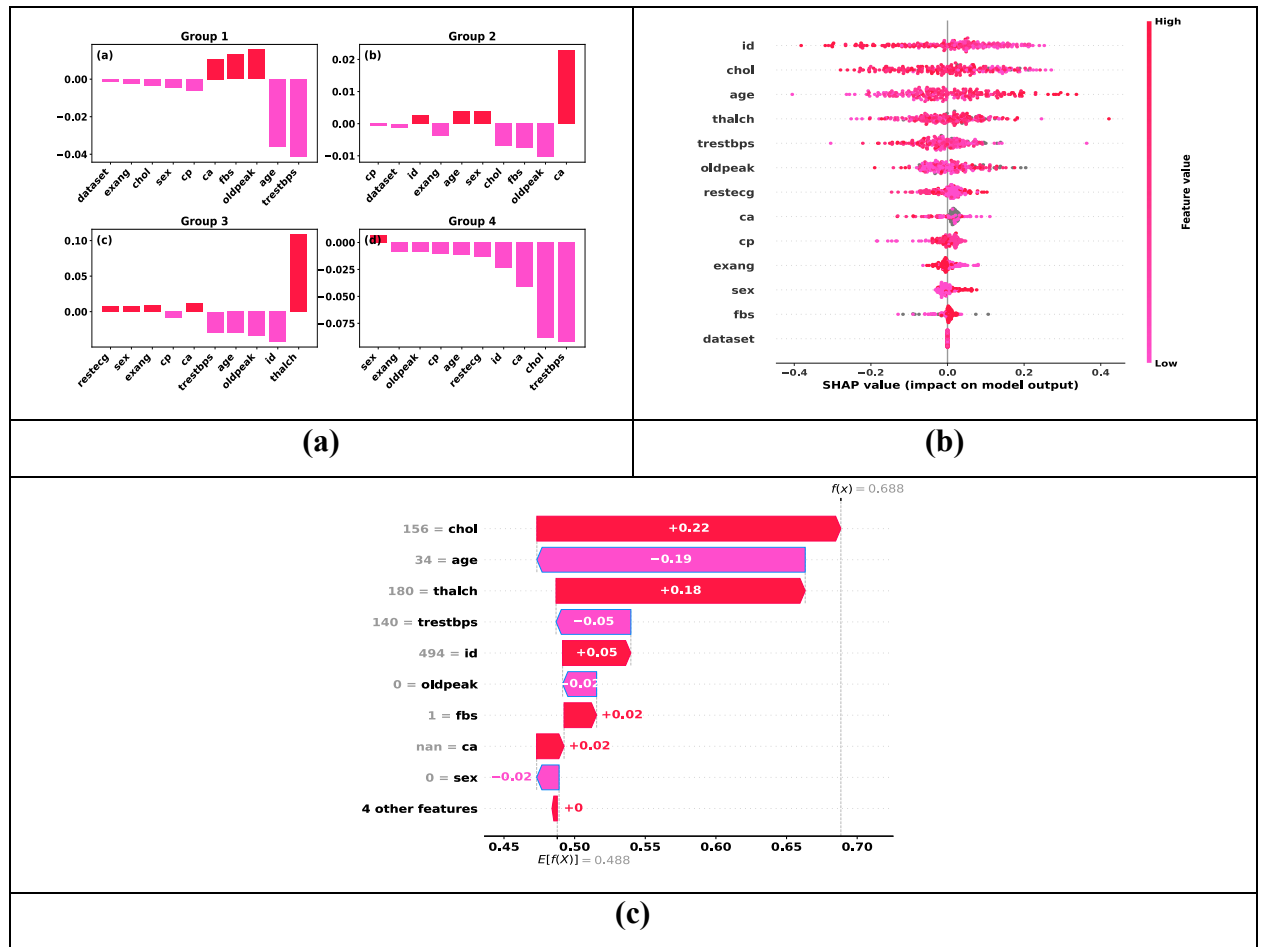


Figure 8. Explainability assessment for UCI Heart Disease Data, a) Multi-group decomposition plot, b) SHAP summary plot, c) Waterfall plot

An explainability assessment of AAMF-Net based on SHAP for Cardiovascular_Disease_Dataset is presented in figure 9. A multi-group decomposition plot is demonstrated in figure 9 a). According to group 1 and group 4, serumcholesterol is the vital feature. Based on other two groups, chestpain and restingBP are significant features for detection task. SHAP summary and waterfall plots are displayed in figure 9 b) and 9 c). Patientid is a vital feature based on summary plot and maxheartrate is an essential feature based on waterfall plot. These features have high overall influence on model's predictions.

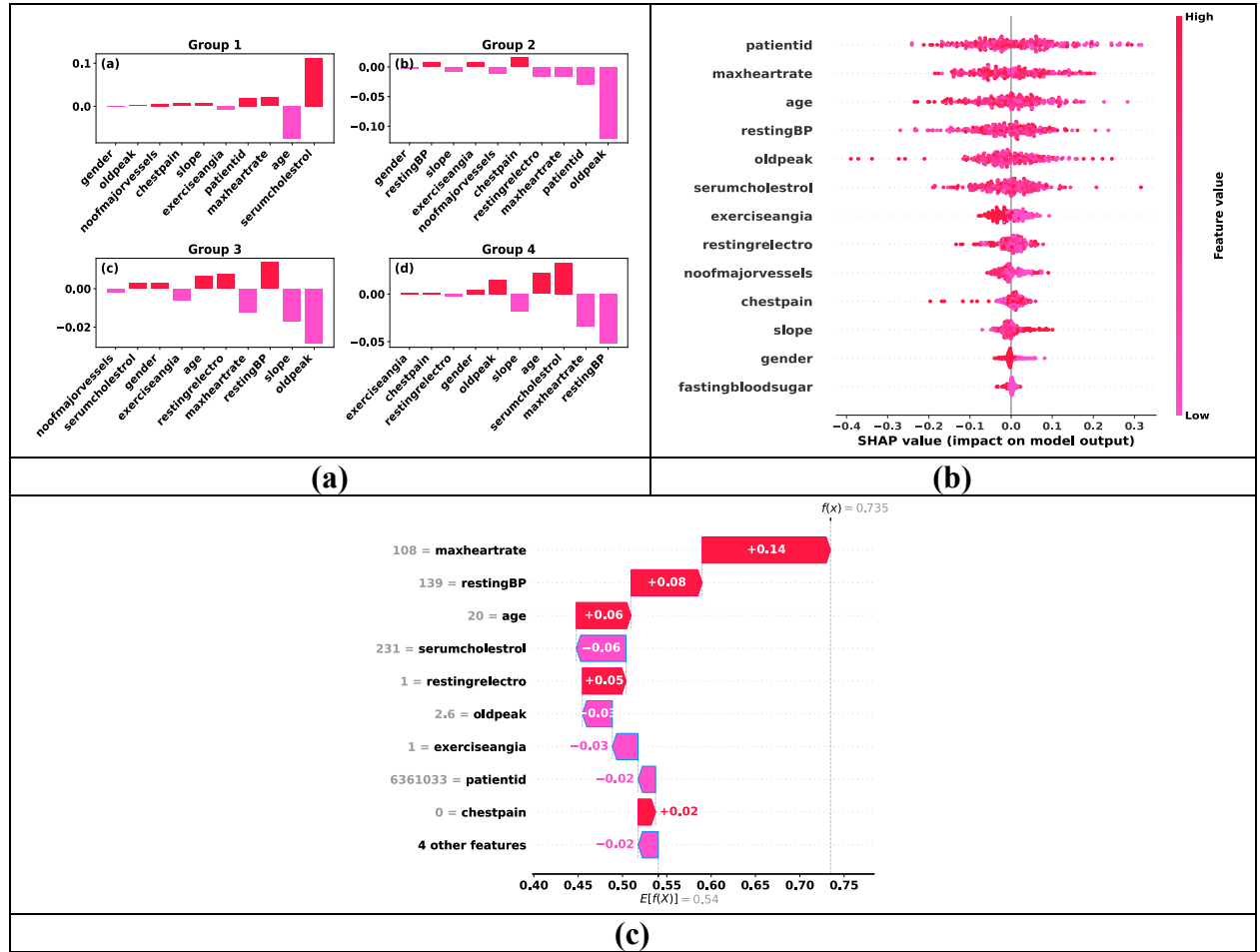


Figure 9. Explainability analysis for Cardiovascular_Disease_Dataset, a) Multi-group decomposition plot, b) SHAP summary plot, c) Waterfall plot

5.6 Comparative techniques

FRIEND, Explainable-IoT framework, CNN and Hybrid mutual authentication approach are the classical approaches compared with AAMF-Net to prove its efficiency.

5.7 Analysis of AAMF-Net

An assessment section of AAMF-Net includes AUC table, ablation study, scalability analysis and calibration curve.

5.7.1 Ablation study

An ablation study is a systematic assessment procedure employed for comprehending a contribution of diverse components or features within a model. An efficiency of AAMF-Net is assessed by comparing it with AASAN and EdgeMAF-Net. Here, ablation study is performed for considered two datasets.

a) Analysis based on UCI Heart Disease Data

Figure 10 signifies ablation study of AAMF-Net for UCI Heart Disease Data. This part interprets values of models for training data considered as 90%. Figure 10 a) represents analysis of AAMF-Net regarding accuracy. AAMF-Net acquired accuracy of 96.250% whereas AASAN and EdgeMAF-Net achieved 94.569% and 95.375% of accuracy. Estimation of AAMF-Net with respect to detection rate is illustrated in figure 10 b). Detection rate obtained by AASAN and EdgeMAF-Net is 95.520% and 96.267% whereas AAMF-Net attained detection rate of 97.021%.

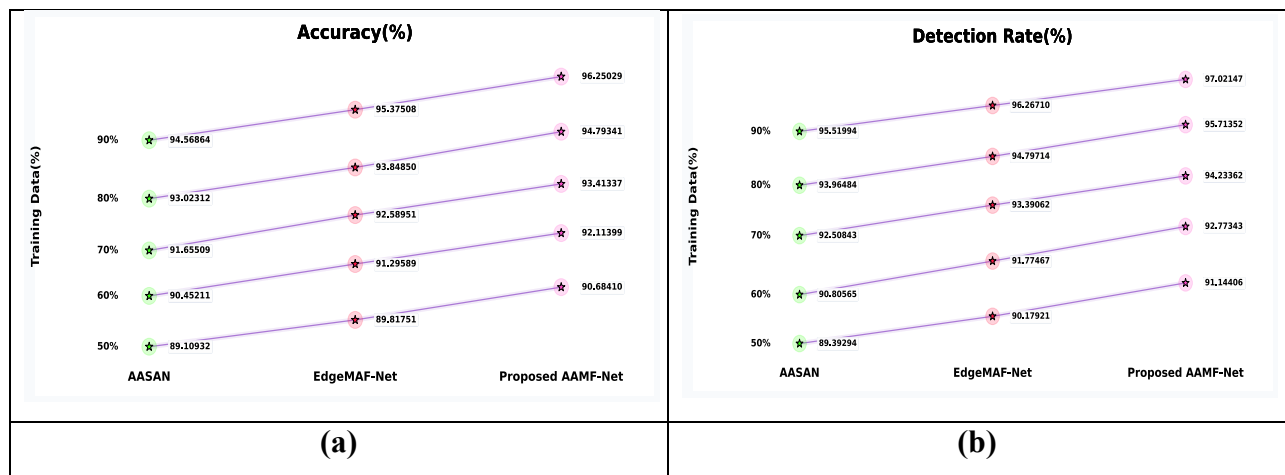


Figure 10. Ablation study of AAMF-Net for UCI Heart Disease Data, a) Accuracy, b) Detection rate

b) Analysis based on Cardiovascular_Disease_Dataset

Ablation study of AAMF-Net for Cardiovascular_Disease_Dataset is demonstrated in figure 11. Here, values of AAMF-Net and other models are explained in this part for considered training data=90%. Estimation of AAMF-Net in terms of accuracy is delineated in figure 11 a). An accuracy achieved by AASAN and EdgeMAF-Net is 94.805% and 95.565% whereas accuracy obtained by AAMF-Net is 96.346%. Figure 11 b) displays analysis of AAMF-Net regarding detection rate. AAMF-Net achieved detection rate of 97.101% whereas AASAN and EdgeMAF-Net obtained 95.380% and 96.202% of detection rate.

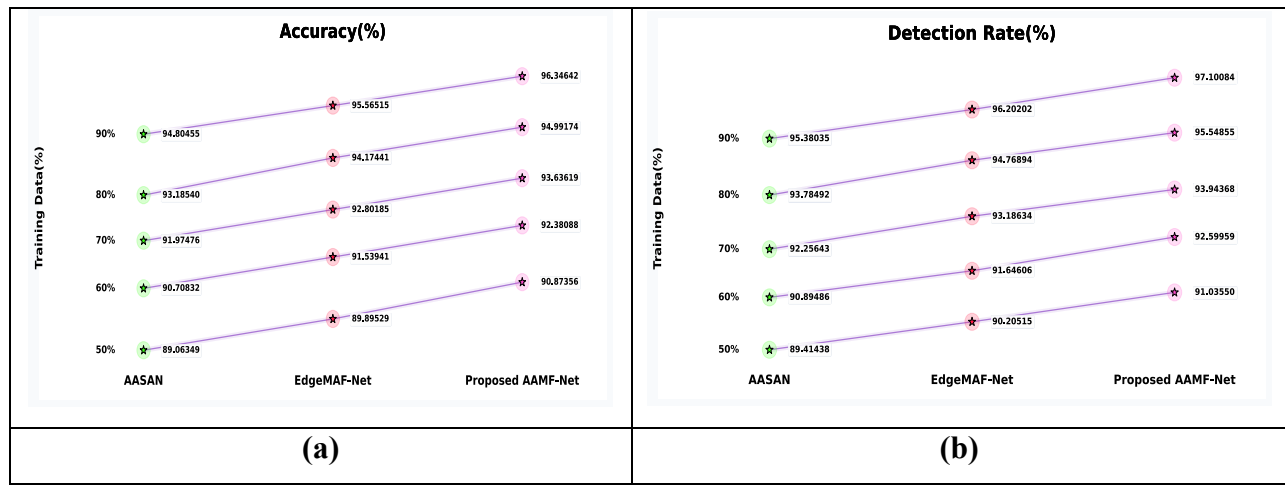


Figure 11. Ablation study of AAMF-Net for Cardiovascular_Disease_Dataset, a) Accuracy, b) Detection rate

5.7.2 Scalability analysis of AAMF-Net

A scalability assessment of AAMF-Net is conducted based on UCI Heart Disease Data and Cardiovascular_Disease_Dataset.

a) Analysis based on UCI Heart Disease Data

Figure 12 displays scalability evaluation of AAMF-Net for UCI Heart Disease Data. This part describes evaluation values of conventional methods and AAMF-Net for feature dimension=10. Evaluation of AAMF-Net based on accuracy is represented in figure 12 a). FRIEND, Explainable-IoT framework, CNN and Hybrid mutual authentication approach attained accuracy of 90.025%, 91.505%, 93.036% and 94.280% whereas AAMF-Net achieved 96.279% of

accuracy. This demonstrates that AAMF-Net's performance is improved by 6.496%, 4.958%, 3.368% and 2.076% when compared to classical techniques. Figure 12 b) shows estimation of AAMF-Net considering detection rate. Detection rate attained by AAMF-Net is 97.039% whereas FRIEND, Explainable-IoT framework, CNN and Hybrid mutual authentication approach acquired 90.906%, 92.267%, 93.787% and 95.061% of detection rate.

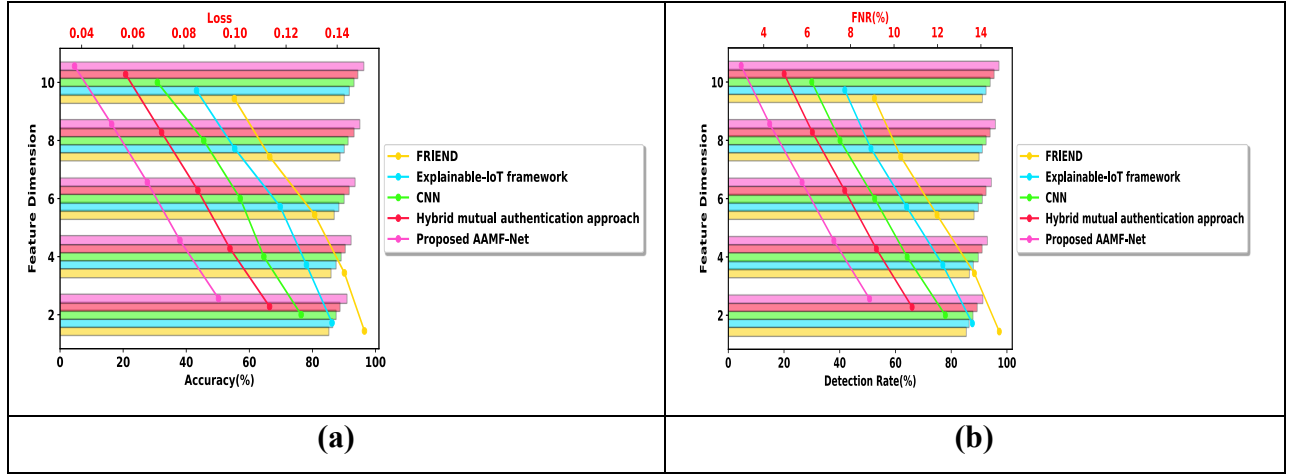


Figure 12. Scalability assessment of AAMF-Net for UCI Heart Disease Data, a) Accuracy, b) Detection rate

b) Analysis based on Cardiovascular_Disease_Dataset

Scalability evaluation of AAMF-Net for Cardiovascular_Disease_Dataset is manifested in figure 13. In this part, values of AAMF-Net and classical models for considered feature dimension=10 are described. Figure 13 a) indicates assessment of AAMF-Net considering accuracy. AAMF-Net achieved accuracy of 96.375% whereas FRIEND, Explainable-IoT framework, CNN and Hybrid mutual authentication approach obtained 89.828%, 91.129%, 92.819% and 94.421% of accuracy. Thus, performance of AAMF-Net is highly gained by 6.793%, 5.443%, 3.689% and 2.028%. Estimation of AAMF-Net with regard to detection rate is shown in figure 13 b). FRIEND, Explainable-IoT framework, CNN and Hybrid mutual authentication approach acquired detection rate of 90.873%, 92.316%, 93.808% and 95.154% whereas AAMF-Net achieved 97.129% of detection rate.

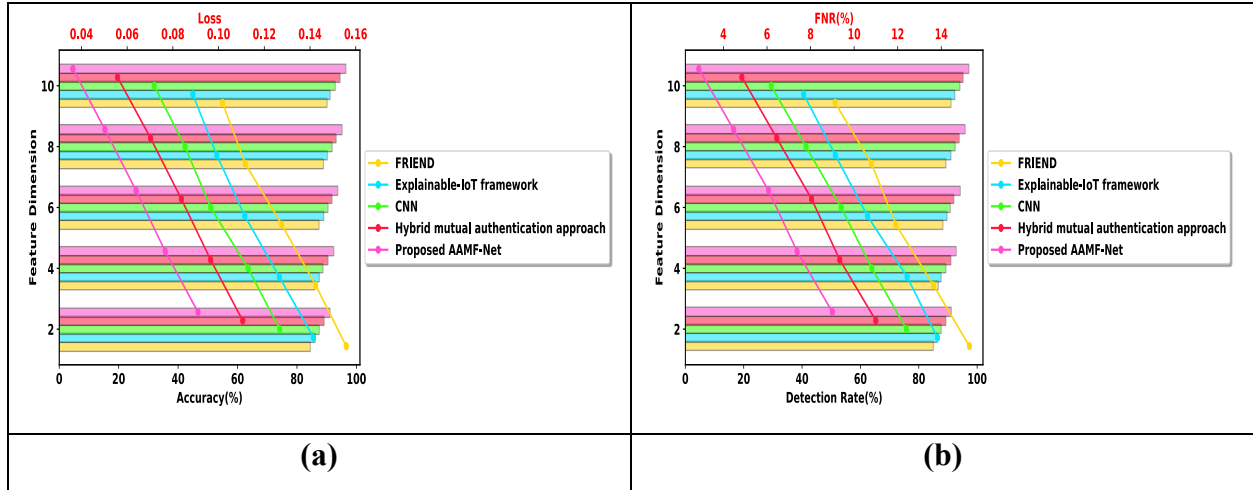


Figure 13. Scalability estimation of AAMF-Net for Cardiovascular_Disease_Dataset, a) Accuracy, b) Detection rate

5.7.3 AUC table

Figure 14 depicts AUC table for two datasets by comparing feature ranking between original model and reduced model. Figure 14 a) displays AUC table for UCI Heart Disease Data. A reduced model obtained its high predictive performance with thalach (AUC=0.9737), cp (AUC=0.9629), thal (AUC=0.9627) and slope (AUC=0.9617). Various features, including oldpeak and slope, became more significant after feature reduction, whereas chol and ca demonstrated considerable reduction in significance. Overall, significantly maximum AUC values represent that reduced model maintained superior discrimination while depending on small group of useful features. The AUC table for Cardiovascular_Disease_Dataset is shown in figure 14 b). An exerciseangia obtained maximum predictive performance (AUC=0.9737), followed by restingBP (AUC=0.9629) and number of major vessels (AUC=0.9617). While gender remained high ranked feature, restingelectro and oldpeak revealed considerable enhancements in ranking after feature reduction, represented improved significance in simplified model. On the other hand, serum cholesterol and slope indicated reduction in significance, specifying that their predictive data overlaps with other variables. Overall, reliably high AUC values represent that reduced model maintains robust predictive ability while employing highly compact group of clinically appropriate features.

Feature	Feature ranking (Original Model)	Feature ranking (Reduced Model)	Predictive Performance (AUC)
thalch	5	2	0.9737
cp	6	10	0.9629
thal	7	8	0.9627
slope	13	3	0.9617
age	12	13	0.9575
oldpeak	11	6	0.9569
restecg	15	14	0.9533
sex	1	1	0.9518
fbs	2	4	0.9477
id	10	11	0.9439
dataset	14	9	0.9431
chol	3	12	0.9431
exang	8	5	0.9374
trestbps	9	7	0.9336
ca	4	15	0.9279

(a)

Feature	Feature ranking (Original Model)	Feature ranking (Reduced Model)	Predictive Performance (AUC)
exerciseangia	8	6	0.9737
restingBP	6	12	0.9629
noofmajorvessels	7	8	0.9617
age	10	11	0.9575
slope	4	13	0.9569
maxheartrate	5	5	0.9533
gender	1	1	0.9518
restingelectro	13	2	0.9477
patientid	12	9	0.9439
chestpain	9	7	0.9431
fastingbloodsugar	2	4	0.9431
oldpeak	11	3	0.9374
serumcholesterol	3	10	0.9336

(b)

Figure 14. AUC table, a) UCI Heart Disease Data, b) Cardiovascular_Disease_Dataset

5.7.4 Calibration curve

The calibration curve for two datasets is delineated in figure 15. Figure 15 a) and 15 b) indicates calibration curve for UCI Heart Disease Data and Cardiovascular_Disease_Dataset. A train data remains closer to ideal calibration line throughout various probability ranges. Also, test data reveals better agreement with ideal calibration line. The vertical error bars illustrate an uncertainty related with every calibration point. The error bars tend to be extensive at higher and lower probability ranges, reflecting few observations within these bins. In spite of this variability, an overlap of error bars with ideal calibration line specifies that observed probability are not considerable. Both test and training calibration curves closely follow 45° reference line across complete range of forecasted probabilities. Overall, calibration assessment reveals that AAMF-Net generates reliable and accurate probability estimates for prediction of heart disease, assisting its applicability in the clinical risk analysis.

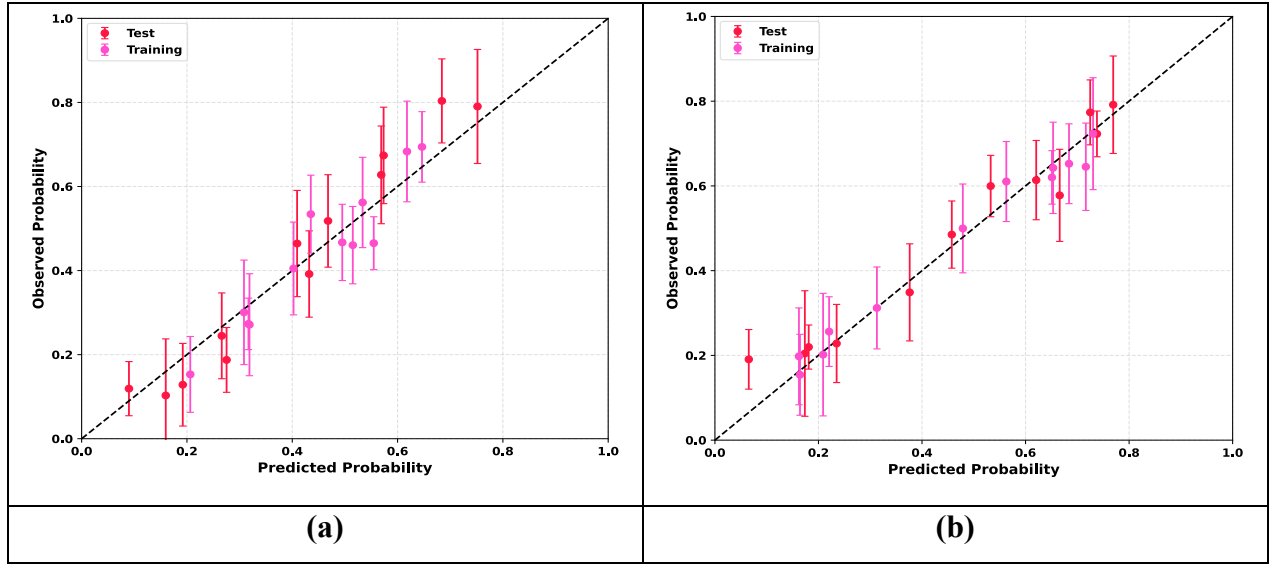


Figure 15. Calibration curve, a) UCI Heart Disease Data, b) Cardiovascular_Disease_Dataset

5.8 Discussion graph

Figure 16 illustrates discussion graph based on two datasets. Figure 16 a) reveals discussion graph for UCI Heart Disease Data. The outcomes demonstrate a stable enhancement across conventional approaches. FRIEND achieved 90.02% of accuracy and 90.91% of detection rate whereas Explainable-IoT Framework obtained 91.51% of accuracy and 92.27% of detection rate. CNN acquired 93.04% of accuracy and 93.79% of detection rate, while Hybrid mutual authentication approach attained 94.28% of accuracy and 95.06% of detection rate. Furthermore, AAMF-Net exhibits better performance with maximum accuracy of 96.28% and maximum detection rate of 97.04%, representing its ability in exactly detecting heart diseases into normal and abnormal. The discussion graph for Cardiovascular_Disease_Dataset is shown in figure 16 b). FRIEND acquired low performance with 89.83% of accuracy and 90.87% of detection rate, accuracy and detection rate achieved by Explainable-IoT Framework is 91.13% and 92.32%, CNN obtained 92.82% of accuracy and 93.81% of detection rate whereas Hybrid mutual authentication approach acquired accuracy of 94.42% and detection rate of 95.15%. Moreover, AAMF-Net performs better than individual existing techniques, attaining high accuracy of 96.37% and detection rate of 97.13%. Overall, the discussion graph emphasizes an efficiency of AAMF-Net, which enhanced accuracy and detection rate, confirming its reliability as well as robustness for heart disease detection. Based on the graph, AAMF-Net is the effectual model for

identifying heart disease. In addition, AAMF-Net acquired accuracy and detection rate of 96.37% and 97.13% for Cardiovascular_Disease_Dataset.

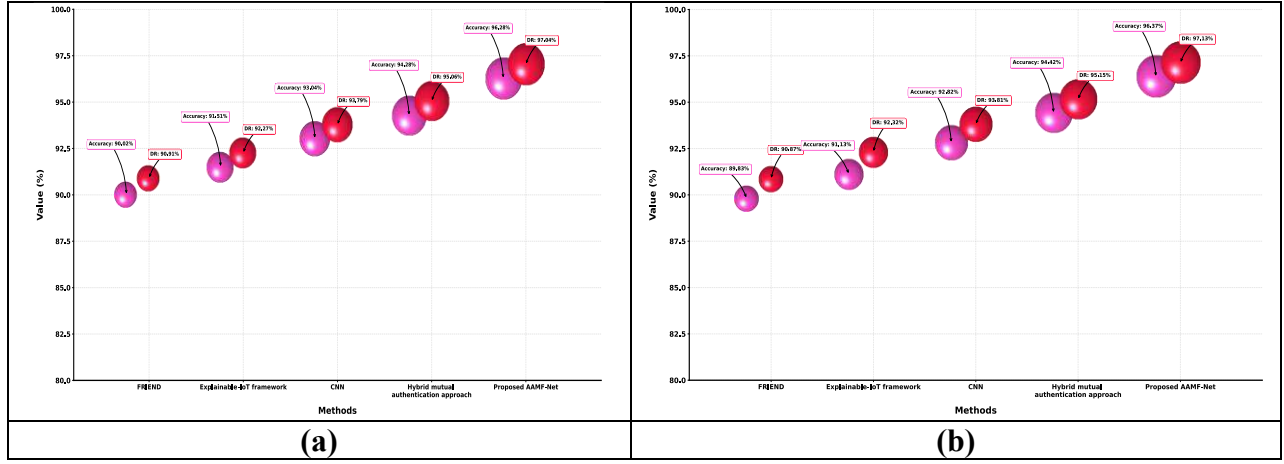


Figure 16. Discussion graph, a) UCI Heart Disease Data, b) Cardiovascular_Disease_Dataset

5.9 Statistical analysis

Statistical analysis graphs for UCI Heart Disease Data are shown in figure 17. Figure 17 a) mentions statistical analysis graph based on accuracy. AAMF-Net reliably performs better than conventional approaches, attaining high accuracy with ($t = 1.110$, $p = 0.0432$) compared to FRIEND ($t = 2.710$, $p = 0.0016$), Explainable-IoT framework ($t = 2.220$, $p = 0.0204$), CNN ($t = 1.980$, $p = 0.0283$), and Hybrid mutual authentication approach ($t = 1.520$, $p = 0.0315$) for normal class. Likewise, AAMF-Net acquired best outcomes regarding accuracy for abnormal class. These resultants represent that AAMF-Net offers reliable and superior performance compared to traditional techniques. The statistical analysis graph in terms of detection rate is mentioned in figure 17 b). In this figure, AAMF-Net acquires high detection performance for normal and abnormal classes. The t-statistics and p-values confirm that AAMF-Net's outcomes are statistically significant. AAMF-Net achieved high detection rate with ($t = 1.340$, $p = 0.0404$) compared to FRIEND ($t = 2.880$, $p = 0.0089$), Explainable-IoT framework ($t = 2.630$, $p = 0.0126$), CNN ($t = 2.310$, $p = 0.0225$), and Hybrid mutual authentication approach ($t = 1.710$, $p = 0.0327$) for abnormal case. Likewise, best outcomes are achieved in terms of detection rate for normal cases. The resultants validate robustness and efficiency of AAMF-Net in exactly detecting heart disease.

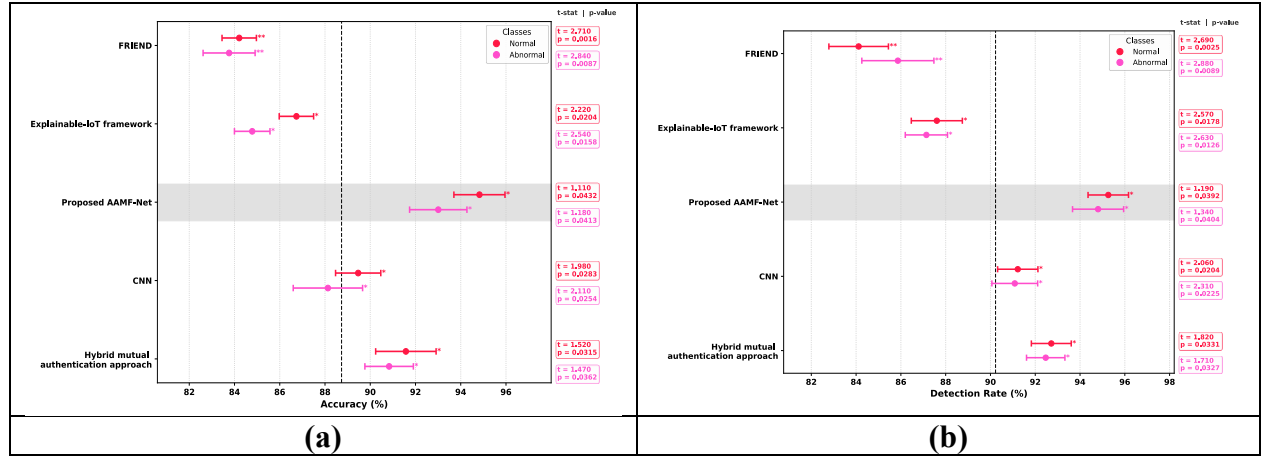


Figure 17. Statistical analysis for UCI Heart Disease Data, a) Accuracy, b) Detection rate

Figure 18 interprets statistical analysis graphs for Cardiovascular_Disease_Dataset. The statistical analysis graph with regard to accuracy is revealed in figure 18 a). Herein, AAMF-Net acquired high detection performance for normal and abnormal classes. The maximum accuracy is obtained by AAMF-Net with ($t = 1.230$, $p = 0.0408$), outperforming FRIEND ($t = 2.790$, $p = 0.0091$), Explainable-IoT framework ($t = 2.490$, $p = 0.0163$), CNN ($t = 2.180$, $p = 0.0248$), and Hybrid mutual authentication approach with ($t = 1.530$, $p = 0.0356$) for abnormal case. Similarly, superior results are acquired for normal cases. The outcomes highlight AAMF-Net's robustness and effectiveness for accurate heart disease detection. Figure 18 b) demonstrates statistical analysis considering detection rate. AAMF-Net performs superiorly, achieving high detection rate with ($t = 1.270$, $p = 0.0408$) compared to classical methods like FRIEND ($t = 2.740$, $p = 0.0031$), Explainable-IoT framework ($t = 2.490$, $p = 0.0169$), CNN ($t = 2.140$, $p = 0.0218$), and Hybrid mutual authentication approach ($t = 1.760$, $p = 0.0323$) for normal class. Also, AAMF-Net attained best resultants with respect to detection rate for abnormal class. These outputs indicate that AAMF-Net is highly efficient and reliable model for detecting heart disease amongst traditional techniques.

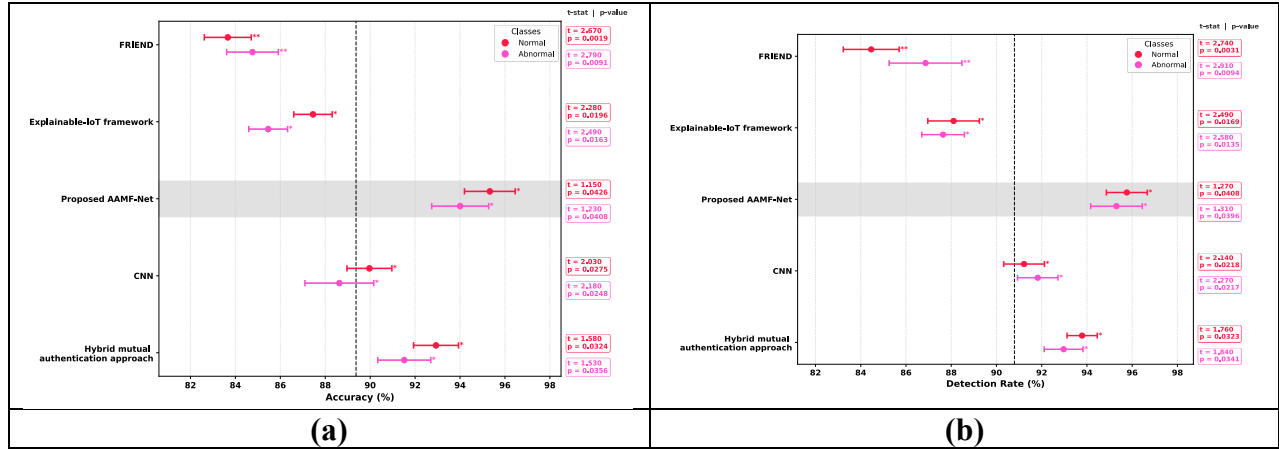


Figure 18. Statistical analysis for Cardiovascular_Disease_Dataset, a) Accuracy, b) Detection rate

6. Conclusion

An adoption of IoMT-cloud-edge has revolutionized various aspects of healthcare management by facilitating personalized treatment, and enhancing patient outcomes in diagnosing heart disease. However, conventional methods face challenges like managing larger volume of data generated, incorporation of diverse systems and devices, as well as data security. Here, AAMF-Net is designed for heart disease diagnosis in edge-cloud-IoMT. Firstly, IoMT is simulated and the various entities involved are cloud, edge as well as IoMT. The various steps performed are initialization, data access control, registration, authorization, data protection, trust-based authentication and key generation, which is accomplished by DHA-Net. The authentication technique is based on several security operations, such as DES encryption, hashing function, X-OR functions, OTP, and so on. The data secured at cloud is utilized for diagnosing heart disease. Initially, an input data is pre-processed based on outlier removal, missing value handling and categorical encoding. After that, VSS is employed to obtain equalized feature contribution. Thereafter, feature dimensionality reduction is conducted employing Inf-FSSs and next, synthetic data is generated by FE-SMOTE. Finally, heart disease is detected employing AAMF-Net, and it is modelled by incorporating AASAN with EdgeMAF-Net. The findings proved that AAMF-Net outperformed conventional methods, attaining 96.37% of accuracy and 97.13% of detection rate. For future research, big data analytics will be combined in cloud with edge processing for predicting heart disease risk factors.

Data Availability Statement:

The datasets generated and/or analysed during the current study are available in the **UCI Heart Disease Data** Dataset repository, <https://www.kaggle.com/datasets/redwankarimsony/heart-disease-data> and **Cardiovascular_Disease_Dataset** repository, <https://data.mendeley.com/datasets/dzz48mvjht/1>

Declarations:

Conflict of Interest: The authors declare that they have no conflict of interest.

Funding: No funding was received for conducting this study or for the preparation of this manuscript.

Clinical Trial Registration Requirement: We confirm that this study is not a clinical trial and does not involve the registration of a clinical trial. Therefore, clinical trial registration details, including the registry, trial registration number, and date of registration, are not applicable to this manuscript.

Ethics, Consent to Participate, and Consent to Publish Declarations: We confirm that the study does not involve human participants, human subjects, or identifiable personal data. Therefore, ethics approval, consent to participate, and consent to publish are not applicable to this study.

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