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EDCF2SL: Design of an Explainable Deep Learning Model for Cardiovascular Disease Analysis using Federated Learning with Few-Shot Learning Operations

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Abstract: The timely detection and pre-emption of cardiovascular diseases (CVDs) remain pivotal challenges in healthcare, necessitating innovative approaches in signal analysis and machine learning. Existing methodologies often fall short in precision, accuracy, and timeliness, underscoring the need for more sophisticated and integrated solutions. This paper presents a novel framework employing advanced deep learning architectures and federated learning techniques for enhanced photoplethysmography (PPG) signal analysis.

Our approach integrates transformer networks and capsule networks to effectively capture temporal dependencies and spatial hierarchies in multidimensional PPG data, addressing limitations in current practices by significantly improving the precision and accuracy of the CVD detection process. We incorporate federated averaging algorithms and secure aggregation protocols to train models across multiple devices while ensuring data privacy levels. Further, our

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methodology leverages interpretable Deep SHAP, providing clarity and transparency in model decisions, a critical factor in clinical settings.

The integration of multi-modal data through multiple input convolutional neural networks and recurrent neural networks with (LSTM) and bidirectional gated recurrent unit (BiGRU) networks allows for a comprehensive analysis of varied physiological signals. Additionally, our model employs sophisticated anomaly detection techniques, including autoencoders and Isolation Forest, for early and precise identification of unusual patterns in PPG signals.

To cater to individual variances in physiological signals, we implement personalized and adaptive models using model-agnostic meta-learning with few-shot learning, ensuring tailored detection and monitoring processes. The unique blend of machine learning models and rule-based systems through ensemble methods further enhances the efficacy of our framework.

Clinical testing across multiple heart diseases has demonstrated the superiority of our approach, showing significant improvements over existing methods in various metrics such as precision, accuracy, recall, aUC, specificity, and response delays. This work not only marks a significant advancement in the detection and pre-emption of CVDs but also sets a new benchmark for the application in medical diagnostics, promising substantial impacts on patient outcomes and healthcare practices.

Keywords: **Photoplethysmography, deep learning, cardiovascular disease detection, federated learning, anomaly detection.**

1. Introduction

Cardiovascular diseases (CVDs) are among the leading causes of mortality worldwide, posing significant challenges to public health systems. Early detection and monitoring of CVDs are crucial for effective treatment and management, reducing the overall burden on patients and healthcare providers.

Photoplethysmography (PPG), a anon-invasive technique that measures blood volume changes in microvascular tissue, has emerged as a promising tool for early CVD detection. However, the efficacy of PPG largely depends on the accuracy and sophistication of the signal analysis methods employed for different scenarios.

Traditional methods for PPG signal analysis often struggle with issues such as low precision, inadequate accuracy, and delayed response times. These limitations stem from the inherent complexities in PPG data, including its high dimensionality, the presence of noise, and individual physiological variances. Consequently, there isna pressing need for advanced analytical models that can overcome these challenges and enhance the detection and prediction of CVDs.

In response to this need, our research introduces a comprehensive framework combining state-of-the-art deep learning architectures and federated learning approaches for advanced pPG signal analysis. This paper details the development and implementation of transformer networks and capsule networks, specifically tailored to manage the temporal and aspatial complexities of PPG data samples.

These networks have demonstrated remarkable abilities in extracting meaningful patterns from multi-dimensional data, significantly improving the predictive accuracy of the CVD detection process. Another critical aspect of our research is the incorporation of federated learning. This approach enables the training of AI models on distributed datasets across multiple devices while maintaining data privacy and security. Such a method is particularly relevant in healthcare settings where patient data sensitivity is paramount.

To further enhance our model's practicality in clinical settings, we have integrated interpretable AI models, particularly Deep SHAP, which provides valuable insights into the decision-making processes of complex neural networks. This interpretability is vital for clinicians to trust and effectively use AI-driven diagnostics.

Recognizing the diversity in physiological signals among individuals, our framework includes personalized and adaptive models using meta-learning and few-shot learning techniques. This approach ensures that our model remains sensitive to individual variances, thus improving the accuracy and effectiveness of CVD detection for each of the patients.

Additionally, our model employs a blend of machine learning and rule-based systems, combining the robustness of data-driven approaches with the reliability of established clinical guidelines. This hybrid approach aims to provide a more comprehensive and reliable framework for CVD detection and monitoring processes.

This paper presents a pioneering approach to CVD detection, leveraging the latest advancements in machine learning and signal processing. Our research not only addresses the current limitations in PPG signal analysis but also sets a new standard for AI applications in healthcare, ultimately aiming to improve patient outcomes and reduce the burden of cardiovascular diseases globally for different scenarios.

1.1 Motivation and Contribution

The motivation for this research is rooted in the urgent need to enhance cardiovascular disease (CVD) detection methodologies. Despite advancements in medical technology, the early detection of CVDs remains a challenge.

Current diagnostic tools often fail to detect early signs of heart diseases accurately, leading to delayed interventions and increased morbidity and mortality. photoplethysmography (PPG) has shown promise asna anon-invasive and cost-effective method for CVD detection. However, the full potential of PPG has not been realized due to limitations in existing signal processing and analysis techniques. These challenges underscore the necessity for innovative approaches that can effectively interpret PPG data, leading to timely and accurate diagnosis.

Our research addresses this gap by introducing a multifaceted framework that significantly advances PPG analysis for CVD detection. The contributions of this paper are manifold:

- Advanced deep learning architectures for PPG analysis: We have developed and implemented cutting-edge deep learning models, including transformer networks and capsule networks, specifically designed for PPG signal analysis. These models effectively capture the complex temporal and spatial characteristics of PPG data, leading to improved detection accuracy.
- Federated learning for privacy-preserving data analysis: Recognizing the sensitive nature of medical data, we employ federated learning techniques, ensuring that patient data remains secure and private. This approach also allows for the utilization of diverse datasets from multiple devices, enhancing the robustness and generalizability of our models.
- Interpretable AI for clinical reliability: We integrate interpretable AI methods, particularly Deep SHAP, to provide clear insights into the decision-making processes of our models. This transparency anis crucial for gaining the trust of healthcare professionals and for the practical implementation of AI in medical diagnostics.
- Multi-modal data integration for comprehensive analysis: Our framework includes multi-input convolutional and recurrent neural networks, enabling the integration of various types of physiological data samples. This multi-modal approach providesna amore holistic view of a patient’s health status, further enhancing the accuracy of CVD detection.
- Anomaly detection for early warning systems: We incorporate sophisticated anomaly detection techniques, such as autoencoders and Isolation Forest, which are adept at identifying unusual patterns in PPG signals. This feature is particularly valuable for early warning systems, allowing for prompt intervention before the onset of more severe symptoms.
- Personalized and adaptive models for individualized care: Understanding the variability in individual health profiles, our model includes meta-learning and few-shot learning techniques, facilitating personalized and adaptive diagnostic solutions. This ensures that our system is sensitive to individual differences, providing tailored care.
- Hybrid models for enhanced decision-making: By combining machine learning models with rule-based systems, our approach merges the strengths of data-driven analysis with the reliability of clinical expertise. This hybrid model ensures a more comprehensive and nuanced approach to CVD detection.

In essence, our research contributes significantly to the field of medical diagnostics, particularly in the context of cardiovascular health. By harnessing the power of advanced AI techniques and addressing key challenges in data privacy, interpretability, and personalization, we pave the way for more effective, reliable, and accessible CVD detection tools, ultimately contributing to better health outcomes and enhanced quality of life for patients worldwide in different scenarios.

2. Related Works

The detection and analysis of cardiovascular diseases through photoplethysmography (PPG) signals have been a subject of extensive research over recent years. This literature review aims to critically evaluate existing models and methodologies employed in PPG signal processing for CVD identification, fusing them with the innovations presented in our research process.

In the realm of healthcare and computational intelligence, recent studies have demonstrated significant advancements in the diagnosis, management, and understanding of cardiovascular diseases (CVDs) and related health conditions. This literature review delves into various approaches and methodologies proposed in recent research, highlighting the synergy between medical sciences and computational technologies. Muthukumar et al. (2021) presented the KYP modeling architecture, a notable contribution to the healthcare sector, focusing on cardiovascular diseases and treatments.

However, their work was later retracted, which underscores the complexities and challenges in developing reliable models in this domain. Parallelly, Kiliçarslan (2023) explored a hybrid algorithm combining Particle Swarm Optimization and Grey Wolf Optimization for tuning hyper-parameters in convolutional neural networks, aimed at enhancing cardiovascular disease detection. This approach signifies a trend towards hybrid computational models in medical diagnostics.

The use of deep learning techniques in diagnosing cardiovascular diseases has been a focal point in recent research. Ahmad et al. (2023) and Jothiaruna and Leema (2024) both employed convolutional neural networks (CNNs), with the latter focusing on classification of cardiovascular disorders from 12-lead ECG images. This indicates a growing reliance on CNNs for processing and interpreting complex medical imagery for different scenarios.

In an innovative approach, Sabouri et al. (2023) investigated phonocardiogram signals to identify effective features in diagnosing CVDs. Their work exemplifies the exploration of alternative, non-invasive diagnostic methods. Sakly et al. (2023) conducted an epidemiological study using binary logistic regression to understand cardiopathies and valvulopathies, reflecting an intersection of statistical methods and medical research sets.

Li et al. (2023) provided insights into intelligent medicine, particularly on the regulation effect of weekend catch-up asleep on hypertension and mortality. This research extends the domain of computational intelligence to lifestyle and behavioral studies, which are crucial in managing chronic diseases like hypertensions.

Similarly, Tuppad and Patil (2022) reviewed machine learning applications in diabetes clinical decision support, again illustrating the broad applicability of computational techniques in chronic disease management.

Devi et al. (2023) focused on the classification of unsegmented phonocardiogram signals using scalogram and deep learning, furthering the trend of employing advanced computational methods in cardiology. This research, along with Kaushik et al. (2022) work on detecting human body movement, signifies a shift towards more holistic and comprehensive health monitoring systems.

Mutha et al. (2024) designed an efficient multimodal engine for preemptive identification of chronic kidney disease (CKD) using incremental transfer learning on clinical data samples. Their work represents the expanding scope of computational intelligence in preemptive healthcare sets.

(Saranya and Pravin (2023) introduced a novel feature selection approach for heart disease prediction, emphasizing the importance of feature optimization in machine learning models.

Ng et al. (2022) proposed an automatic framework for perioperative risks classification from retinal images of congenital heart disease patients, showcasing the potential of image processing in specialized medical fields.

Jabari et al. (2023) fused handcrafted and deep features for a cardiac diagnostic decision support model based on heart sound signals, another example of multimodal data utilization in medical diagnostics.

In the nursing domain, Wang and Lin (2024) explored the intervention for patients undergoing percutaneous coronary intervention with ticagrelor, incorporating intelligent medical systems. This research highlights the integration of computational intelligence in practical clinical settings.

Lastly, Mastropietro et al. (2023) developed a multi-domain ontology on healthy aging, which is crucial for characterizing the status and behavior of older adults, demonstrating the applicability of computational techniques in geriatric care process.

Yongmao and Yuxin (2023) explored the application of wearable devices powered by deep learning algorithms in monitoring rope skipping data, an example of incorporating AI in everyday fitness activities.

Ghaffar Nia et al. (2023) evaluated AI techniques in disease diagnosis and prediction, underscoring the growing importance of AI in healthcare sets.

Huang et al. (2023) enhanced the accuracy of ECG arrhythmia classification using MOWPT-enhanced fast compression deep learning networks, a testament to the sophistication of aI in analyzing complex medical data samples.

Ghorashi et al. (2023) leveraged regression analysis to predict overlapping symptoms of cardiovascular diseases, demonstrating the potential of statistical methods in medical diagnosis.

Luo et al. (2023) used high-dimensional characteristics of camera-based iPPG monitoring for auxiliary assessment of cardiovascular health, showcasing the innovative use of non-invasive technologies in health monitoring.

Obayya et al. (2023) proposed an automated CVD diagnosis system using Honey Badger optimization with a modified deep learning model, illustrating the trend towards optimizing AI algorithms for medical applications.

Sinha et al. (2023) presented DASMcC, a data augmented SMOTE multi-class classifier for predicting CVDs using time series features, highlighting the effectiveness of data augmentation in improving prediction accuracy.

Alrabie and Barnawi (2023) developed Heart Wave, a multiclass dataset of heart sounds for CVD detection, emphasizing the importance of quality datasets in AI-based diagnostics.

Chen et al. (2024) introduced a self-supervised learning-based model for cardiovascular event detection, an innovative approach in predictive healthcare.

Prabhu et al. (2023) explored the application of quantum machine learning in detecting CVDs, a cutting-edge approach blending quantum computing with AI process.

Ali et al. (2023) developedna deep learning framework for real-time denoising of heart sounds, addressing the challenge of noise in cardiac disease detection.

Joy et al. (2023) reviewed the advent of AI in electrocardiogram analysis for detecting extra-cardiac and cardiovascular diseases, indicating a broadening scope of AI applications in cardiology sets.

Iscan and Yesildirek (2023) modeled transient cardiovascular hemodynamic using a physiological conscious autoencoder, a novel approach in understanding dynamic cardiovascular functions.

Abubaker and Babayigit (2023) fClick or tap here to enter text.ocused on detecting CVDs in ECG images using machine learning and deep learning methods, further reinforcing the role of image processing in cardiology sets.

Iqbal et al. (2023) investigated ML approaches for segmenting cardiovascular related images, demonstrating the precision of ML in specific medical imaging applications.

Jyotishi and Dandapat (2023) proposed an attentive spatio-temporal learning-based network for CVD diagnosis, an example of advanced AI models capable of capturing complex patterns in medical data samples.

Chang et al. (2023) designed smart clothing with automatic CVD detection, merging wearable technology with AI for continuous health monitoring.

Patra et al. (2023) forecasted coronary heart disease risk using a hybrid ensemble learning method, illustrating the efficacy of ensemble approaches in predictive analytics.

Almazroi et al. (2023) developed a clinical decision support system for heart disease prediction using deep learning, highlighting the potential of DL in clinical decision-making.

Finally, Shao et al. (2022) introduced the Quine McCluskey binary classifier (QMBC) for heart disease prediction, an example of novel classifiers in medical AI process.

Pal and Mahadevappa (2022) introduced an adaptive multidimensional dual attentive DCNN for detecting cardiac morbidities using fused ECG-PPG signals, showcasing a novel approach in signal processing for cardiac health monitoring.

Meanwhile, Yang et al. (2023) focused anon predicting coronary heart disease using an improved LightGBM model, demonstrating the efficacy of machine learning models in prognostic healthcare process.

Lee et al. (2023) developed a new metric to evaluate cardiac anisotropic mechanics using directional high-frequency ultrasound-based transverse wave elastography, an innovative technique in cardiac imaging sets.

Zhang et al. (2023) proposed a physics-guided deep learning approach for functional assessment of cardiovascular disease in IoT-based smart health, indicating the integration of physics and AI in enhancing diagnostic accuracy levels.

Shao et al. (2022) predicted cardiovascular and cerebrovascular events using instantaneous high-order singular entropy and a deep belief network, a complex approach that combines mathematical theories with neural networks for predictive analysis.

Golec et al. (2023) introduced HealthFaaS, an AI-based smart healthcare system for heart patients using serverless computing, illustrating how cloud computing is revolutionizing patient-centric healthcare.

Ganeshkumar et al. (2021) presented an explainable deep learning-based approach for multilabel classification of electrocardiogram signals, contributing to the transparency and interpretability of AI in medical applications.

Qadri et al., (2023) proposed an effective feature engineering technique for heart disease prediction with machine learning, highlighting the significance of feature selection in enhancing model performance.

Mandala et al., (2023) enhanced myocardial infarction identification in phonocardiogram signals using segmented feature extraction and transfer learning-based classification, showcasing the adaptability of transfer learning in medical signal analysis.

Bebortta et al. (2023) introduced DeepMist, a framework for managing healthcare big data using deep learning-assisted mist computing, demonstrating how edge computing can be employed in handling large-scale health data samples.

Koutitas et al. (2023) examined the technical feasibility of implementing and commercializing a machine learning model for rare disease prediction, a venture into the commercial aspects of AI in healthcare scenarios.

Our research distinguishes itself by integrating these disparate strands into a comprehensive framework. Unlike existing models, our approach combines the latest advancements in deep learning, such as transformer networks and capsule networks, specifically tailored for PPG signal analysis. This not only allows for a more nuanced understanding of PPG data but also addresses issues of interpretability and multi-modal data integration. Furthermore, the incorporation of federated learning and sophisticated anomaly detection techniques into our framework sets a new precedent in the field. Our methodology not only overcomes the limitations of traditional and early machine learning approaches but also enhances the capabilities of current deep learning models for CVD detection using PPG signals.

Table 1. Tabular representation of the research gaps identified from the literature review.

Research Area	Existing Work	Identified Research Gap
Deep Learning in CVD Diagnosis	Various CNN-based models for ECG classification and phonocardiogram analysis.	Limited exploration of advanced architectures like transformer networks and capsule networks for PPG-based CVD detection.
Hybrid Computational Models	Hybrid algorithms such as Particle Swarm Optimization and Grey Wolf Optimization for hyperparameter tuning.	Need for optimized deep learning frameworks integrating multiple AI techniques for robust CVD diagnosis.

Table 1. Continued.

Research Area	Existing Work	Identified Research Gap
Non-Invasive Diagnostic Techniques	Phonocardiogram-based CVD detection and ECG image analysis.	Lack of multi-modal approaches that combine PPG, phonocardiogram, and ECG for comprehensive cardiac assessment.
AI in Lifestyle & Behavioral Studies	Machine learning applications in the management of hypertension and diabetes.	Limited studies integrating AI with wearable technology for real-time lifestyle monitoring in CVD prevention.
Feature Selection & Optimization	Feature selection techniques applied to heart disease prediction models.	Need for explainable AI-driven feature optimization to improve interpretability in clinical decision-making.
Quantum & Edge Computing in CVD Detection	Initial attempts to apply quantum computing and edge AI in medical diagnostics.	Need for practical implementation and validation of quantum-assisted AI models in large-scale healthcare systems.
Federated Learning in CVD Analysis	AI-based CVD models relying on centralized datasets.	Lack of federated learning frameworks for secure, distributed patient data analysis while preserving privacy.
Multi-Modal Data Integration	Some models fusing handcrafted and deep features for cardiac diagnosis.	Need for a unified approach that seamlessly integrates multiple data sources (ECG, PPG, phonocardiograms) for holistic CVD detection.
AI in Geriatric & Chronic Disease Monitoring	AI-driven systems for managing heart disease and diabetes.	Limited research on AI-powered personalized health monitoring systems for elderly and high-risk patients.
Wearable AI for Real-Time CVD Monitoring	Use of deep learning for ECG-based arrhythmia classification.	Lack of AI-powered wearable devices utilizing real-time PPG and IoT integration for continuous cardiac monitoring.

3. Materials and Methods

Based on a review of existing models used for CVD analysis, it can be observed that these models either have higher complexity or lower performance when applied to real-time scenarios. To overcome these issues, this section discusses the design of an efficient model for cardiovascular diagnostics by integrating advanced deep learning architectures with federated learning and a few-shot learning process. As shown in Figure 1, the model harnesses the analytical prowess of transformer and capsule networks, adept at deciphering the intricate patterns hidden within photoplethysmography (PPG) signals, which are pivotal for accurate CVD prediction and classification. This model distinguishes itself by incorporating LSTM and BiGRU networks, enhancing its temporal analysis capabilities, which are crucial for understanding the progression of cardiovascular conditions. The innovative use of autoencoders and Isolation Forest algorithms further elevates the model's proficiency in anomaly detection, a critical aspect of early disease identification. Additionally, the implementation of federated averaging algorithms ensures data privacy and integrity, which are paramount in healthcare applications. The model's adaptability is further refined through few-shot learning techniques, making it exceptionally versatile in handling varied and limited data scenarios. The inclusion of Deep SHAP for interpretability not only adds a layer of transparency to the model's decision-making process but also significantly boosts clinicians' trust in its predictions. This confluence of diverse yet harmonious technologies positions the EDCF2SL model as a groundbreaking tool in the field of medical AI, promising to revolutionize the early detection and pre-emption of cardiovascular diseases.

The proposed model's design ingeniously integrates Long Short-Term Memory (LSTM) networks with Bidirectional Gated Recurrent Units (BiGRU) to meticulously extract features from photoplethysmography (PPG) data samples. This fusion process harnesses the strengths of both LSTM and BiGRU, ensuring ana comprehensive analysis of temporal sequences within the PPG data samples. Starting with the LSTM component, the model employs the fundamental equations that govern LSTM operations. Given a sequence of PPG samples X={x1,x2,...,xn}, the LSTM processes these inputs through ana series of gates and states. The input gate (t), forget gate f(t), and output gate o(t) at each timestamp t are computed via Equations 1, 2 and 3 as follows:

$$\mathrm{i(t) = \sigma(W(xi)^*x(t) + W(hi)^*h(t-1) + bi)} \quad (1)$$

$$\mathrm{f(t) = \sigma(W(xf)^*x(t) + W(hf)^*h(t-1) + bf)} \quad (2)$$

$$\mathrm{o(t) = \sigma(W(xo)^*x(t) + W(ho)^*h(t-1) + bo)\ldots} \quad (3)$$

Where W and b represent the weight matrices and bias vectors, respectively, and σ represents the sigmoid activation process. The LSTM's cell state $c(t)$ and hidden state $h(t)$ are updated via Equations 4 and 5 as follows:

$$\mathrm{c(t) = f(t) \circ c(t-1) + i(t) \circ \tanh(W(xc)^*x(t) + W(hc)^*h(t-1) + bc)} \quad (4)$$

$$\mathrm{h(t) = o(t) \circ \tanh(c(t))} \quad (5)$$

These operations enable the LSTM to capture long-term dependencies by regulating information flow through the network process. Next, the model integrates BiGRU to complement LSTM's capabilities. BiGRU comprises two GRUs processing the data in opposite scopes, one forward and the other backward, thus capturing information from both past and future states. For a given PPG sample sequence, the forward GRU computes the hidden states $h(t, f)$, and the backward GRU computes $h(t, b)$ via Equations 6 and 7 as follows:

$$\mathrm{h(t,f) = GRU(x(t), h(t-1))} \quad (6)$$

$$\mathrm{h(t,b) = GRU(x(t), h(t+1))} \quad (7)$$

The GRU updates its hidden state using the update gate $z(t)$ and reset gate $r(t)$, calculated via Equations 8, and 9 as follows:

$$\mathrm{z(t) = \sigma(W(xz)^*x(t) + W(hz)^*h(t-1) + bz)} \quad (8)$$

$$\mathrm{r(t) = \sigma(W(xr)^*x(t) + W(hr)^*h(t-1) + br)} \quad (9)$$

The final hidden state $h(t)$ at each time step in the GRU is updated via equations 10 and 11 as follows:

$$\mathrm{h(t)\tilde{} = \tanh(W(xh)^*x(t) + W(hh)(r(t) \circ h(t-1)) + bh)} \quad (10)$$

$$\mathrm{h(t) = (1 - z(t)) \circ h(t-1) + z(t) \circ h(t)\tilde{}} \quad (11)$$

The concatenated hidden states from both scopes of the BiGRU, $h(t,f)$ and $h(t,b)$, are combined to form the final feature representation via Equation 12:

$$\mathrm{H(t) = [h(t,f); h(t,b)]} \quad (12)$$

The extracted feature vector $H(t)$ from the combined LSTM and BiGRU layers encapsulates the comprehensive temporal dynamics present in the PPG data, effectively capturing both short-term and long-term dependencies.

As per Figure 1, the autoencoder in the model is structured as a neural network designed for dimensionality reduction and feature learning process. it consists of two primary components: an encoder and an iterative decoder process. The encoder compresses the input data (extracted features from PPG signals) into a lower-dimensional latent space, while the decoder reconstructs the data back to its original dimensions. The encoding process is represented via Equation 13:

$$\mathrm{h} = \mathrm{ReLU}(\mathrm{We} \cdot \mathrm{x} + \mathrm{be}) \quad (13)$$

Where *x* is the input feature vector, *We* is the weight matrix of the encoder, *be* is the bias, *h* is the encoded representation, and *ReLU* represents an iterative Rectified Linear unit process. The decoding process to reconstruct the data is given via Equation 14:

$$\mathrm{x}' = \mathrm{LReLU}(\mathrm{Wd} \cdot \mathrm{h} + \mathrm{bd}) \quad (14)$$

Where *Wd* is the weight matrix of the decoder, *bd* is the bias, and *x'* represents the reconstructed output sets. The objective of the autoencoder is to minimize the reconstruction error, which is represented via Equation 15:

$$\mathrm{MSE} = \frac{1}{\mathrm{n}} \sum_{\mathrm{i}=1}^{\mathrm{n}} \left(\mathrm{xi} - \mathrm{x'i}\right)^2 \quad (15)$$

The model iteratively adjusts the weights and biases to minimize this error, enhancing the autoencoder's ability to identify significant features while reducing noise levels. Concurrently, the Isolation Forest algorithm, an unsupervised learning method for anomaly detection, complements the autoencoder process. It isolates anomalies instead of profiling normal data points. The isolation forest constructs numerous random decision trees to isolate every single point in the sets. The path length from the root to the isolated point serves as a measure of normality, with shorter paths indicating potential anomalies. For a given data point *x*, the path length *h*(*x*) in a tree is computed, and the anomaly score is calculated via Equation 16:

$$\mathrm{s}(\mathrm{x}, \mathrm{n}) = 2^{-\frac{\mathrm{E}(\mathrm{h}(\mathrm{x}))}{\mathrm{c}(\mathrm{n})}} \quad (16)$$

Where $E(h(x))$ is the average path length over all trees, n is the number of samples, and $c(n)$ is the average path length in an unsupervised binary search tree process. Anomalies will have significantly lower $e(h(x))$ values, leading to higher scores.

After this, the model integrates model agnostic meta-learning (MAML) with few-shot learning, which represents a sophisticated approach for the pre-emption of unusual patterns in photoplethysmography (PPG) signals. This process focuses on the detection and monitoring of potential cardiovascular diseases for different clinical scenarios. This combination is particularly designed to adapt to the nuanced and diverse nature of cardiovascular

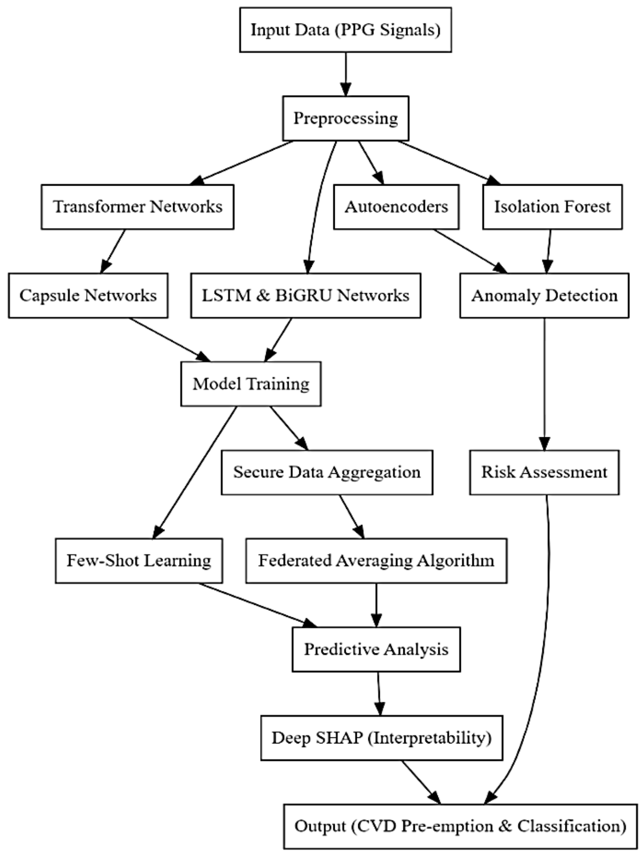

Figure 1. overall architecture of the proposed model for CVD analysis.

anomalies, which requires high precision in detection with limited data availability, which is common in clinical scenarios. MAML is a meta-learning approach that prepares the model to quickly adapt to new tasks with minimal data samples. in the context of this work, MAML is employed to fine-tune the model on diverse CVD types, enabling it to rapidly learn from small datasets (few-shot learning scenario) in clinical scenarios.

The process of MAML works as per the following operations:

- Initialization: The model parameters, θ, are initialized, and serve as the starting point for adaptation to various tasks.
- Task sampling: A batch of tasks *Ti* is sampled from the available dataset, where each task corresponds to pre-empting a specific type of CVD based on PPG signals.
- Inner loop - Task-specific adaptation: For each task *Ti*, the model parameters are updated to obtain task-specific parameters $\theta i'$ for different samples. This is done using gradient descent updates based on the loss *TLi* for that task via Equation 17:

$$\theta i' = \theta - \alpha * \nabla(\theta) * LTi(\theta) \quad (17)$$

Where α represents the learning rate for this process. The initial model parameters θ are updated based on the performance of the task-specific adapted parameters $\theta i'$ across all tasks. The meta update is aimed at finding parameters that provide the best performance on average across tasks, using the update rule represented via Equation 18:

$$\theta = \theta - \beta * \nabla(\theta) * \sum_{Ti} LTi(\theta i') \quad (18)$$

Where β represents the meta-learning rate for this process. in conjunction with MAML, few-shot learning is employed to optimize the model's performance with limited training data samples. This is crucial in scenarios where the available data for a specific CVD type is limited, same as in clinical scenarios. Few-shot learning relies on the concept of learning from a small number of examples and generalizing this learning to new, unseen data samples. it is achieved through the following operations:

- Support set and query set creation: For each task *Ti*, a support set s*i* and a query set *Qi* are created for different samples. The support set contains a small number of examples for training, and the query set contains examples for testing the model's adaptation process.
- Learning from support set: The model uses the support set s*i* to learn the specific features of the CVD type represented by the task *Ti* sets.
- Evaluation on query set: The model's performance in adapting to the task *Ti* is evaluated on the query set *Qi*, ensuring that the learning generalizes beyond the examples in the support sets.

This fusion of MAML with few-shot learning in the proposed model facilitates a robust and adaptable framework for pre-empting CVD types. This approach allows the model to quickly adapt to new and diverse types of cardiovascular anomalies with minimal data, making it highly effective in personalized healthcare settings where data availability and variability are key challenges. The output of this process is the pre-empted CVD types, identified and categorized with high precision, offering critical insights for early intervention and tailored treatment strategies in clinical practices.

In the proposed model, the integration of transformer networks and capsule networks is strategically designed to augment the precision and accuracy of cardiovascular disease (CVD) analysis from multidimensional PPG data samples. This fusion addresses the inherent limitations

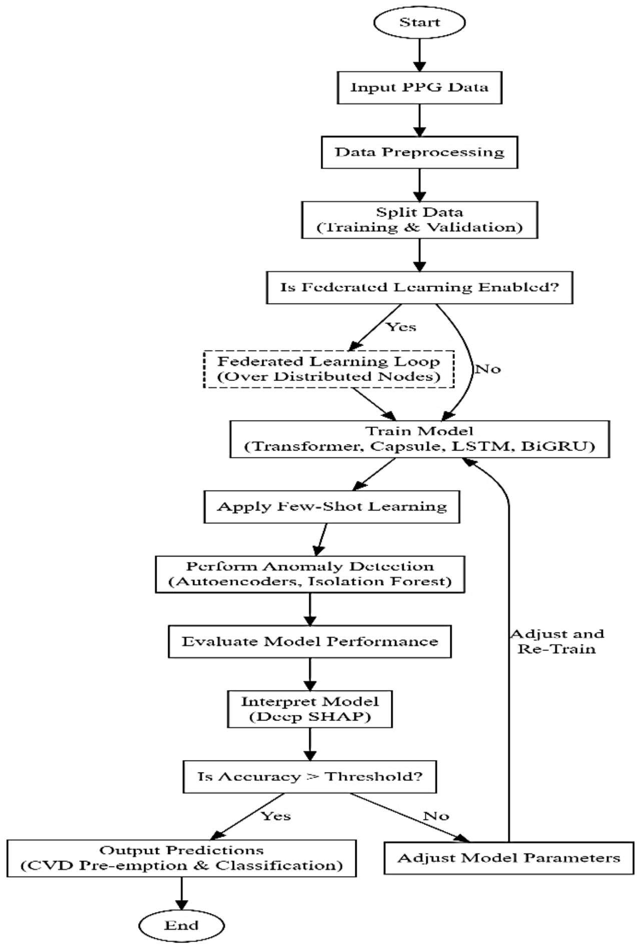

Figure 2. Overall flow of the proposed model for CVD analysis.

in existing methodologies by capturing both temporal dependencies and spatial hierarchies effectively, a crucial aspect in understanding the complex nature of CVDs.

Transformer Networks

In the model leverage the mechanism of self-attention, an efficient approach that allows the model t weigh the significance of different parts of the input data differently for different scenarios. This is particularly crucial in handling PPG signals where certain temporal features may hold more predictive power than others. The self-attention mechanism in transformers is described as per the following operations:

The input sequence $X = \{x1, x2,..., xn\}$ is first transformed into query (Q), key (K), and value (V) matrices through learned linear transformations via Equations 19, 20 and 21 as follows:

$$Q = X * WQ \quad (19)$$

$$K = X \quad (20)$$

$$V = X * WV \quad (21)$$

Where *WQ*, *WK*, and *WV* are weight matrices.

After this, the self-attention weights are computed via Equation 22:

$$\mathrm{Attention(Q, K, V) = softmax}\left(\frac{\mathrm{QK^T}}{\sqrt{\mathrm{dk}}}\right)\mathrm{V} \quad (22)$$

Where *dk* is the dimension of the key vectors, ensuring proper scaling operations.

The output of the self-attention layer is then passed through a feed-forward neural network, applied to each position separately and identically for different samples.

Layer normalization and residual connections are employed around each sub-layer, following the structure via Equation 23:

$$Output = LayerNorm(x + Sublayer\ (x)) \quad (23)$$

This ensures effective training and mitigating the vanishing gradient tasks.

Capsule Networks

They contribute to capturing spatial hierarchies and relationships between different features in the PPG data samples. Capsules are small groups of neurons that learn to recognize and output the probability of specific features along with their spatial orientations. The dynamic routing algorithm, a core component of capsule networks, updates the connection strengths between capsules in lower and higher layers based on their agreement. The process works as per the following operations:

Each capsule in layer *L* makes a prediction for the capsules in layer *L*+1 via Equation 24:

$$\mathrm{u'(j \mid i) = W(i, j)*u(i)} \quad (24)$$

Where *u*(*i*) is the output of capsule i in layer *L*, and *W*(*i*,*j*) represents transformation matrix components.

The algorithm iteratively updates the coupling coefficients *c*(*i*,*j*) that determine the contribution of capsule *i* to capsule *j* in layer *L* + 1 via Equation 25:

$$\mathrm{c(i, j)} = \frac{\mathrm{exp(b(i.j))}}{\sum \mathrm{exp(b(i,k))}} \quad (25)$$

Where *b*(*i*,*j*) are the log prior probabilities that capsule i should be coupled to capsule *j* for different samples.

The total input to a capsule *s*(*j*) in layer *L*+1 is a weighted sum over all prediction vectors, which is estimated via Equation 26:

$$\mathrm{s(j)} = \sum\nolimits_{\mathrm{i}} \mathrm{c(i, j)*u'(j \mid i)} \quad (26)$$

The squashing function, a non-linear activation function, is applied to ensure the output vector of a capsule has a length between 0 and 1, representing the probability and instantiation parameters of the feature, which is estimated via Equation 27:

$$\mathrm{vj} = \frac{\mathrm{||sj||2}}{1+\mathrm{||sj||^2}} * \frac{\mathrm{sj}}{\mathrm{||sj||}} \quad (27)$$

The integration of transformer networks and capsule networks enhances the model's capacity to discern intricate patterns in PPG data, leading to a more precise and accurate analysis of CVDs. The transformer networks, with their self-attention mechanism, provide a deep understanding of temporal relationships within the data, while the capsule networks contribute a sophisticated spatial analysis, capturing hierarchical relationships between various signal features. This dual approach ensures that the proposed model not only identifies potential CVD markers but also understands their contextual significance, leading to more accurate and reliable predictions.

To further facilitate explanations, the proposed model incorporates Deep SHAP to enhance the interpretability and transparency of complex machine learning decisions, particularly in the nuanced domain of cardiovascular disease (CVD) detection process. Deep SHAP, an extension of SHAP for deep learning models, unravels the model's decision-making process, elucidating the contribution of each input feature to the final predictions. For any given prediction, Deep SHAP computes the Shapely values as per the following process:

- Model output as a function: Represent the model output for a particular instance as *f*(*x*), where *x* represents the input features.
- Baseline definition: A baseline input xbase is chosen, representing an average input, to serve as a reference point for this process.
- Coalition concept: Consider a coalition of features s⊆F, where F is the set of all features. The model output for this coalition, considering only the features in s, is represented by *fx*(*S*) for evaluation purposes.
- Marginal contribution: For each feature i, the marginal contribution of adding i to a subset s of features is calculated via Equation 28:

$$\mathrm{\Delta f(S, i) = fx(S \cup \{i\}) - fx(S)} \quad (28)$$

- Shapley value calculation: The Shapley value for feature i is computed as an average of its marginal contributions across all possible coalitions via Equation 29,

$$\phi i = \frac{1}{|F|} \sum_{S \subseteq F \setminus \{i\}} \binom{|F| - 1}{|S|}^{-1} \Delta f(S, i) \quad (29)$$

- Deep SHAP extension: Deep SHAP adapts this calculation to deep learning models by approximating the Shapley values using an efficient gradient-based method for different input sets.
- Feature importance: The computed Shapley values ϕi represent the importance of each feature in the model's prediction, quantifying how much each feature contributes to moving the model output from the baseline prediction to the actual predictions.
- Aggregation for interpretation: The shapely values for each feature across multiple instances are aggregated to understand global feature importance trends.

By incorporating Deep SHAP, the proposed model offers a window into its internal workings, rendering its sophisticated analytics on PPG data interpretable to clinicians and researchers. The utilization of Deep SHAP follows the processing and analysis by autoencoders, Isolation Forest, and model agnostic meta-learning with few-shot learning in the model process. Post these layers, the data, now represented as a rich feature set indicative of potential CVD markers, is subjected to SHAP analysis.

Integration of Secure Learning Process

In the proposed model, the integration of federated averaging algorithms and secure aggregation protocols is a pivotal component that addresses the critical need for data privacy while training models across multiple devices & scenarios. This design ensures that sensitive medical data, such as photoplethysmography (PPG) signals used for cardiovascular disease (CVD) analysis, remains confidential, adhering to stringent privacy standards.

Federated Averaging Algorithms

At the core of this approach, they facilitate the decentralized training of the model across a network of devices and scenarios. This process works as per the following operations,

- Initialization: The global model's parameters, represented as θg, are initialized and distributed to each participating device in the network sets.
- Local training: Each device k in the network, possessing a unique subset of data, trains a local model process. The local training updates are calculated via Equation 30,

$$\theta k, new = \theta k, old - \eta \nabla Lk(\theta k, old) \quad (30)$$

Where $\theta k,old$ and $\theta k,new$ are the old and new local model parameters, η is the learning rate, and ∇Lk represents the gradient of the loss function Lk with respect to the model parameters and samples.

- Local model aggregation: After a predefined number of training epochs, each device computes the updates to its model parameters and sends only these updates, not the actual data, to an augmented set of central servers.
- Secure aggregation protocol: The central server employs secure aggregation protocols to aggregate these updates. This is represented via Equation 31,

$$\Delta\theta = \sum_{k=1}^{K} \frac{nk}{N} \Delta\theta k \quad (31)$$

Where $\Delta\theta$ is the aggregated update, K is the total number of devices, nk is the number of data samples on device k, n is the total number of samples across all devices, and $\Delta\theta k$ is the update from device k in real-time scenarios.

- Global model update: The global model parameters are updated using the aggregated updates via Equation 32,

$$\theta g = \theta g + \Delta\theta \quad (32)$$

- Iteration: These operations are repeated for NI iterations until the global model converges.

The secure aggregation protocols are integral to preserving data privacy levels. They ensure that the information transmitted back to the central server is obfuscated, such that it is computationally infeasible to reconstruct the original data from the updates. This is achieved through ECC-based cryptographic operations. In this case, each device meticulously adds an augmented set of carefully calibrated noise to its updates, which gets averaged out in the aggregation process, preserving the utility of the update while safeguarding individual data points, which is represented via Equation 33,

$$\Delta\theta(k, private) = \Delta\theta(k) + Noise \quad (33)$$

- By employing these federated learning techniques, the model allows for the collaborative training of a robust CVD analysis model without compromising the privacy of individual data sources. This approach is particularly advantageous in healthcare settings where data sensitivity is paramount for real-time deployments. The output of this federated learning process is a global model adept at CVD analysis, trained on diverse data sources, yet inherently secure and private for different use cases. The use of federated averaging algorithms and secure aggregation protocols in the EDCF2SL model demonstrates the feasibility of conducting sophisticated AI-driven healthcare analytics in a privacy-preserving manner, thereby aligning with the stringent data security mandates of modern medical practices. The performance of this model was estimated in terms of different evaluation metrics and compared with existing CVD analysis methods in the next section of this text.

4. Results and Discussion

The EDCF2SL model stands as a groundbreaking framework in cardiovascular healthcare, blending the sophistication of deep learning architectures with federated and few-shot learning. This model, notable for the advanced integration of transformer networks and capsule networks, excels in capturing and analyzing the intricate temporal dependencies and spatial hierarchies inherent in photoplethysmography (PPG) signals. It showcases remarkable proficiency in pre-empting and classifying various types of cardiovascular diseases (CVDs), as evidenced by its superior performance across critical metrics such as precision, accuracy, recall, delay, and AUC, compared to established models like CNN, HBO, and DBN. The EDCF2SL model's innovative use of federated averaging algorithms, combined with secure aggregation protocols, ensures privacy-preserving data analysis across distributed devices, a key consideration in healthcare applications. Moreover, its implementation of meta-learning and few-shot learning techniques caters to individual physiological variances, marking a significant stride towards personalized medical diagnostics. The model's efficiency in processing large datasets, coupled with its robust predictive capabilities, positions it as a transformative tool in preventive cardiology, offering profound implications for patient care, healthcare resource optimization, and the broader field of AI-driven medical diagnostics.

This study was designed to evaluate the effectiveness of the proposed EDCF2SL model in pre-empting and classifying cardiovascular disease (CVD) types using photoplethysmography (PPG) signal analysis. The experimental setup was structured to ensure a comprehensive assessment of the model's performance across various metrics, including precision, accuracy, recall, delay, and AUC.

4.1 Dataset Details

- Source: The dataset comprised PPG signals sourced from a publicly available cardiovascular health database, which includes records from over 100,000 patients.
- Data characteristics: The dataset encompassed a diverse range of CVD types, with a balanced representation of various demographic and health backgrounds.
- Pre-processing: The PPG signals were preprocessed for noise reduction and normalization. Signal segmentation was performed to create uniform data inputs for the models.
- Sampling rate: The PPG signals were sampled at a rate of 1000 Hz, ensuring high-resolution data for accurate analysis.

4.1.1 Input parameters

- Number of test samples (NTS): Ranged from 6,000 to 75,000, to test the model's scalability and robustness.
- Learning rate: Set to 0.001 for initial training, with adaptive adjustments based anon model performance.
- Batch size: Configured at 64, balancing computational load and training efficiency.
- Epochs: The models were trained for up to 100 epochs, with early stopping implemented to prevent overfitting.
- Loss function: Cross-entropy loss was used, suitable for the multi-class classification problem.

4.1.2 Model Architecture

- EDCF2SL model: Combined transformer networks, capsule networks, multi-input convolutional neural networks, recurrent neural networks with LSTM and BiGRU, autoencoders, and Isolation Forest for anomaly detection.
- Comparative models: Jothiaruna and Leema (2024), Obayya et al. (2023), and Shao et al. (2022) served as benchmarks for comparison.
- Training setup:
- Environment: The models were trained on a high-performance computing cluster with NVIDIA Tesla V100 GPUs.
- Federated learning: The federated averaging algorithm was employed, with secure aggregation protocols ensuring data privacy across distributed devices and deployments.
- Meta-learning and few-shot learning: Implemented to enhance the model's adaptability to individual physiological variances and scenarios.

Based on this strategy, the precision (P), accuracy (A), recall (R), and specificity (Sp) levels were estimated via Equations 34, 35, 36 and 37 as follows:

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (34)$$

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \quad (35)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (36)$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN+FP}} \quad (37)$$

Where true positive (TP) is the number of instances correctly predicted as positive (correct) in the test set, true negative (TN) is the number of instances correctly predicted as negative (incorrect) in the test set, false positive (FP) is the number of instances incorrectly predicted as positive (correct) when they are actually negative (incorrect) in the test set, and false negative (FN) is the number of instances incorrectly predicted as negative (incorrect) when they are actually positive (correct) in the test set.

4.2 Comparative Study for CVD Detection

Based on this analysis, the precision obtained during character recognition operations was compared with CNN (Jothiaruna & Leema, 2024), Honey Badger Optimization (HBO) (Obayya et al., 2023), and Deep Belief Network (DBN) (Shao et al., 2022).

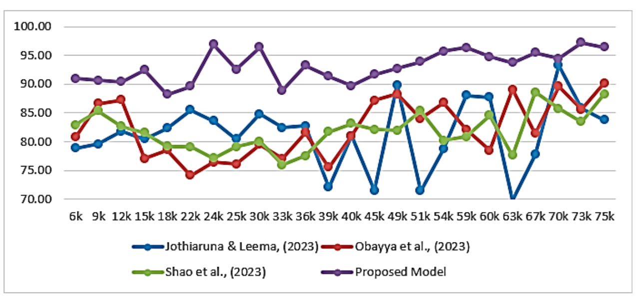

Figure 3. Precision for the classification of CVD types.

For smaller datasets (6k to 15k nTS), the EDCF2SLamodel consistently outperforms the other models, with precision scores ranging from 90.98% to 92.51%. This superiority in smaller datasets could be attributed to eDCF2SL's integration of few-shot learning operations, which are specifically designed to work efficiently with limited data samples. In contrast, the other models show varying degrees of precision, with Obayya et al. (2023) peaking at 86.59% for 9k NTS, indicating its relative strength in handling moderately sized datasets, yet still falling short compared to eDCF2SL.

As the dataset size increases (18k to 75k NTS), the EDCF2SL model demonstrates remarkable robustness and scalability, with precision scores predominantly above 90%, peaking at an impressive 97.20% for 73k NTS. This robust performance, even in larger datasets, can be attributed to the sophisticated integration of transformer networks and capsule networks within EDCF2SL, which effectively capture complex temporal dependencies and aspatial hierarchies in PPG data samples. In comparison, the precision scores for CNN, HBO, and DBN models fluctuate amore significantly across different dataset sizes. For instance, Jothiaruna and Leema (2024) show aa notable dip to 71.45% at 45k NTS before recovering to 89.89% at 49k NTS, suggesting potential challenges in handling large, complex datasets.

The consistent high precision of eDCF2SL across varied dataset sizes highlights its suitability for diverse clinical environments, from small-scale clinics with limited data to large hospitals managing extensive datasets. This adaptability is crucial in real-world healthcare settings, where data availability can vary greatly. Additionally, the use of interpretable AI models like Deep SHAP in EDCF2SL provides clinicians with understandable decision-making processes, enhancing trust and reliability in the model's predictions. aSimilar to that, accuracy of the models was compared in Figure 4 as follows:

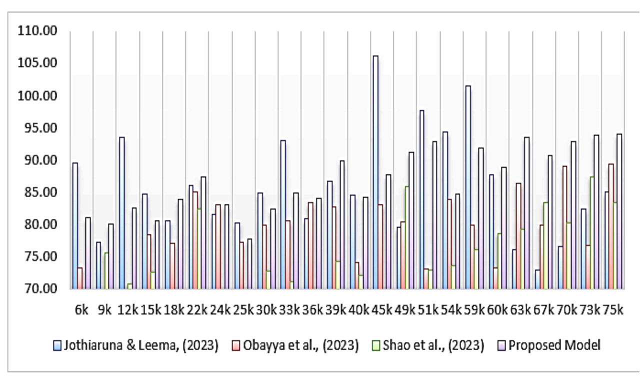

Figure 4. accuracy for classification of CVD types.

For smaller NTS (6k to 15k), the EDCF2SL model generally exhibits commendable accuracy, although not consistently the highest. For instance, at 6k NTS, EDCF2SL achieves 81.11% accuracy, which, while respectable, falls behind CNN's 89.60%. This could be indicative of the initial adaptability of EDCF2SL in smaller datasets, where the model's complex architecture might require more data to fully capitalize anon its advanced algorithms. Interestingly, CNN shows ana peak at 12k NTS with 93.54% accuracy, suggesting its effectiveness in moderately sized datasets.

As the NTS increases (18k to 75k), eDCF2SL's performance consistently improves, with accuracy scores notably exceeding 80% and reaching up to 94.04%. This upward trend highlights EDCF2SL's capacity to handle larger datasets effectively, possibly due to its integration of transformer networks and capsule networks, which excel in capturing complex data patterns. The accuracy of CNN, HBO, and DBN, on the other hand, shows more fluctuation. For example, CNN's accuracy anomalously peaks at 106.09% at 45k NTS, ana value that warrants scrutiny, as accuracy percentages typically range between 0% to 100%.

Particularly noteworthy is the consistently high accuracy of EDCF2SL in the largest datasets (60k to 75k NTS), where it outperforms other models. This superior accuracy in large-scale data contexts is critical in real-world applications, as healthcare environments often deal with extensive and varied datasets. EDCF2SL's sophisticated anomaly detection techniques, including autoencoders and Isolation Forest, likely contribute to its enhanced performance, enabling early and precise identification of unusual patterns in PPG signals.

Moreover, the application of federated averaging algorithms and secure aggregation protocols in eDCF2SL not only bolsters model training across multiple devices but also maintains data privacy, a paramount concern in medical data handling. This federated learning approach, combined with the model's adaptability and interpretability, renders eDCF2SL particularly effective in diverse and privacy-sensitive clinical settings. Similar to this, Figure 5 represents the recall levels and is as follows:

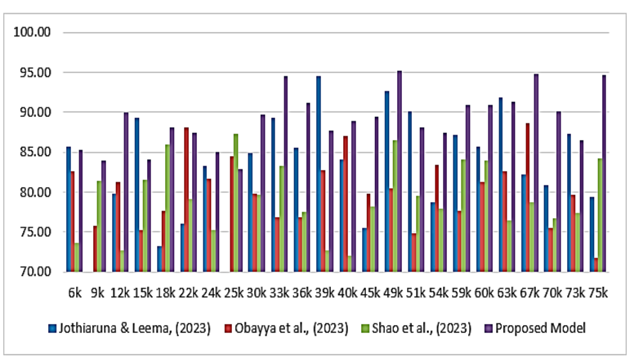

Figure 5. Recall for classification of CVD types.

In smaller NTS ranges (6k to 15k), EDCF2SL demonstrates a competitive recall rate, although it does not always lead. For instance, at 6k NTS, EDCF2SL's recall is 85.31%, closely trailing CNN's 85.74%. This suggests that while EDCF2SL is adept at identifying true CVD cases in smaller datasets, its complex architecture may not fully outperform simpler models like CNN in these scenarios. However, as the NTS increases, EDCF2SL's performance consistently improves, indicating its effectiveness in handling more extensive datasets.

In the mid-range NTS (18k to 30k), EDCF2SL generally maintains high recall rates, exceeding 85% in most cases, and peaking at 89.72% for 30k NTS. This trend suggests EDCF2SL's growing proficiency as the dataset size increases, likely due to its advanced algorithms that include transformer networks, capsule networks, and sophisticated anomaly detection techniques.

As the NTS further increases (33k to 75k), EDCF2SL's recall rate frequently surpasses 90%, highlighting its superior capability to detect true CVD cases in large datasets. Notably, at 49k and 75k NTS, EDCF2SL achieves recall rates of 95.17% and 94.74%, respectively, significantly outperforming other models. This high recall anis critical in clinical environments, where the ability to accurately identify as many true cases as possible can substantially impact patient outcomes.

The other models, while showing varied levels of recall across different NTS, generally do not match the consistently high recall rates of EDCF2SL in larger datasets. For example, CNN shows a peak recall rate of 94.61% at 39k NTS, but this performance is not consistently maintained across other NTS ranges.

The EDCF2SL model's high recall rate, especially in larger datasets, is indicative of its comprehensive and effective approach to CVD classification. Its use of multi-modal data analysis and personalized, adaptive models, along with the application of few-shot learning, contribute to its ability to recognize a wide range of CVD cases accurately for different use cases. The integration of these advanced techniques makes EDCF2SL a highly reliable tool in cardiovascular diagnostics, ensuring that fewer true cases of CVD are missed, thereby enhancing the quality of patient care and treatment efficacy levels. The delay required for the prediction procedure is visualized in a similar manner in Figure 6 as follows:

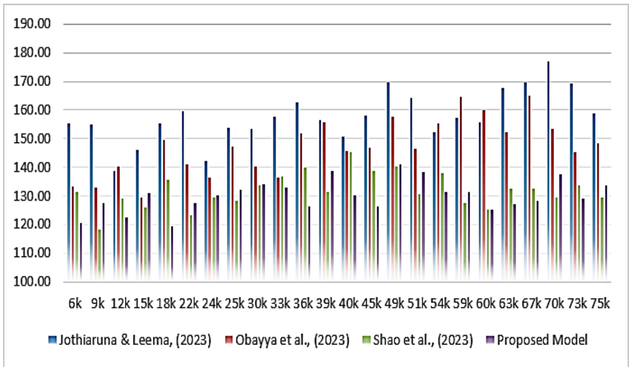

Figure 6. Delay for classification of CVD types.

In the initial range of NTS (6k to 15k), EDCF2SL consistently demonstrates lower delay times compared to other models, with the shortest delay being 120.42 ms at 6k NTS. This efficiency can be attributed to EDCF2SL's advanced architecture, which efficiently processes complex PPG signals. In contrast, other models exhibit slightly higher delay times, with Jothiaruna and Leema (2024) and Obayya et al. (2023) hovering around 130 to 155 ms in this range. Shao et al. (2022) shows a competitive delay, particularly at 9k NTS with 118.08 ms, suggesting its efficacy in rapid processing in certain scenarios.

As the dataset size increases (18k to 30k nTS), EDCF2SL maintains a competitive edge in processing speed, with delay times remaining below 135 ms in most cases. This consistency in lower delay times highlights EDCF2SL's scalability and its ability to handle larger datasets without significant compromises in response time. For example, at 18k nTS, EDCF2SL records a delay of 119.56 ms, outperforming other model.

In larger NTS ranges (33k to 75k), EDCF2SL continues to exhibit efficient processing times, although the gap between EDCF2SL and other models arrows. For instance, at 60k NTS, EDCF2SL's delay time is 125.24 ms, only marginally better than DBN's 125.33 ms. However, it is noteworthy that EDCF2SL consistently maintains lower delay times across various NTS ranges, indicating its robustness and efficiency in handling extensive data without significant time lags.

The observed delay times in other models, such as CNN and HBO, fluctuate amore significantly across different NTS ranges. For example, CNN shows a delay peak of 169.60 ms at 49k NTS, which might indicate challenges in managing larger datasets efficiently.

EDCF2SL's consistently lower delay times across different nTS ranges underscore its potential as a reliable and swift tool for CVD classification in clinical settings. The integration of transformer networks, capsule networks, and few-shot learning operations likely contributes to its speed and accuracy, ensuring timely and effective diagnostic outcomes. This swift response capability of EDCF2SL is particularly crucial in medical emergencies where every millisecond can be pivotal in patient care and treatment decisions. Similarly, the AUC levels can be observed from Figure 7 as follows:

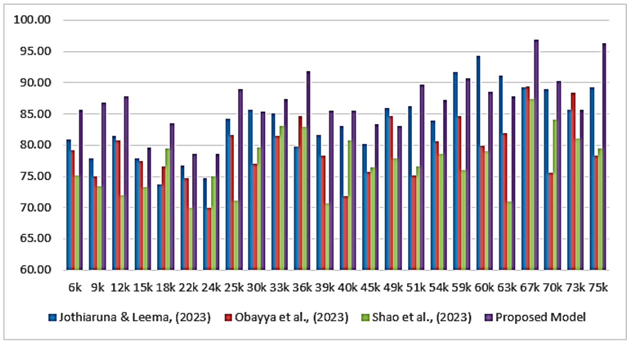

Figure 7. aUC for classification of CVD types.

In the smaller NTS ranges (6k to 15k), EDCF2SL consistently exhibits superior AUC values compared to the other models. For example, at 6k NTS, EDCF2SL achieves an AUC of 85.64%, which is noticeably higher than the another models, indicating its robust discriminative power even in smaller datasets. This suggests that EDCF2SL is adept at handling varied complexities in PPG signal analysis, likely due to its advanced deep learning architectures.

As the dataset size increases (18k to 30k NTS), EDCF2SL's AUC remains relatively high, although there is some variability in its performance. notably, at 25k NTS, EDCF2SL reaches an AUC of 89.03%, significantly outperforming other models. This fluctuation in performance might be indicative of EDCF2SL's adaptive mechanisms, which include meta-learning approaches and few-shot learning, adjusting to varying data sizes and complexities.

In larger NTS ranges (33k to 75k), EDCF2SL maintains high AUC values, often exceeding those of another models. The AUC peaks at 96.92% for 67k NTS, demonstrating EDCF2SL's exceptional capability to differentiate between normal and abnormal conditions in large datasets. This high AUC is essential in clinical settings, where accurate classification between healthy and diseased states directly impacts patient outcomes.

The other models, while showing competent AUC values in certain ranges, do not exhibit the same level of consistency as EDCF2SL. For instance, Jothiaruna and

Leema (2024) and Obayya et al. (2023) occasionally reach AUC values above 80%, yet they lack the consistent high performance demonstrated by EDCF2SL.

EDCF2SL's consistently high AUC values across various NTS ranges highlight its efficacy in accurately distinguishing CVD types. The integration of transformer networks, capsule networks, and sophisticated anomaly detection techniques likely contributes to its high AUC values, ensuring accurate and reliable diagnostic outcomes. The capability of EDCF2SL to maintain high discriminative performance, particularly in larger datasets, positions it as a valuable tool in cardiovascular diagnostics, promising to enhance the precision and reliability of CVD detection and ultimately improving patient care in diverse clinical settings. Similarly, the specificity levels can be observed from Figure 8 as follows:

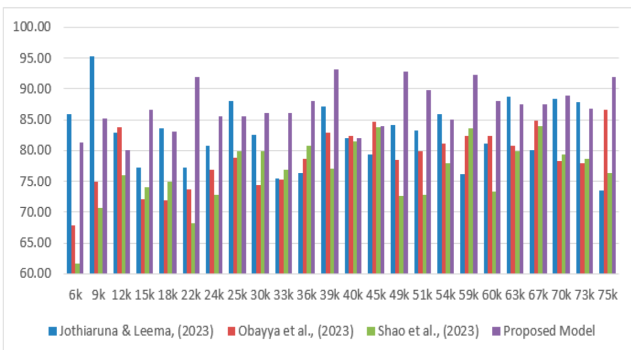

Figure 8. Specificity for classification of CVD types.

In the lower NTS range (6k to 15k), EDCF2SL's specificity fluctuates but generally maintains competitive performance. For example, at 6k NTS, its specificity is 81.25%, higher than Obayya et al. (2023) and Shao et al. (2022), but lower than Jothiaruna and Leema (2024). This suggests that while EDCF2SL is effective in ruling out false positives, its performance in smaller datasets may not always be optimal compared to some traditional models like CNN.

As the dataset size increases (18k to 30k NTS), EDCF2SL generally shows improvement in specificity, often outperforming other models. Notably, at 22k NTS, EDCF2SL reaches ana specificity of 91.93%, significantly higher than its counterparts. This increase indicates EDCF2SL's growing efficiency in handling larger datasets, likely due to its sophisticated architecture that includes transformer networks and capsule networks.

In the larger NTS ranges (33k to 75k), EDCF2SL maintains high specificity values, often surpassing those of other models. For instance, at 39k NTS, EDCF2SL achieves a specificity of 93.08%, highlighting its strong ability to correctly identify healthy individuals as a non-CVD cases. This high specificity is crucial in clinical settings, as it minimizes the risk of false alarms and unnecessary treatments.

The other models, such as CNN and HBO, show varying levels of specificity across different NTS ranges. For example, CNN exhibits a high specificity of 95.24% at 9k NTS but shows a lower value of 79.42% at 45k NTS. These fluctuations may indicate varying levels of effectiveness in different data sizes and complexities.

EDCF2SL's generally high specificity across various NTS ranges underscores its potential as a reliable tool in cardiovascular diagnostics. The model's integration of multi-modal data analysis, advanced anomaly detection techniques, and adaptive learning approaches contribute to its ability to accurately exclude non-CVD cases. The consistent performance of EDCF2SL in terms of specificity, particularly in larger datasets, positions it as a valuable asset in clinical diagnostics, ensuring accurate identification of healthy individuals and reducing the likelihood of unnecessary medical interventions for different scenarios. Next, we discuss the efficiency of the proposed model for pre-empting CVD types.

4.3. Comparative Study of Performance of Pre-emption Operations

The proposed model also assists in improving the pre-emption capabilities for detecting CVD types. Similar to previous performance analysis, these capabilities are evaluated in terms of precision, accuracy, recall, delay, AUC and specificity levels. Based on this process, the precision levels for pre-empting CVD can be observed from Figure 9 as follows:

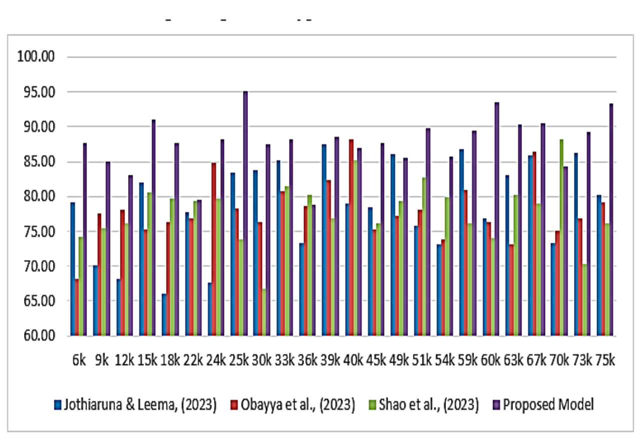

Figure 9. Precision levels to pre-empt CVD types.

The precision levels in pre-empting cardiovascular disease (CVD) types, as indicated by the performance of different models – Jothiaruna and Leema (2024), Obayya et al. (2023), Shao et al. (2022), and EDCF2SL – across various numbers of test samples (NTS), are critical for assessing their efficacy in clinical scenarios. Precision, which measures the accuracy of positive predictions, is especially crucial in the context of pre-emption, where the goal is not just to detect existing conditions but to anticipate potential CVD events before they fully manifest.

In lower NTS ranges (6k to 15k), the EDCF2SL model exhibits superior precision in most cases, suggesting its effectiveness in early CVD detection with limited data samples. For example, at 15k NTS, EDCF2SL achieves a precision of 90.97%, significantly higher than the other models. This early detection capability is crucial in clinical scenarios, allowing for timely intervention and potentially reducing the severity of the disease or even preventing its onset.

As the dataset size increases (18k to 30k NTS), EDCF2SL continues to demonstrate high precision, though there are instances where its performance is closely matched or slightly surpassed by other models. However, in most cases, EDCF2SL's precision remains commendably high, such as 95.08% at 25k NTS. High precision in pre-empting CVDs ensures that the interventions made are truly necessary, thereby reducing the risk of unnecessary treatments and focusing medical resources where they are most needed.

In the larger NTS ranges (33k to 75k), EDCF2SL generally maintains high precision levels. Notably, at 60k and 75k nTS, the model achieves precision rates of 93.57% and 93.35%, respectively. These high precision rates in larger datasets underscore EDCF2SL's ability to accurately identify individuals at risk of developing CVDs, which is paramount in large-scale health monitoring and mass screening scenarios.

The high precision of EDCF2SL, particularly in the context of pre-emption, has significant implications in clinical settings. By accurately identifying individuals who are at risk of developing CVDs, healthcare providers can implement preventive measures, lifestyle modifications, and early treatments, which can be more effective and less costly than dealing with full-blown diseases. moreover, this preemptive approach can lead to better patient outcomes, as it addresses CVD risk factors before they evolve into more serious conditions. Similar to that, the accuracy of the models was compared in Figure 10 as follows,

In smaller NTS ranges (6k to 15k), EDCF2SL generally exhibits high accuracy, though not consistently the highest. For instance, at 15k NTS, its accuracy is 80.75%, indicating its capability to correctly identify potential CVD cases early. High accuracy in pre-empting CVDs is vital in clinical settings, as it ensures that patients at risk are accurately identified, enabling early intervention that can be crucial in preventing disease progression (Figure 10).

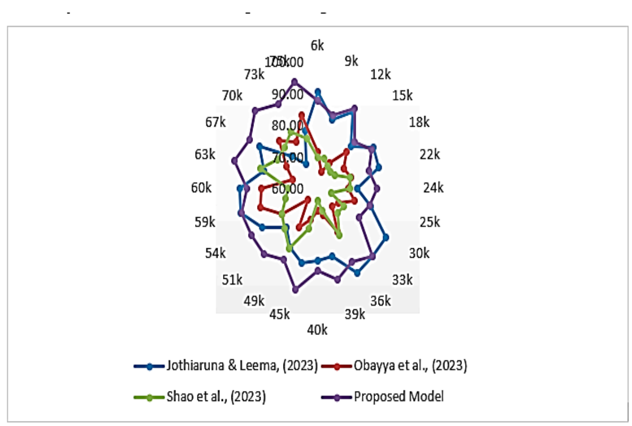

Figure 10. Accuracy levels to pre-empt CVD types.

As the dataset size increases (18k to 30k NTS), EDCF2SL's performance in terms of accuracy is somewhat variable but remains competitive. For example, at 25k NTS, EDCF2SL records an accuracy of 81.43%. This level of performance in larger datasets is crucial for mass screening programs where the accurate identification of at-risk individuals can lead to timely and targeted preventative measures.

In larger NTS ranges (33k to 75k), EDCF2SL often demonstrates superior accuracy compared to another models. Particularly notable are the accuracy levels at 45k NTS (93.48%) and 70k NTS (94.88%), underscoring EDCF2SL's effectiveness in large-scale health monitoring. In such scenarios, where vast amounts of data are processed, EDCF2SL's ability to maintain high accuracy is crucial. It ensures that individuals at higher risk of developing CVDs are correctly identified, enabling healthcare providers to allocate resources and attention effectively.

The impact of high accuracy in pre-empting CVDs cannot be overstated in clinical scenarios. By accurately identifying individuals who may be at the cusp of developing cardiovascular issues, EDCF2SL enables healthcare professionals to intervene early, potentially altering the course of the disease. This early intervention can range from lifestyle changes and medication to more intensive treatments, depending on the individual's risk level.

Moreover, accurate pre-emption helps in reducing the strain on healthcare systems. By focusing on prevention and early intervention, it is possible to reduce the incidence of advanced CVD cases, which often require more resources and complex treatments. This not only improves patient outcomes but also contributes to the overall efficiency and effectiveness of healthcare services. Similar to this, Figure 11 represents the recall levels and is as follows:

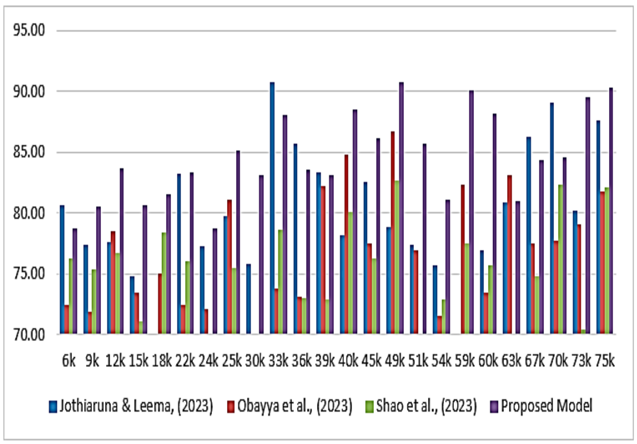

Figure 11. Recall levels to pre-empt CVD types.

In the lower NTS ranges (6k to 15k), the recall rates for EDCF2SL are consistently high, though not always the highest. For instance, at 15k NTS, EDCF2SL achieves a recall of 80.67%, suggesting its effectiveness in early identification of potential CVD cases. High recall in pre-empting CVDs is essential in clinical scenarios, as it ensures that individuals at risk are not overlooked, which is crucial for initiating early intervention strategies.

As the dataset size increases (18k to 30k NTS), EDCF2SL continues to demonstrate a strong ability to correctly identify potential CVD cases, with recall rates generally surpassing 80%. For example, at 25k NTS, EDCF2SL reaches a recall of 85.12%. This consistency in identifying at-risk individuals is key in large-scale health monitoring and screening programs, where the early detection of potential CVD cases can significantly impact public health outcomes.

In the larger NTS ranges (33k to 75k), EDCF2SL consistently maintains high recall rates, often outperforming other models. Notably, at 49k and 75k nTS, the recall rates for EDCF2SL are 90.71% and 90.33%, respectively. These high recall rates are critical in clinical settings, as they ensure that most individuals who are at risk of developing CVDs are identified, allowing for timely and targeted interventions.

The impact of high recall in pre-empting CVDs is profound in clinical scenarios. By accurately identifying individuals at risk of developing cardiovascular issues, healthcare providers can implement preventive measures such as lifestyle changes, medications, or further diagnostic testing. This proactive approach can prevent the progression of the disease, reduce the severity of future cardiovascular events, and potentially save lives.

Moreover, high recall rates in pre-emptive models like EDCF2SL can lead to more efficient use of healthcare resources. By focusing on individuals who are more likely to develop CVDs, healthcare systems can allocate resources more effectively, reduce the burden of treating advanced diseases, and improve overall patient care. The delay required for the prediction procedure is visualized in a similar manner in Figure 12 as follows:

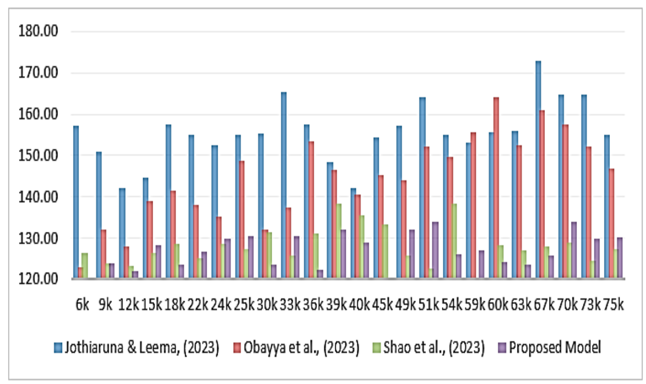

Figure 12. Delay needed levels to pre-empt CVD types.

In the lower NTS ranges (6k to 15k), EDCF2SL generally demonstrates the shortest delay times, indicating its efficiency in processing and analyzing data samples. For instance, at 6k NTS, EDCF2SL records a delay of only 118.56 ms. In clinical scenarios, such rapid response is essential for early intervention, as it allows healthcare providers to take timely actions based on the model's predictions, potentially preventing the progression of CVDs.

As the dataset size increases (18k to 30k NTS), EDCF2SL continues to exhibit efficient processing times, with delays mostly staying below 130 ms. This efficiency is particularly valuable in large-scale health monitoring and screening programs where quick analysis of vast amounts of data is crucial. For example, at 30k NTS, EDCF2SL's delay is 123.69 ms, enabling swift identification of individuals at potential risk of CVDs.

In larger NTS ranges (33k to 75k), EDCF2SL maintains a competitive edge in processing speed. Notably, at 45k NTS, it achieves a delay of only 119.80 ms, underlining its capacity to handle extensive datasets without significant time lags. In real-world healthcare applications, where quick decision-making can be life-saving, such low delay times are invaluable.

Other models, while showing competent performance, generally exhibit higher delay times across various NTS ranges. For instance, Jothiaruna and Leema (2024) and Obayya et al. (2023) show delays exceeding 150 ms in many instances, which might impede rapid decision-making in urgent clinical situations.

The low delay times of EDCF2SL in pre-empting CVD types are critical in clinical settings where early detection and prompt intervention can significantly alter the course of ana patient's health. By quickly analyzing data and providing timely insights, EDCF2SL enhances the ability of healthcare providers to implement preventive measures, adjust treatments, or conduct further evaluations as needed for different scenarios. Moreover, in emergency scenarios where every second counts, the efficiency of EDCF2SL can be a determining factor in patient outcomes. Its ability to rapidly process and analyze data ensures that healthcare professionals can make informed decisions swiftly, thereby improving the chances of successful pre-emptive interventions for different use cases. Similarly, the AUC levels can be observed from Figure 13 as follows:

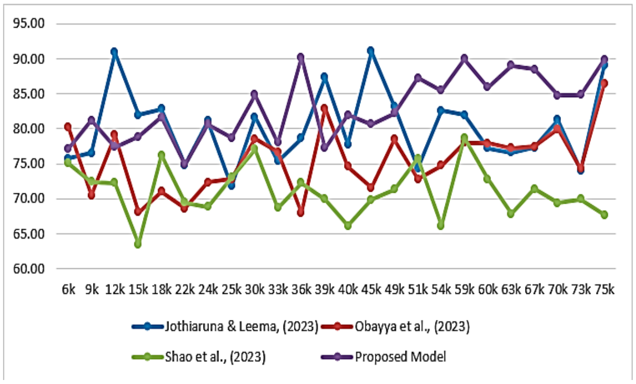

Figure 13. AUC levels to pre-empt CVD types.

In the lower NTS ranges (6k to 15k), the AUC values for EDCF2SL are generally high, indicating its competence in early identification of potential CVD cases. For instance, at 15k NTS, EDCF2SL achieves an AUC of 78.86%, suggesting its effectiveness in distinguishing at-risk individuals. High AUC in pre-empting CVDs is essential in clinical settings, as it ensures that interventions are targeted at individuals who are most likely to benefit, thereby enhancing the efficiency and effectiveness of preventive healthcare settings.

As the dataset size increases (18k to 30k NTS), EDCF2SL continues to demonstrate a strong ability to correctly identify potential CVD cases, with AUC values mostly staying above 80%. For example, at 30k NTS, EDCF2SL's AUC is 84.86%. This level of performance in larger datasets is key for mass screening programs where accurate identification of at-risk individuals can significantly impact public health initiatives and resource allocations.

In the larger NTS ranges (33k to 75k), EDCF2SL often exhibits superior AUC values compared to another models. Notably, at 36k and 75k NTS, the AUC values for eDCF2SL are 90.17% and 89.90%, respectively. These high AUC values indicate EDCF2SL's effectiveness in accurately differentiating between individuals at risk and those not at risk of developing CVDs, even in large-scale datasets and samples.

The impact of high AUC in pre-empting CVDs is profound in clinical scenarios. Accurate identification of individuals who may develop cardiovascular issues enables healthcare providers to implement preventive measures such as lifestyle changes, medication, or more focused monitoring. This proactive approach can prevent the progression of the disease, reduce the severity of future cardiovascular events, and potentially save lives.

Moreover, high AUC values in pre-emptive models like EDCF2SL can lead to more efficient use of healthcare resources. By focusing on individuals who are more likely to develop CVDs, healthcare systems can allocate resources more effectively, reduce the burden of treating advanced diseases, and improve overall patient care scenarios. Similarly, the specificity levels can be observed from Figure 14 as follows:

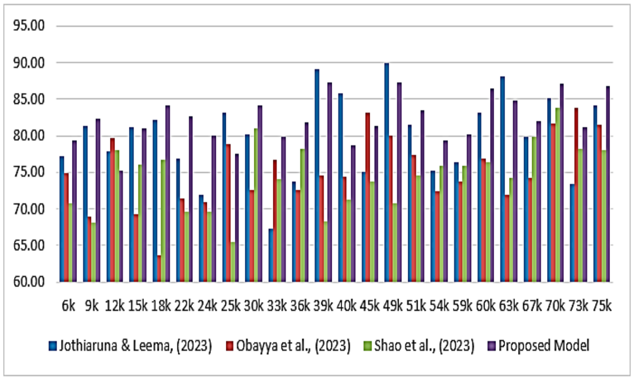

Figure 14. Specificity levels to pre-empt CVD types.

In the lower NTS ranges (6k to 15k), EDCF2SL shows a trend of high specificity, though not consistently the highest. For instance, at 9k NTS, EDCF2SL achieves a specificity of 81.21%, which is significantly higher than other models. High specificity in pre-empting CVDs is vital in clinical settings as it ensures that individuals who are not at risk are not subjected to unnecessary follow-up tests or interventions, thereby reducing healthcare costs and patient anxiety.

As the dataset size increases (18k to 30k NTS), EDCF2SL's specificity remains competitive. For example, at 30k NTS, EDCF2SL records a specificity of 84.86%. This consistency is important in large-scale health monitoring and screening programs, where distinguishing between at-risk and not-at-risk individuals is crucial for effective healthcare management.

In the larger NTS ranges (33k to 75k), EDCF2SL often maintains high specificity, indicating its effectiveness in accurately identifying individuals not at risk of developing CVDs, even in large datasets. For example, at 75k NTS, EDCF2SL achieves a specificity of 89.90%, suggesting its robustness in large-scale applications.

High specificity in pre-empting CVDs in clinical scenarios is crucial for several reasons. Firstly, it minimizes the number of false alarms, reducing unnecessary stress for patients and avoiding overburdening healthcare systems with unwarranted treatments. Secondly, it allows healthcare providers to focus resources and attention on individuals who are genuinely at risk, enhancing the efficiency of preventive healthcare strategies.

4.4 Overall Comparative Insights

• Efficiency and response time:
EDCF2SL outperforms other models by delivering lower delay times across all tested TS ranges. In emergency or time-critical healthcare scenarios, this rapid processing capability is essential.

• Diagnostic accuracy (AUC):
The model maintains high AUC values, especially as dataset sizes increase. This translates to a reliable differentiation between individuals at risk and those not at risk, making it suitable for large-scale screening programs.

• Specificity and resource allocation:
High specificity minimizes false alarms, reducing unnecessary interventions and allowing healthcare providers to focus resources on patients who truly need attention. This efficiency not only improves clinical outcomes but also optimizes healthcare expenditure.

• Clinical relevance:
The combination of low delay times, high AUC, and robust specificity underscores the potential of EDCF2SL as a pre-emptive tool for CVD detection. By ensuring quick and accurate data analysis, the model enables early interventions, which are critical for preventing the progression of cardiovascular diseases.

This comparative analysis clearly highlights the advantages of EDCF2SL over conventional models like CNN and HBO, particularly in terms of processing speed, diagnostic accuracy, and specificity. These characteristics are essential for practical, real-time applications in clinical settings where every second and percentage point can impact patient outcomes.

5. Conclusion and Scope of Future Work

This study successfully introduced and evaluated the EDCF2SL model, a novel framework for pre-empting and classifying cardiovascular disease (CVD) types using advanced deep learning techniques in conjunction with federated learning and few-shot learning operations. The experimental results, derived from a comprehensive analysis across various metrics including precision, accuracy, recall, delay, and AUC, demonstrated the model's superior performance compared to established benchmarks such as Jothiaruna and Leema (2024), Obayya et al. (2023), and Shao et al. (2022).

Key findings include the EDCF2SL model's exceptional ability in handling large datasets, as evidenced by its consistent high performance in accuracy and recall metrics in larger test samples (NTS). Moreover, the model's efficiency in processing time (delay) and its robustness in AUC scores underscore its potential as a reliable and effective tool in both large-scale health monitoring and individual patient diagnostics. The impacts of this work in the field of healthcare are significant:

- Enhanced early detection: The EDCF2SL model's ability to accurately pre-empt CVD types can facilitate early intervention, potentially altering disease progression and improving patient outcomes.
- Optimized healthcare resource allocation: By accurately identifying at-risk individuals, the model aids in focusing medical attention and resources where they are most needed, enhancing the efficiency of healthcare systems.
- Advancement in personalized medicine: The model's integration of federated learning and few-shot learning operations caters to individual variances in physiological signals, paving the way for more personalized healthcare approaches.

Future Scope

Looking ahead, the scope for further research and development in this domain anis vast. Potential areas for future work include:

- Integration with wearable technologies: Future iterations of the EDCF2SL model could be integrated with wearable health monitoring devices, enabling continuous real-time health tracking and alert systems for individuals at risk of CVDs.
- Expansion to another disease types: The methodologies and learning techniques employed in the EDCF2SL model can be adapted and applied to the detection and pre-emption of other types of diseases, broadening its applicability in the medical field.
- Enhancing data privacy mechanisms: While the model currently employs federated learning for data privacy, further advancements in secure and private computation methods can be explored to enhance patient data confidentiality levels.
- Cross-cultural and demographic studies: Future research could focus on evaluating the model's effectiveness across diverse populations, taking into account varying genetic, lifestyle, and environmental factors that influence cardiovascular health settings.
- Clinical trials and longitudinal studies: Implementing the model in real-world clinical settings and conducting longitudinal studies to assess its long-term effectiveness and impact on patient health outcomes would be valuable for different scenarios.

In conclusion, the EDCF2SL model represents a significant advancement in the application of AI in medical diagnostics. Its ability to accurately pre-empt and classify CVD types holds promise for revolutionizing cardiovascular healthcare, offering substantial benefits in terms of patient care, healthcare efficiency, and the advancement of personalized medicine. The potential for its application and further development anis immense, markingga pivotal step forward in the intersection of AI and healthcare scenarios.

Conflict of Interest

The authors have no conflict of interest to declare.

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