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A Contextual Intervention Consistency Selector and Temporal Casual Memory Network for Explainable Personalized Cardiovascular Risk Factor Identification and Prediction

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Abstract:

One of the leading causes of mortality worldwide is cardiovascular disease (CVD) to emphasize the requirements personalized risk, interpretable and accurate prediction models thereby supporting early clinical intervention. Most of the previous works rely on correlation based feature selection; the promising prediction performance achieves existing Machine Learning (ML) models. For personalized cardiovascular risk factor identification and prediction, this work presents the Contextual Intervention Consistency Selector-Temporal Causal Memory Network (CICS-TCMN) framework. This work initializes the data pre-processing and feature engineering in which the cause-and-effect relationships among clinical lifestyle variables are discovered using casual structure learning. Across multiple patient contexts, the stability of casual effects is evaluated via proposed Contextual Intervention Consistency Selector (CICS). Based dynamic memory mechanisms, the temporal accumulation of casual dependencies are captured via Temporal Casual Memory Network (TCMN). The patient-specific disease trajectories and long-term cardiovascular progression patterns are learned. Individualized risk factors contributions are quantified with an influential casual pathway are traced via explainability module. The physician confidence and clinical interpretability is enhanced to provide transparent prediction. Compared to previous state-of-art models, an enhanced explainability, enhanced temporal risk modeling and superior predictive performances are accomplished using proposed CICS-TCMN framework based on the evaluation of benchmark cardiovascular disease datasets. The clinically and reliable interpretable decision-support systems are offered using proposed framework for personalized CVD risk assessment and early disease prevention.

Keywords: Cardiovascular Disease, Contextual Intervention Consistency Selector, Temporal Causal Memory Network and Temporal Casual Memory Network.

1. Introduction:

The widely causes of disability and mortality in worldwide is Cardiovascular Disease (CVD). The complicated interplay of demographic, lifestyle, generic, physiological and clinical related factors influences the progression of cardiovascular disorders [1]. While enhancing patient outcomes and reducing mortality, the healthcare professionals to make informed decisions are enabled; the significant research direction in precision medicine is an intelligent cardiovascular risk prediction development [2]. The cardiovascular disease prediction model performances improve using recent developments in Artificial Intelligence (AI). The clinical measurements and structured electronic health records demonstrates the promising predictive capabilities [3]. The nonlinear interaction among improve predictive accuracy and cardiovascular risk factors are captured to introduce hybrid learning frameworks, transformer-based architectures, graph neural networks and deep neural network.

Based on statistical models, the complex models are extracting complex feature representations and handling large-scale heterogeneous healthcare data with superior capability shows theses approaches [4]. The correlation based feature selection models are relied via most current approaches. Across diverse patient populations, the spurious relationships are learned and independent predictions are previous models that treat the factors of CVD [5]. The multiple interacting risk factors are developed via CVD; both clinically interpretability and prediction reliability is reduced to neglect casual relationships. The sequential learning improves the temporal models, long short term memory networks and recurrent neural networks [6]. The personalized risk prediction robustness is reduced and coincidental temporal associations are influenced. The major challenge remained the interpretability in the clinical adoption of AI-based CVD systems. It shows limited explanation regarding to classify the high risk. The transparent evidence is required via clinician in medical decision-support applications [7]. In real-world healthcare environments, an advanced deep learning system of practical deployment is restricted with limited regulatory acceptance and reduces physician confidence.

The substantial variability in cardiovascular risk profiles are introduced using patient heterogeneity. Various responses to identical risk factors often exhibited via individual to different groups. Without evaluating across diverse patient contexts, the global feature importance is generally estimated with previous feature selection [8]. The limited contextual consistency leads to inaccurate personalized risk assessment and minimized model robustness. While temporal evolution, the contextually stable and casually relevant cardiovascular risk are identified using for intelligent prediction models. For explainable personalized cardiovascular risk factors, a novel Contextual Intervention Consistency Selector-Temporal Causal Memory Network (CICS-TCMN) framework is proposed to addresses these challenges. Based on temporal disease progression, the prediction of an individualized cardiovascular risk is enabled as well as the long-term accumulations of casual influences are captured via TCMN. Influential risk factors are quantified as well as the patients specific casual pathways are identified using explainability module. The following section summarizes the major contribution of this work.

- To develop a novel CICS-TCMN framework for the prediction and identification of explainable personalized cardiovascular risk factors. Integrate a unified architecture

from explainable artificial intelligence, temporal memory modeling and casual learning.

- To introduce CICS for the identification cardiovascular risk factors due to the effects of casual intervention across multiple patient contexts. The casually significant risk and contextually stable factors are selected thereby personalized prediction reliability and improves robustness.
- To capture temporal accumulation of casual influences using TCMN. The patient-specific cardiovascular risk trajectories and long-term disease progression patterns are learned via proposed temporal modeling mechanism.
- To incorporate an explainability model for quantify an influential cardiovascular risk factors contribution and identifying patient-specific casual pathways. The prediction outcome interpretability and transparency is improved.
- To demonstrate comprehensive experimental evaluation using proposed CICS-TCMN. The potential as intelligent clinical decision support systems are highlighted.

Organization: The related works based on CVD is presented in Section 2 and the proposed CICS-TCMN framework is described in Section 3. The experimental investigational followed by the discussion is outlined in Section 4 and the conclusion is concluded in Section 5.

2. Related Works:

For predicting incident heart failures, the Explainable Transformers assisted Deep Learning (XT-DL) was suggested by Rao et al. [9]. To incorporate an attention assisted explainability mechanism, the long-range dependencies among clinical variables were captured to employ the architecture of transformers. An enhanced clinical decision support was enhanced to provide interpretable prediction contrasted with conventional ML models. Rather than explicit casual relationships, the correlation based feature interactions were learned to enhance interpretability and effective longitudinal healthcare data utilization. Moreover, it not explicitly computes the casual effects of contextual consistency as well as shown limited robustness. Bandyopadhyay et al. [10] presented the Stacked Meta Neural Network (SMNN) to integrate the selection of statistical risk factor. The clinically significant features were identified to employ rigorous statistical evaluation as well as it offers correct CVD prediction. To reduce computational complexity, the insignificant risk factors eliminated to provide enhanced accuracy for prediction. Through systematic risk factor selection, it described improved robustness, reduced model complexity and effective optimization to statistical features. This model non-incorporate the patient-specific explainability and casual dependency also it limited to describe interpretable and personalized assessment for risk.

An Explainable Graph Neural Network (XGNN) was established by Lundström et al. [11] to predict the atherosclerotic CVD progression. The correlation among treatment trajectories, clinical variables and patient admissions are captured to utilize the representation of temporal graph. While supporting clinical decision making, the model transparency as enhanced with the integration of XGNN. This model has the ability for complicated relational depend ices capturing and better predictions for explainable. However, this model limits the personalized casual risk factors. To stratify heart failure patients, Chowdhury et al. [12] suggested Grapgh

Neural Network based Transformer framework (GNN-T) that shows individual drug response prediction. The structural relationships between clinical variables were captured to employ GNN and it indicated enhanced prediction accuracy, enhanced patient stratification and temporal clinical information. However, this model limits the explainability performances and excluding contextual interventions.

According to the prediction of CVD, the Expandable Machine Learning (XML) was presented by Paul et al. [13]. The feature contributions based local and global interpretations were provided based on SHAP. While showing feature level explainability based transparency enhancements, the multiple performance criteria as shown comprehensive evaluation along with enhanced clinician trust. Across various populations of patients, the contextual consistencies of risk factors were evaluated with limited generalization ability. To predict CVD, the ML based models was introduced by Guarneros-Nolasco et al. [14] for assessing various CVD datasets based disease predictions. The predictive classifier performance assesses significant risk attributes to detect the top-two feature ranking. To minimize model complexity, an enhanced performance of prediction and most appropriate clinical attributes were selected using ML. Based on multiple datasets, the robust validation and significant CVD risk factors were identified using comprehensive evaluations. This model indicated limited personalized interpretable effectiveness.

The hyperparameter tuned ML models was suggested by Uddin et al. [15] to predict CVD with the usage of UCI heart disease datasets. For diagnosis process, the hyper-parameter tuning and feature engineering effectiveness were highlighted to achieve the prediction accuracy as superior. Therefore, the prediction model indicates enhanced predictive accuracy, minimized computational complexity and optimized tuning of hyperparameters. Moreover, this model not provides a temporal disease procession and absence of explainability. Due to interpretable prediction of multi-class heart disease risk prediction, the Deep Fuzzy Inference System (DFIS) was introduced by Ramasami et al. [16]. For hierarchical feature learning, the deep neural network with Adam cuckoo search optimization was employed as well as it categorizes patient disease classes like high risk, critical and normal. To enhance interpretability, the DFIS framework delivers enhanced accuracy for prediction. This model shows more run time and limited ability for capturing long-term disease progression. The literature for explainable CVD prediction and risk factor identification is delineated Table 1.

Table 1: Previous literature for explainable CVD prediction and risk factor identification

Authors	Methods	Datasets	Merits	Limitations
Rao et al. [9]	XT-DL	Longitudinal electronic health records	Provides interpretable attention based predictions and captures long-	Lack of contextual consistency evaluation and explicit casual relationships

			term temporal dependencies	
Bandyopadhyay et al. [10]	SMNN	UCI heart disease	Enhances prediction performances and detects significant cardiovascular risk factors	Without temporal modeling and depends on statistical feature ranking
Lundström et al. [11]	XGNN	Longitudinal HER for atherosclerotic CVD	Enhance model interpretability and learn complex graph relationships	Long-term temporal casual evolution and does not explicitly model casual dependencies
Chowdhury et al. [12]	GNN-T	EHR of heart failure patients	Temporal patient representations for drug responses prediction and effectively captures graph	Lacks of contextual intervention analysis and focuses on temporal associations
Paul et al. [13]	XML	Structured clinical health data	Improves clinical trust and provides local and global feature explanations	Does not detect casual relationships and complication time
Guarneros-Nolasco et al. [14]	ML	Structural clinical health data	Improves clinician trust, provides local and global feature representations	It not discover casual relationships and not offers temporal disease progression
Uddin et al. [15]	Hyperparameter tuned ML	UCI heart disease datasets	Enhanced hyperparameter	Without casual learning of

			optimization and improved prediction accuracy	personalized temporal modeling and limited to correlation based ML
Ramasami et al. [16]	DFIS	UCI heart disease datasets	Fuzzy resoning and interpretable with better prediction accuracy	Failed to capture temporal disease progression and does not shows casual interactions

2.1 Research Gap

According to cardiovascular disease prediction, achieve the significant progress are indicated in the literature review through fuzzy inference systems, explainable artificial intelligence, transformer architectures, graph neural networks, deep learning and machine learning. An unresolved major critical research challenges. Without explicitly learning, the statistical associations between CVD risk factors with previous studies on correlation assisted prediction models and feature selection. The prediction model generalizability and robustness was reduced and not reflects the casual mechanisms responsible for the progression of disease. The post-hoc explanations were provided with current explainable AI models. The multiple interacting risk factors based temporal accumulation progressively develops CVD. The previous model shows lower reliable personalized risk assessment and absence of context-aware casual evaluation. Within the unified architecture, the patient-specific explainability is integrated with an intelligent CVD risk prediction framework, which describes interpretable, accurate and personalized CVD for supporting clinical decision.

3. Proposed Methodology

The personalized and interpretable CVD risk prediction system is provided based on the design of proposed CICS-TCMN, which integrates the temporal DL with casual inference. The cardiovascular risk based temporal evolution is captured to evaluate casual effects across various patient contexts. Each selected risk factor contribution is quantified and the casual pathways learn the explainability module evaluation. The personalized treatment planning is facilitated to enable clinicians to compute the rationale behind every prediction. Figure 1 exemplifies the proposed CICS-TCMN framework with its work flow.

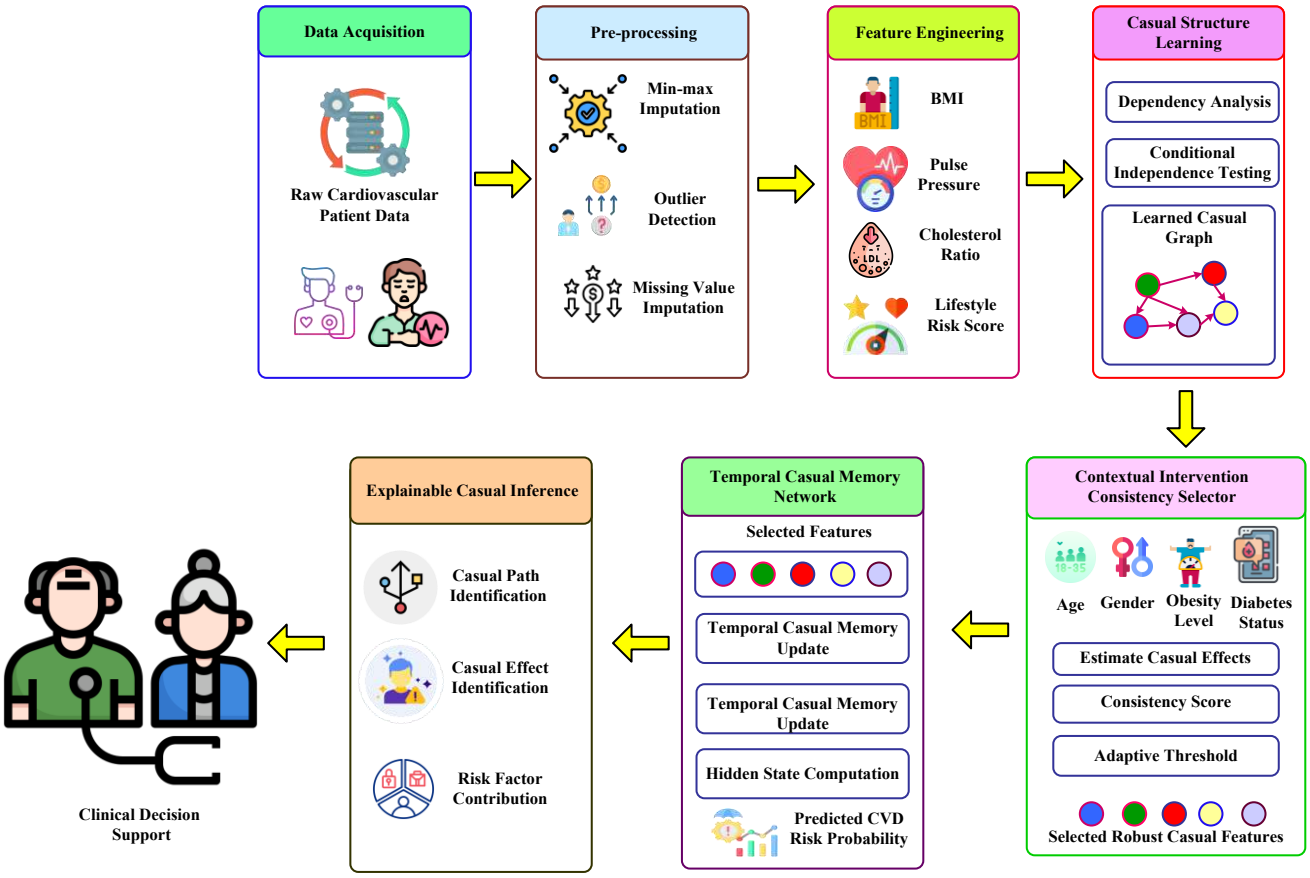


Figure 1: Proposed workflow model for CICS-TCMN framework

3.1 Data Collection

The publicly available CVD dataset [17] provides the data that evaluates the proposed CICS-TCMN framework for disease as well as risk prediction. During clinical examination routine, the dataset consist of 70,000 anonymized patient records with 11 clinical attributes. It provides cardiovascular health with comprehensive evaluation of lifestyle, biochemical, and physiological, anthropometric and demographic oriented information. Further, the value 0 represents absence of CVD indicates presence of CVD. The complex casual interactions between risk variables are captured to the combination of heterogeneous behavioral and clinical factors.

3.2 Data Pre-processing

The comprehensive pre-processing stages are undergone via collected clinical data prior to cardiovascular risk prediction and casual structure learning. Based on varying numerical scales, the dataset contains features, abnormal physiological measurements and missing observations. The reliable and consistent feature representation is generated to propose CICS-TCMN framework. For subsequent analysis, the consistent and reliable feature representation is generated to perform missing value imputation, outlier detection and min-max normalization.

3.2.1 Missing Value Imputation

Incomplete clinical examinations are occurred due to missing values. For all numerical attribute values, the median imputation is employed instead of incomplete patient record discarding [18]. The features based on all observed values are represented as $W = \{w_1, w_2, ..., w_n\}$. Equation (1) represents the imputation process.

$$w_j = \begin{cases} w_j, & if\ w_j \neq \varphi \\ Median(W), & if\ w_j = \varphi \end{cases} \tag{1}$$

The median value for all available observation is $Median(W)$. To minimize missing data influences, the clinical variables with the statistical characteristics are preserved.

3.2.2 Outlier Detection

The abnormal values have the clinical measurements like weight, height, diastolic and systolic blood pressures. The Interquartile Range (IQR) is adopted to detect and neglect such abnormalities. Below formula formulates both upper and lower bound threshold.

$$Low = q_1 - 1.5(q_3 - q_1) \tag{2}$$

$$Up = q_3 - 1.5(q_3 - q_1) \tag{3}$$

From this, the first and third quartile is q_1 and q_3. To preserve overall distribution, the extreme observation impacts are reduced to clip the detected outliers. Both temporal prediction and casual structure learning with its robustness is enhanced.

3.2.3 Min-max Normalization

Various units and numerical ranges like blood pressure, weight, height and age that measures in cardiovascular dataset [19]. The min-max normalization normalizes all continuous attributes that scaled to [0, 1] interval. Following formula calculates the normalized feature value.

$$w_j^{Nor} = \frac{w_j - w_{Min}}{w_{Max} - w_{Min}} \tag{4}$$

From this, w_j, w_{Min} and w_{Max} original feature, minimum and maximum value with w_j^{Nor} is normalized features. To ensure all variables are ensured with the relative relationships among samples are preserved. An enhanced predictive performance, improved numerical stability and faster convergence is accomplished Temporal Casual Memory Network.

3.3 Feature Engineering

The cardiovascular biomarkers representations from multiple clinical measurements are integrated to extract additional discriminative features. The proposed model ability is enhanced thereby showing improved casual relationship detection, enhanced predictive ability and richer physiological information [20]. From the original clinical variables, computes the lifestyle risk

score (LRS), cholesterol ratio (CR), pulse pressure (PP) and body mass index. The patient's weight and height is to compute BMI.

$$BMI = \frac{wei}{hei^2} \tag{5}$$

From this, the height and weight of the body is denoted as hei and wei. The risk of cardiovascular is increased to indicate overweight. The significance of vascular health and arterial stiffness is served with the variation of systolic and diastolic blood pressure is reflected based on pulse pressure.

$$PP = hi_{AP} - lo_{AP} \tag{6}$$

The systolic and diastolic is hi_{AP} and lo_{AP}. The cardiovascular complications with higher probability and increased arterial rigidity associates elevated pulse pressure. The categorical levels of cholesterol derive the normalized cholesterol ratio to quantify abnormal cholesterol severity conditions.

$$CR = \frac{C_{cat}}{Max_C} \tag{7}$$

Here, C_{cat} and Max_C are individual cholesterol category and highest level of cholesterol. The continuous risk representations from the categorical cholesterol measurements are transformed using normalization. The physical in activity, alcohol consumption and smoking status is aggregated to introduce lifestyle risk score. The enriched cardiovascular feature W^* representations are formed to concatenate engineered biomarkers with original clinical variables.

3.4 Casual Structure Learning

The target outcome and strong statistical associations are exhibited identify variables. Underlying lifestyle, biochemical, physiological and demographic based cardiovascular risk factors; the casual structure learning is incorporated via proposed CICS-TCMN framework. The casual interaction between clinical variables is represented to construct the Directed Acyclic Graph (DAG) [21]. The cardiovascular disease with genuine casual determinates are enabled. Following expression represents the cardiovascular dataset.

$$W = \{w_1, w_2, .., w_n\} \tag{5}$$

The total number of clinical variables and j^{th} cardiovascular feature is n and w_j .The directed graph is estimated based on casual structure learning objective.

$$G = (v, e) \tag{6}$$

The casual relationships among them are described as well as the directed edges set represented as e. The cardiovascular variables based on node set are denoted v. The meaningful casual interactions are captured with directed edges $w_j \rightarrow w_k$. The cardiovascular dataset observe posterior probability of graph is maximized to obtain optimal casual graph.

$$\hat{G} = \arg\max_{G} p\left(G|W\right) \tag{7}$$

The learned graph not present dependencies are ensured using acyclic constraint [22]. The valid directional flow form causes to effects are followed to allow the casual relationships. Without forming feedback loops, the downstream variable is influenced with each cardiovascular variable. The casual model consistency and interpretability is preserved. From confounding relationships and indirect associations, the DAG effectively learned unlike conventional correlation oriented models. The cardiovascular disease risk is elevated to increase blood pressure is revealed. Equation (8) represents learned casual pathways.

$$Age \leftrightarrow CVD \tag{8}$$

The clinically meaningful interactions between variables are identified using casual graph. While enhancing interpretability and robustness, the confounding and redundant attributes influences are reduced; the feature selection stage propagates the relevant variables. The clinically meaningful and stable relationships are operated with subsequent model.

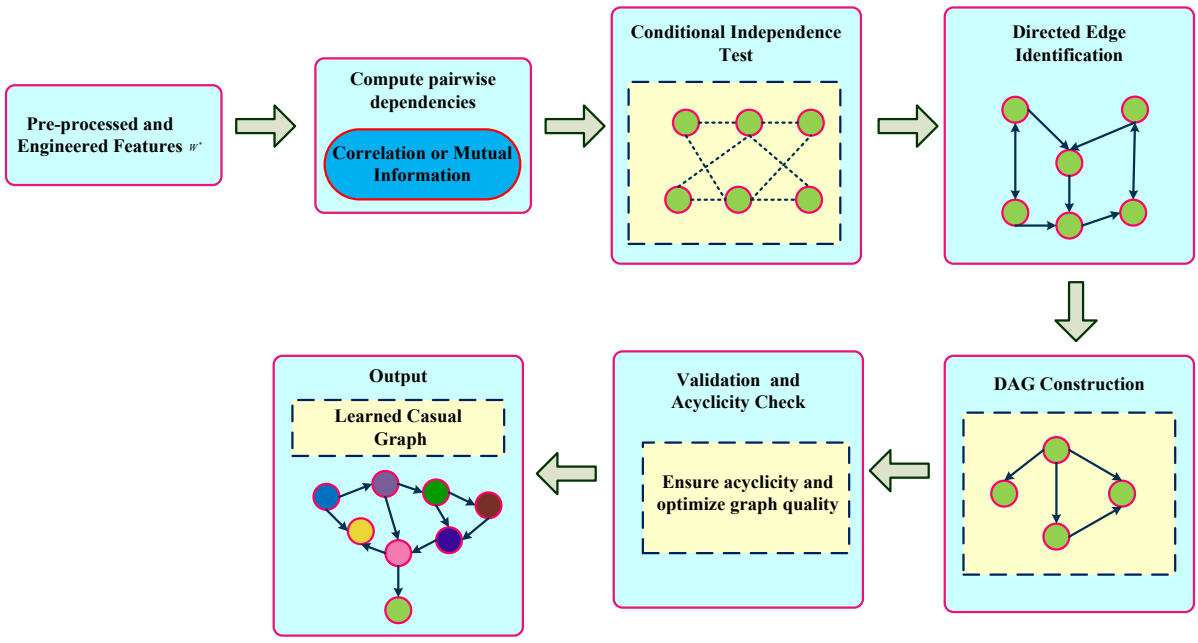


Figure 2: Architecture of proposed casual structure learning module

3.5 Contextual Intervention Consistency Selector

Across diverse patient populations, the casual effects stability is evaluated with clinically meaningful and reliable cardiovascular risk factors are identified to propose CICS following

casual structure learning [23]. Under varying clinical conditions, the statistical relevance of individual variables is measured using conventional feature selection models. Each cardio vascular risk factor is estimated to introduce a context-aware casual feature election strategy. Higher contextual consistency and strong casual influences are exhibited under multiple patient contexts.

Each cardiovascular feature effect casual invention is estimated to utilize learned DG from casual structure learning module. The multiple clinically relevant intervention contexts divides patient population that includes physical activity status, alcohol consumption, smoking habits, diabetic condition, gender classes and various age groups. Individual cardiovascular risks factors influences with the diverse behavioral and physiological conditions are represented using intervention contexts. Compared to single global distribution, the casual effects across multiple subpopulations are evaluated. Let C_j^k as the computed casual intervention effects. The total number of intervention contexts is K. For each feature, this formula computes the contextual consistency score.

$$CS_j = \frac{1}{k}\sum_{k=1}^{K} ce_j^k - \chi \operatorname{var}\left(ce_j^k\right) \tag{9}$$

Here, $\operatorname{var}\left(ce_j^k\right)$, CS_j and χ are casual effect variance across all intervention, contextual consistency score and stability regularization parameters [24]. The high casual influence receive larger scores are influenced with the features are ensured to compute average casual intervention effects. The larger consistency scores obtained and low contextual variances with average casual impacts are exhibited. The robust cardiovascular risk factors regards the larger consistency scores are obtained.

To retain most reliable variables, employ an adaptive threshold after evaluate score consistency scores of each candidate features. Equation (10) determines the selected feature subset.

$$Selected_F = \left(w_j \middle| R_j > \lambda\right) \tag{10}$$

The j^{th} cardiovascular features are denoted as w_j followed by the contextual consistency score and adaptive consistency threshold is R_j and λ. Retain an adaptive threshold for subsequent risk prediction. Across various patient intervention contexts, discard $R_j \le \lambda$ with features and represents either weak causal influences. To preserve cardiovascular risk factors, the redundant, confounding and unstable variables are eliminated under lifestyle, physiological and demographic conditions. The block diagram for proposed contextual intervention consistency selector is outlined in Figure 3.

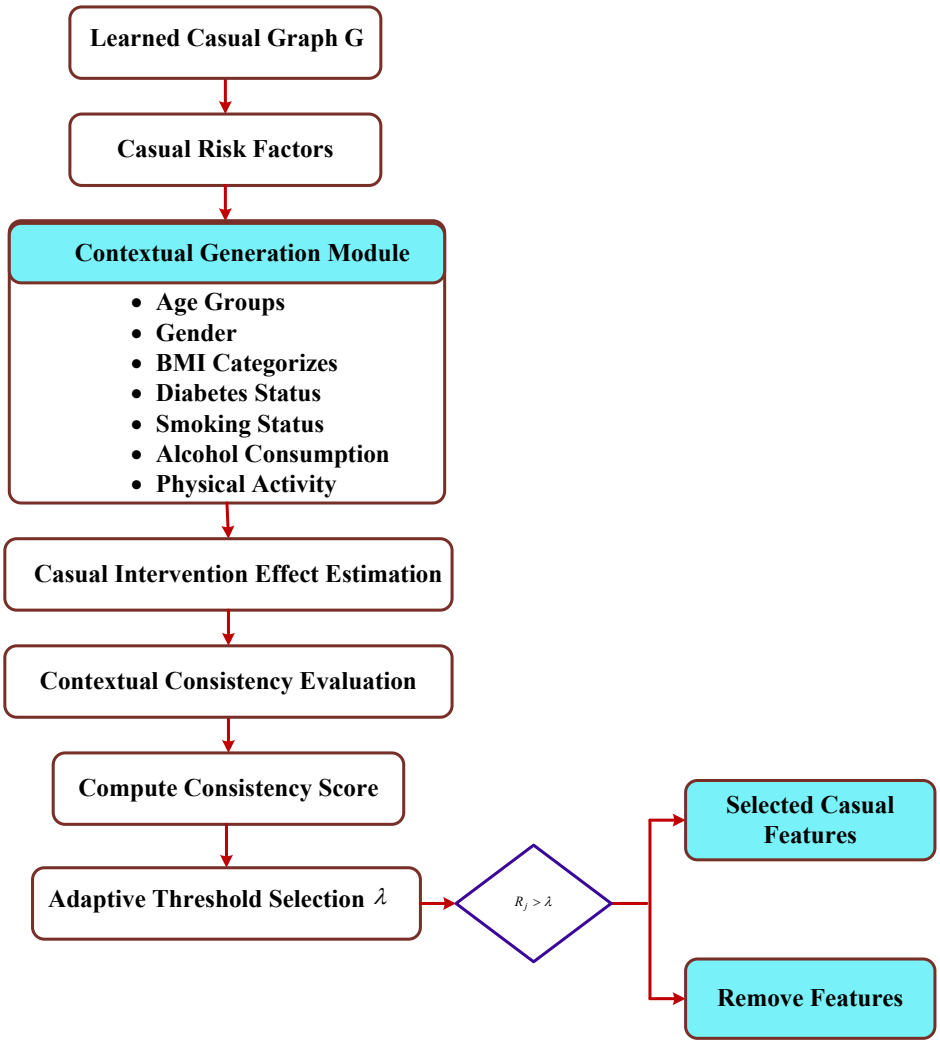


Figure 3: Blockdiagram for proposed contextual intervention consistency selector

3.6 Temporal Casual Memory Network

Forward the casual features to the proposed Temporal Casual Memory Network (TCMN) for the personalized cardiovascular risk prediction. The progressive disorder is CVD and accumulates physiological abnormalities. While observe patient conditions, the historical casual information is preserved using an effective prediction model. Within the dynamic memory state, the casual knowledge is stored using proposed TCMN [25]. From temporary physiological fluctuations, the persistent pathological progression is distinguished and captures long-term casual evolution.

$$Y_d = \{y_1, y_2, ..., y_T\} \tag{11}$$

The proposed CICS module generates the selected cardiovascular feature vector sequences. The total number of temporal observations is T and the feature vector is $y_T \in \Re^d$. By using nonlinear encoder, the higher dimensional latent casual transforms each casual feature vector before memory updating.

$$Y_t = F(y_t) = \delta\left(M_e y_t + B_e\right) \tag{12}$$

The encoder weight matrix, bias vector, ReLU activation function and encoded casual representation is described as M_e, B_e, $\delta(\cdot)$ and y_t. Before temporal memory integration, the complex interactions between cardiovascular risk factors are learned to enable the network. The Temporal Casual Memory (TCM) is introduced via proposed TCMN to preserve cumulative casual knowledge. Below expression defines the memory update.

$$m_t = \alpha m_{t-1} + (1-\alpha) x_t \tag{13}$$

The temporal casual memory, previous memory state and forgetting factor m_t, m_{t-1} and $\alpha \in [0,1]$. The quick adaption to observed physiological changes is enabled using smaller values. Below expression computes a casual attention weight to emphasize clinically casual observations.

$$\beta_t = \frac{\exp\left(M_\beta W_t\right)}{\sum_{j=1}^{T} \exp\left(M_\beta W_j\right)} \tag{14}$$

The attention weight matrix and current casual memory state is assigned as M_β and W_t. To suppress less informative observations, the greater significance of relevant temporal events is assigned to allow attention mechanism [26]. Following formula obtains the attended casual memory.

$$\tilde{W}_t = \beta_t \Theta W_t \tag{15}$$

Where, Θ is element-wise multiplication; the current casual features are combined to compute proposed TCMN.

$$h_t = \tanh\left(M_y y_t + M_n W_t + B\right) \tag{16}$$

Here, M_y, M_n and B are feature weight matrix, memory weight matrix and bias vector. The sigmoid activation function estimates the CVD probability.

$$P(z=1) = \gamma\left(M_o h_t + b_o\right) \tag{17}$$

The weight matrix output, output bias and sigmoid activation function is indicated as M_o, b_o and γ. Rather than raw temporal observations, the casual information is memorized via proposed TCMN. The persistent pathological progression is differentiated via proposed memory mechanism to integrate current patient specific clinical conditions with historical casual effects. To provide stronger theoretical foundations, the clinical interpretable, robust and accurate personalized cardiovascular risk predictions are generated. The patient-specific casual pathways are identified based on explainability module; an individual cardiovascular risk factor

contribution to final prediction is quantified. The architecture of proposed TCMN model is outlined in Figure 4.

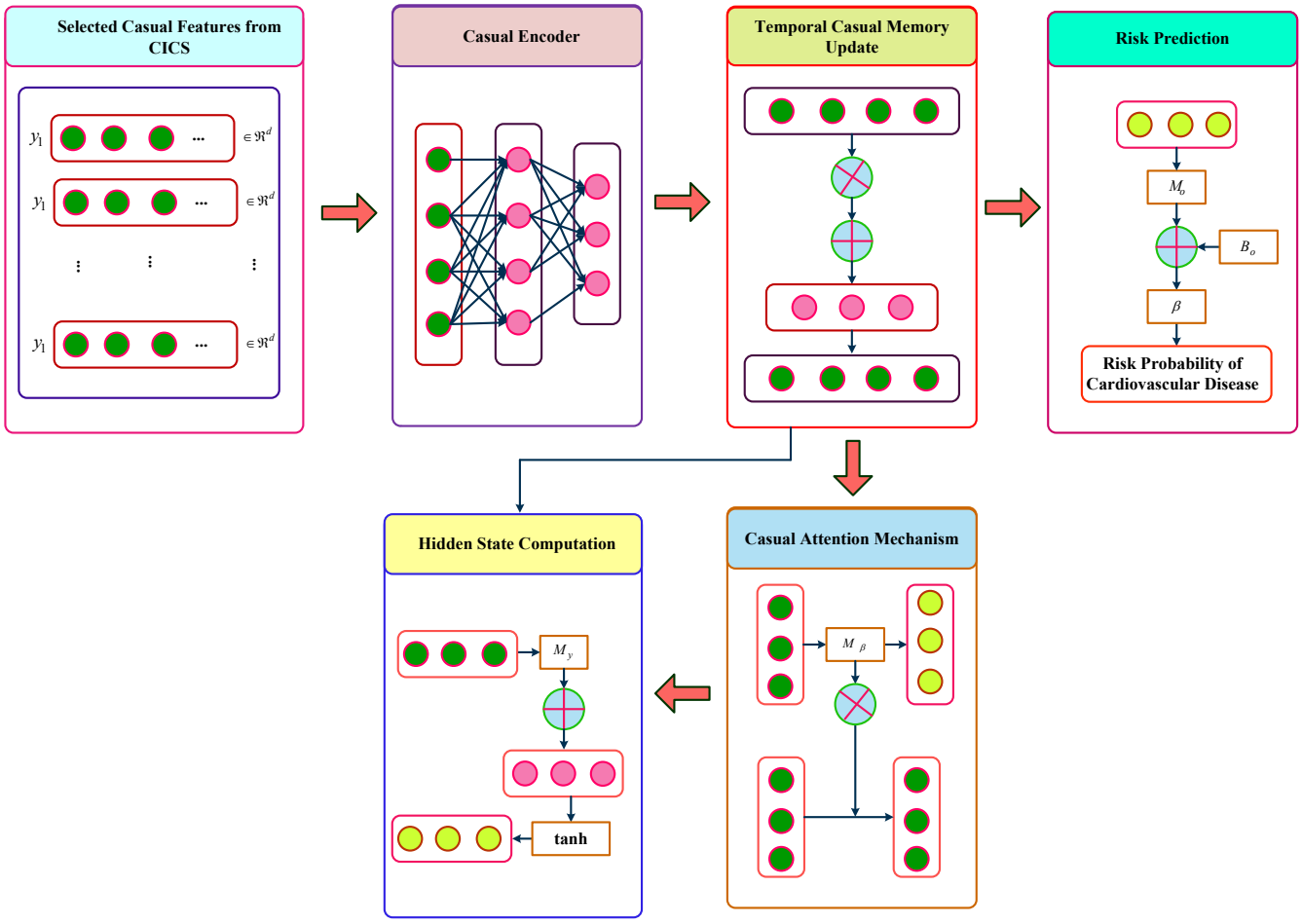


Figure 4: Architecture of proposed TCMN model

3.7 Explainability Module

To understand and trust model predictions, the transparent explanations are required as healthcare professionals. Based on predicted cardiovascular risk, the patient-specific casual factors are indentified with the incorporation of CICS-TCMN. Each selected cardiovascular risk factor contribution is quantified using TCMN that learns the temporal attention weight. Below formula computes j^{th} feature importance [27].

$$\mathrm{Im}_j = R_j \times \beta_j \tag{18}$$

The contextual consistency score of selected feature, temporal attention weight and final feature contribution scores are R_j , β_j and Im_j . The personalized intervention recommendations, temporal influence trajectories, casual dependency graphs and patient specific risk factors are generated via explainability module based on these importance scores. Each risk factor contribution is quantified. The clinically meaningful explanations and explainability module

clinical trust is provided thereby supporting explainable cardiovascular disease prediction and facilitating personalized treatment planning.

4. Result Analysis

The proposed Contextual Intervention Consistency Selector-based Temporal Causal Memory Network (CICS-TCMN) is thoroughly tested by a series of quantitative and qualitative experiments on benchmark cardiovascular disease datasets. The analysis covers aspects of predictive performance, temporal learning capabilities, interpretability, convergence behavior, computational efficiency, and statistical reliability of the framework.

4.1 Experimental Setup

For the implementation of the CICS-TCMN framework, Python 3.11, along with the PyTorch 2.2 deep learning library, was used. Numerous data preprocessing, feature engineering, and performance evaluation tasks were performed using NumPy 1.26, Pandas 2.2, and Scikit-learn 1.5. Matplotlib 3.9 was used to create visualizations of the model and statistical plots. The experiments were conducted on a workstation with an Intel Core i9-13900K processor, 32 GB of RAM, an NVIDIA GeForce RTX 4090 (24 GB VRAM), and a Windows 11 Pro (64-bit) operating system.

4.2 Hyperparameter Configurations

The hyperparameter setting used for training the proposed CICS-TCMN framework is summarized in Table 2. The model is trained using the Adam optimizer with a learning rate of 0.001, batch size of 32, and 100 training epochs to guarantee its convergence. Two temporal memory layers with 128 hidden units are used to model long-term causal dependencies. Furthermore, to boost generalization and minimize overfitting, dropout (0.30), $L2$ regularization (1×10^{-4}), and early stopping are added.

Table 2: Hyperparameter Configuration of the Proposed CICS-TCMN Framework

Hyperparameter	Configuration
Optimizer	Adam
Initial Learning Rate	0.001
Batch Size	32
Number of Epochs	100
Learning Rate Scheduler	Reduce on Plateau
Hidden Memory Dimension	128

Temporal Memory Layers	2
Dropout Rate	0.30
Activation Function	ReLU (Hidden), Sigmoid (Output)
Weight Initialization	Xavier Uniform
Weight Decay ($L2$ Regularization)	1×10^{-4}
Early Stopping Patience	10 Epochs
Loss Function	Binary Cross-Entropy
Explainability Method	Causal Pathway Attribution

4.3 Performance Analysis

Cardiovascular risk factors are ranked based on the causal importance scores shown in Figure 5. Age (0.24) and BMI (0.18) have the next greatest influence, followed by cholesterol (0.14), smoking (0.08), and alcohol consumption (0.05). These rankings enable clinically meaningful implications to be drawn about individualized cardiovascular risk assessment.

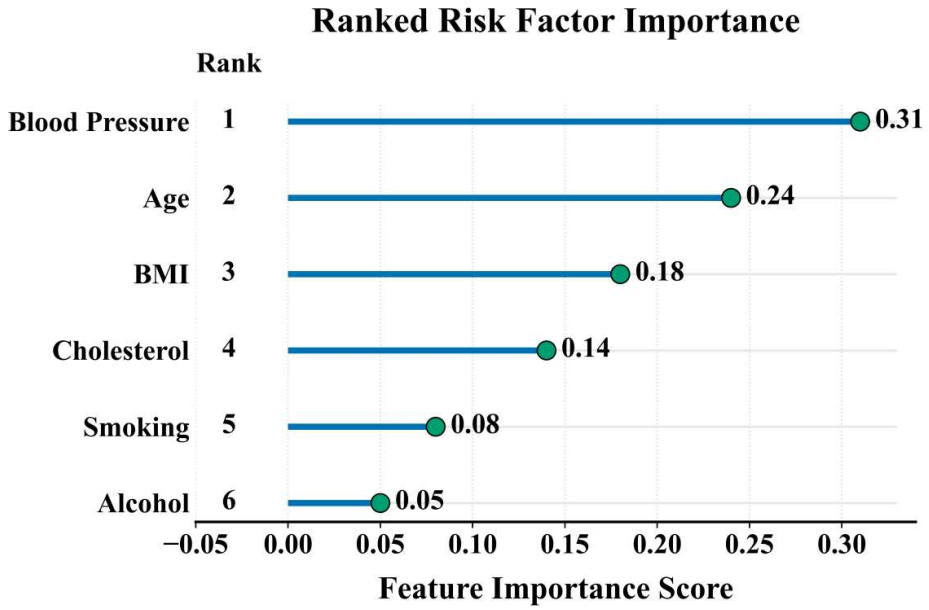


Figure 5: Ranked Risk Factor Importance

Figure 6 shows how the proposed Contextual Intervention Consistency Selector works. Risk factors with low causal effect and/or inconsistent intervention are removed from the model

learning. The selection strategy increases robustness by maintaining clinically relevant causal relationships in various patient situations.

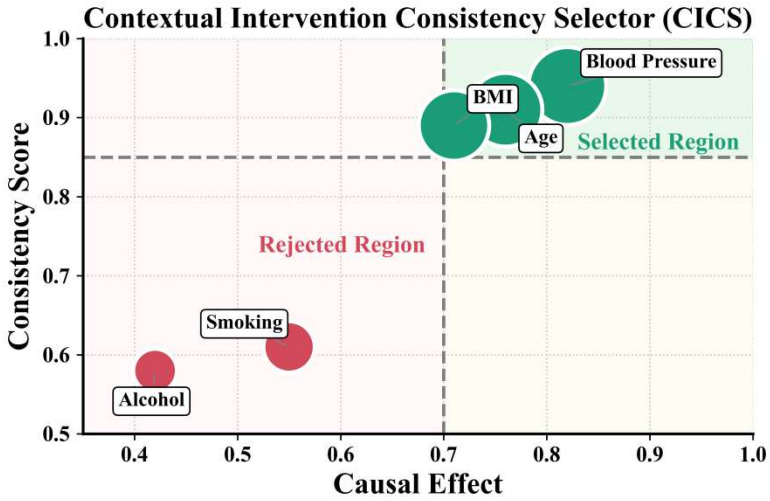


Figure 6: Contextual Intervention Consistency Selector (CICS)

Figure 7 shows the successive stages of learning that are related to the evolution of the temporal causal memory. As shown in the figure, memory scores strengthen on each of the four assessments, from 0.42 (T1) to 0.58 (T2), 0.69 (T3), and 0.83 (T4), reflecting the progressive build-up of causal dependency. This temporal memory allows the model to capture well the progression patterns observed over time with regard to cardiovascular conditions.

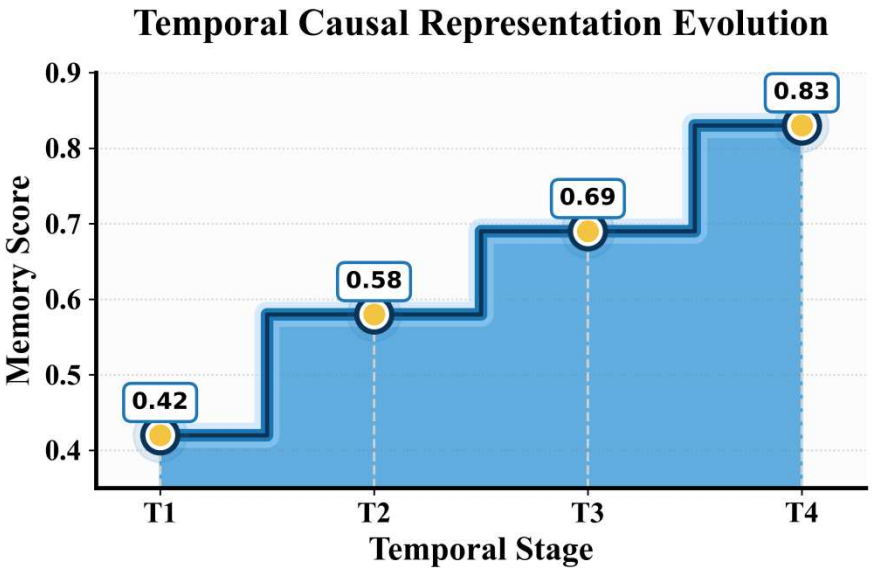


Figure 7: Temporal Causal Representation Evolution

Figure 8 shows the relative contribution of the major cardiovascular risk factors that were identified by the proposed explainable framework. However, blood pressure is the most significant risk (31%), with BMI (24%), cholesterol (19%), age (16%), and lifestyle factors (10%). The module proposed for CICS analysis is not based on statistical correlations, but on

stable causal factors, allowing for the interpretation of patient-specific cardiovascular risk profiles.

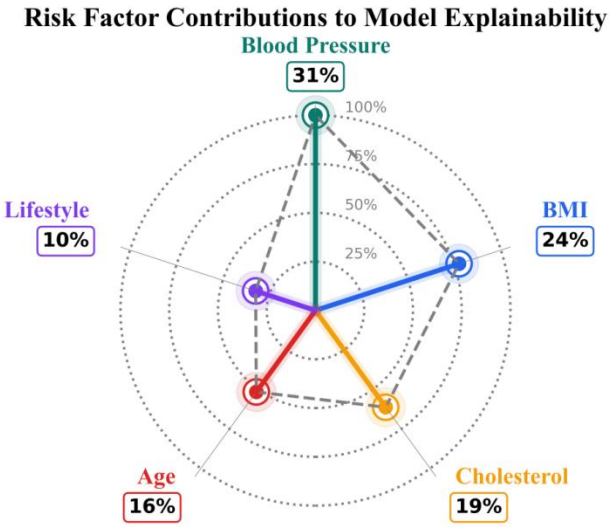


Figure 8: Explainability of Risk Factors in Models

The learning performance during training is illustrated in Figure 9. Continual improvement of both training and testing accuracy towards 99% stability shows good generalization capability. This close alignment of both curves indicates that the proposed framework learns the discriminative cardiovascular representations well without overfitting.

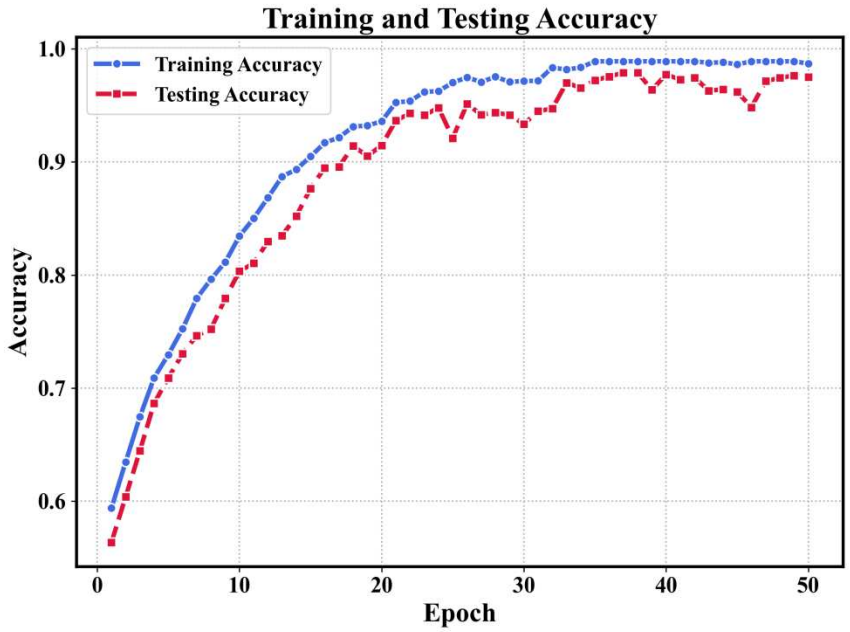


Figure 9: Training and Testing Accuracy

The convergence behaviour of the proposed network during training is shown in Figure 10. The training as well as testing losses converge over epochs and reach a near minimum value after about 35 epochs. The gap between both curves is rather small, which suggests that the model was optimized, features were learned, and no excessive overfitting occurred during the training process.

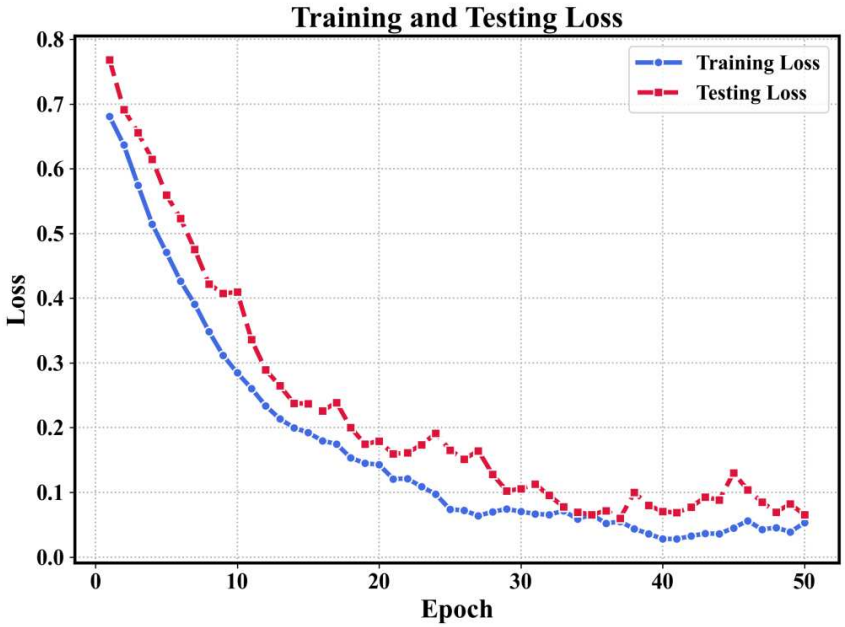


Figure 10: Training and Testing Loss

Figure 11 illustrates the confusion matrices for different approaches. The proposed CICS-TCMN model clearly shows that the largest number of correctly classified samples are along the main diagonal and the false classification of positive and negative samples is minimized, while the existing models exhibit comparatively higher false positive and false negative classifications, indicating limitations in accurately distinguishing between diseased and healthy patients. The better classification performance is achieved by temporal causal memory learning and contextual causal feature selection.

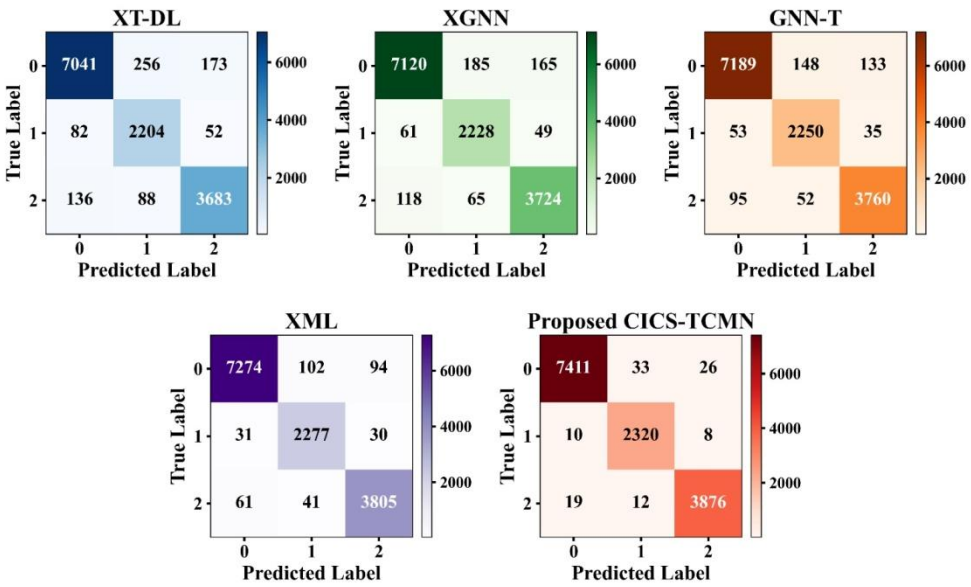


Figure 11: Confusion Matrix Comparison of Different Models

4.4 Comparative Analysis

To demonstrate the superiority of the proposed CICS-TCMN framework, it was compared against the four state-of-the-art cardiovascular disease prediction methods XT-DL [9], XGNN [11], GNN-T [12], and XML [13].

Figure 12 shows the computational complexity measured by memory usage in GPUs. The requirements of XT-DL are 3.2 GB, XGNN is 4.1 GB, GNN-T is 5.4 GB, XML is 6.0 GB, and the proposed CICS-TCMN is only 5.1 GB. Although the proposed architecture includes temporal causal memory, it still employs efficient computational resources through the selective causal feature representation.

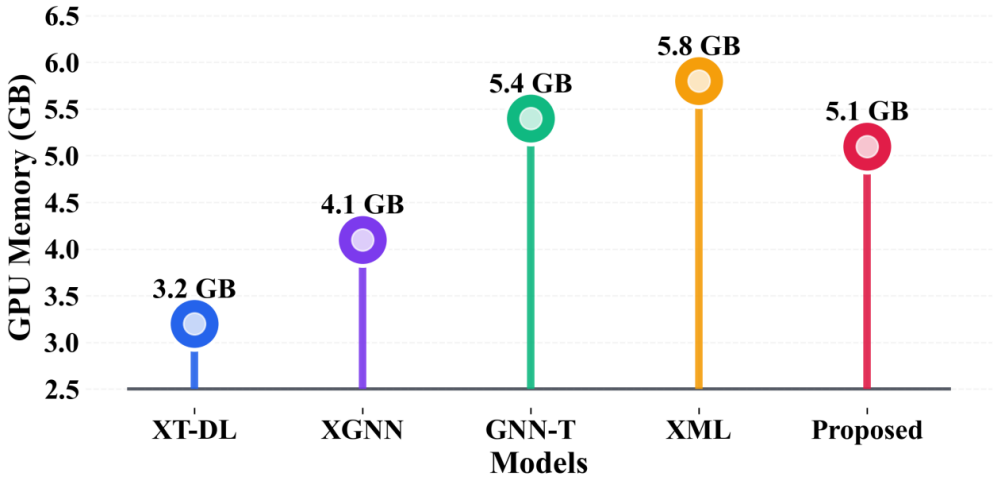


Figure 12: Computational Complexity

The Explainability of models is compared for various approaches based on Figure 13. The results of XT-DL, XGNN, GNN-T, XML, and the proposed framework are 71.8%, 80.4%, 86.3%, 90.1%, and 96.7%, respectively. The explainability module is able to identify relevant causal routes in a successful way, enabling clear predictions which enhance doctors' trust in making clinical decisions.

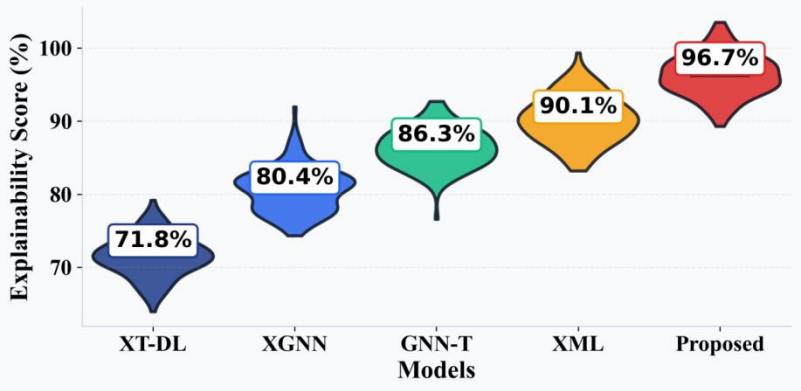


Figure 13: Explainability Score Comparison

The recall results obtained by the various cardiovascular prediction models are shown in Figure 14. XT-DL records 94.30%, XGNN achieves 95.10%, GNN-T reaches 97.32%, and XML obtains 98.10%. The proposed CICS-TCMN framework achieves the highest recall of 99.40%, which shows the best performance in correctly identifying patients with cardiovascular disease without any false negative predictions.

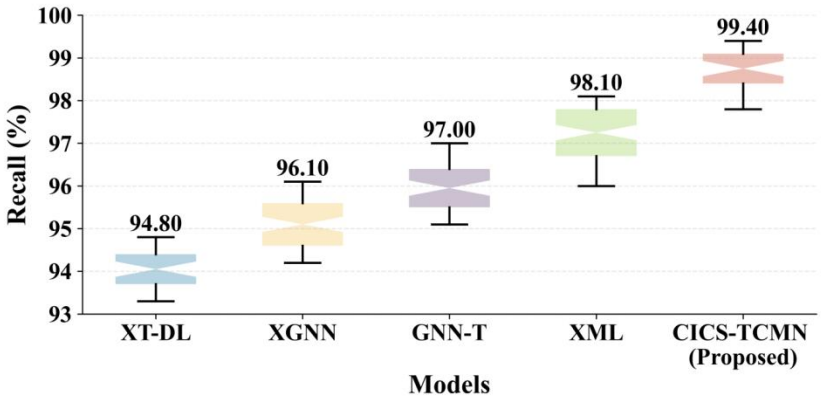


Figure 14: Recall Comparison of Different Models

Figure 15 compares precision among existing approaches. The precision value of XT-DL is 94.63%, XGNN is 95.81%, GNN-T is 96.12%, XML is 97.26%, and the proposed CICS-

TCMN is 99.08%. The increased accuracy means that more true cardiovascular cases are being identified, and fewer false-positive predictions are made.

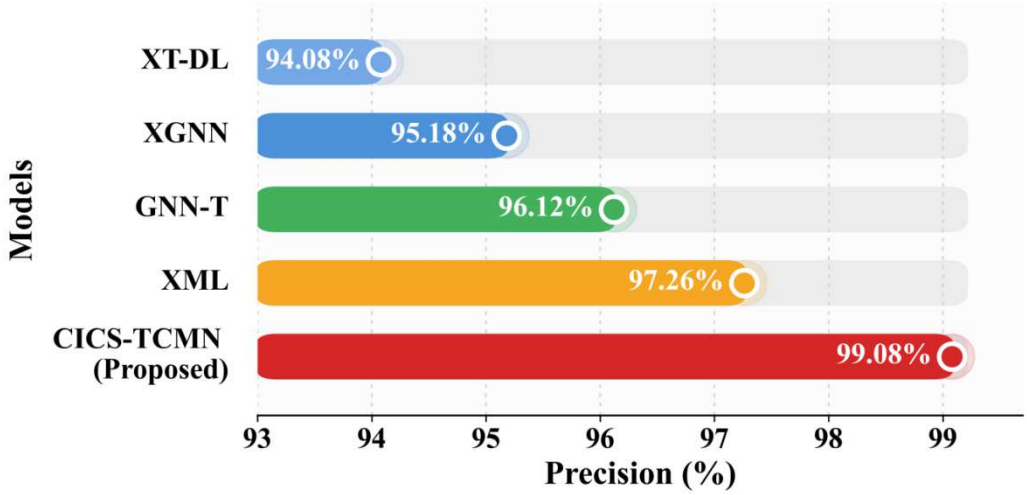


Figure 15: Precision Comparison Analysis

The ROC curves for the various methods are shown in Figure 16. The proposed CICS-TCMN achieves an AUC of approximately 0.999, outperforming XT-DL (0.973), XGNN (0.982), GNN-T (0.989), and XML (0.995). The almost perfect ROC curve highlights good discrimination between cardiovascular and non-cardiovascular cases across different decision levels.

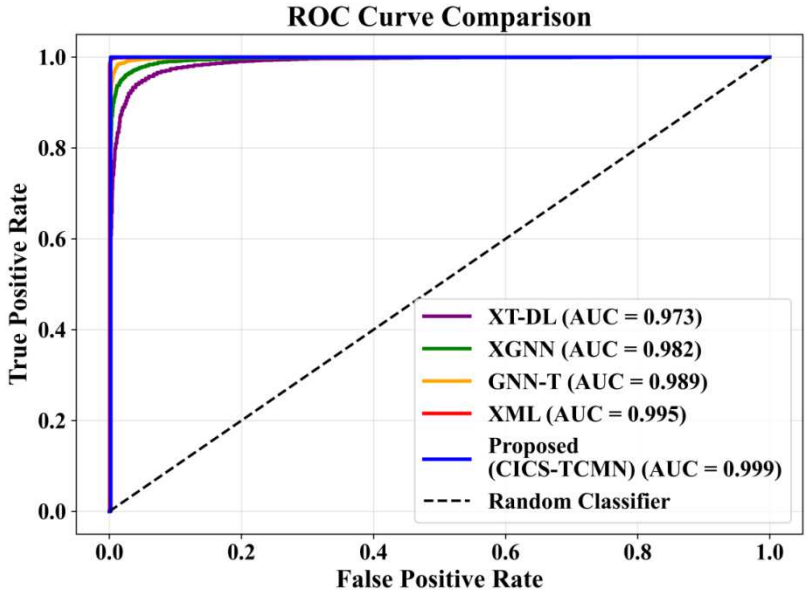


Figure 16: ROC Curve Comparison Analysis

Figure 17 illustrates the overall accuracy of prediction of various methods. The accuracy of CICS-TCMN is up to 99.21%, the result of XT-DL is 94.26%, XGNN is 95.31%, GNN-T is 96.16%, XML is 97.38%, and the proposed CICS-TCMN achieves the highest accuracy of

99.21%. The enhancement has been attributed to the contextual intervention consistency analysis and temporal causal dependency modeling.

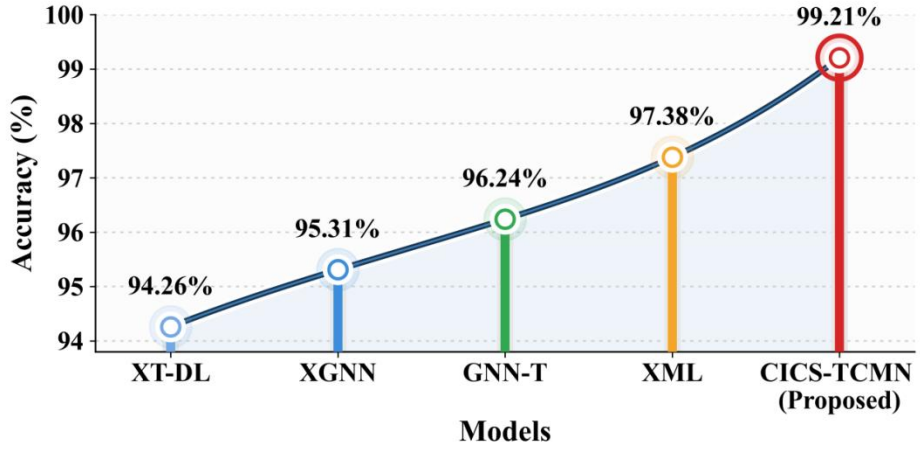


Figure 17: Accuracy Comparison Analysis

Figure 18 compares the F1-scores of different prediction models. The proposed CICS-TCMN achieves the highest F1-score 99.21%, while XML obtains 97.20%, XGNN 95.11%, and XT-DL 94.00%. This superior balance of precision and recall further validates the effectiveness of using contextual causal feature selection combined with temporal memory learning in cardiovascular disease prediction for personalization.

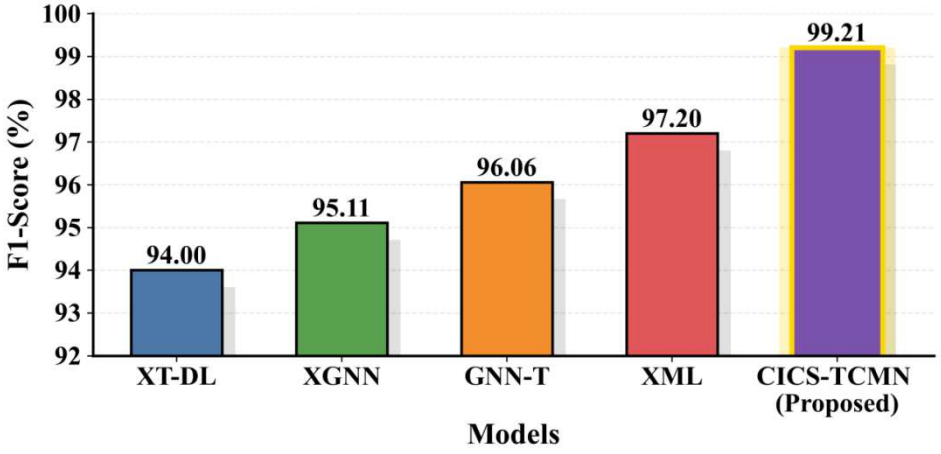


Figure 18: F1-Score Comparison Analysis

To determine the statistical significance of the performance improvements generated by the proposed CICS-TCMN framework, a statistical significance analysis was performed at an alpha level $\alpha = 0.05$. Table 3 shows the comparison of the proposed and existing models, with the significance criterion ($\rho < 0.05$) and ρ-value. CICS-TCMN has the lowest ρ value (0.003) and the highest prediction accuracy (99.21%). The lower the ρ value, the more likely that the performance increase is not random. The results show that the proposed contextual causal feature selection and temporal causal memory learning framework statistically significantly

improves the prediction of cardiovascular disease over traditional methods.

Table 3: Statistical Significance Analysis of Cardiovascular Disease Prediction Models

Method	**Accuracy (%)**	ρ **- value**	α **(Significance Level)**	**Statistical Decision**
XT-DL	94.26	0.031	0.05	Significant
XGNN	95.31	0.024	0.05	Significant
GNN-T	96.16	0.017	0.05	Significant
XML	97.38	0.011	0.05	Significant
Proposed CICS-TCMN	99.21	0.003	0.05	Highly Significant

Table 4 presents the error rate of various cardiovascular disease prediction models. The proposed CICS-TCMN achieved the lowest error rate of 0.79%, which is significantly lower than XT-DL (5.74%), XGNN (4.69%), GNN-T (3.84%), and XML (2.62%). The reduction of the classification error indicates that the proposed causal feature selection and temporal memory learning are effective in minimizing misclassifications, thus generating more reliable clinical decision support.

Table 4: Error Rate Comparison of Different Methods

Method	**Error Rate (%)**
XT-DL	5.74
XGNN	4.69
GNN-T	3.84
XML	2.62
Proposed CICS-TCMN	0.79

5. Conclusion

A novel CICS-TCMN framework for explainable and personalized identification and prediction of cardiovascular disease risk factors was presented in this study. The proposed framework combines contextual causal intervention analysis and temporal causal memory learning to discover stable risk factors and long-term disease progression, while avoiding the focus on correlation-based feature selection used by conventional machine learning methods. Moreover, the embedded explainability module offers clear causal paths, enhancing the interpretability and clinical validity of prediction results. The performance of the proposed framework was evaluated through experiments on benchmark cardiovascular disease datasets, which showed its superior performance over the existing methods. CICS-TCMN outperforms all comparative models with an accuracy of 99.21% and an explainability score of 96.7%. The confusion matrix and ROC analysis also validated the framework's robustness to minimize misclassification and ensured high discriminative power, thereby meeting the requirement for personalized clinical decision support and early cardiovascular disease prevention. Although it is effective, the proposed framework needs causal structure learning and temporal memory modeling, which makes the computational complexity and training time larger than those of traditional machine learning models. Moreover, its performance is critically dependent on the presence of rich longitudinal clinical data to enable accurate learning of patient-specific disease trajectories. Future research will be directed towards multimodal healthcare data integration, such as medical imaging, signals from wearable sensors, genomic data, and electronic health records, to enhance prediction robustness. The framework can be further developed by incorporating federated learning, real-time clinical monitoring, and ongoing learning strategies to enable privacy-preserving, scalable, and adaptive cardiovascular risk prediction in real-world healthcare settings.

Compliance with Ethical Standards

Conflict of interest

The authors declare that they have no conflict of interest.

Human and Animal Rights

This article does not contain any studies with human or animal subjects performed by any of the authors.

Informed Consent

Informed consent does not apply as this was a retrospective review with no identifying patient information.

Funding: Not applicable
Conflicts of interest Statement: Not applicable
Consent to participate: Not applicable
Consent for publication: Not applicable

Availability of data and material:

Data sharing is not applicable to this article as no new data were created or analyzed in this study.
Code availability: Not applicable

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