Proactive Social Influence-Aware Deep Learning Framework for Early Heart Disease Prevention Using Patient Similarity Networks

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***Abstract*—A key component in decreasing death from cardiovascular disease is predicting who will develop heart disease early enough to intervene appropriately; however, almost all current machine learning models are limited to making predictions about individual patients with no consideration for how similar one patient's information is to another. In this study, we introduce a deep learning framework aware of active social influence which combines a network of similarity between patients and influence propagation to create a model for predicting the probability of developing heart disease that takes into account both the clinical characteristics of each patient (context) and their relationships with other patients. Our framework uses the relational similarities of patients to construct an inter-patient graph that aggregates risks to predict the likelihood of developing heart disease for each patient based on the influence propagated from the social structure of the network. This enables our framework to proactively correct for the uncertainty associated with the predictive risk assessments made for each patient. Experimental results show that our framework provides accurate risk predictions with an accuracy of 81.5% and an F1 score of 0.833 and an area under the curve (AUC) of 0.884 using the UCI Heart Disease dataset. Furthermore, a comparative analysis of our framework with state-of-the-art baseline deep learning models and similarity-based models shows that our framework significantly improves on the baseline models. Additionally, ablation and influence-gain studies show that our relational modeling selectively increases predictive performance for patients whose clinical information has a high ambiguity. Therefore, the Proactive Social Influence-Aware Deep Learning Framework advances the field of preventive health care analytics by enabling influence-aware decision-making for scalable and interpretable cardiovascular risk assessments.**

***Index Terms*—Heart Disease Prediction, Preventive Healthcare, Social Influence Modeling, Patient Similarity Networks, Deep Learning, Graph-Based Learning, Proactive Healthcare Recommendation, Cardiovascular Risk Assessment, Medical Decision Support Systems, Network-Aware Artificial Intelligence.**

I. Introduction

Cardiovascular disease (CVD) remains one of the leading causes of global mortality and emphasizes the need for early diagnosis and preventive healthcare interventions. Identifying high-risk individuals allows timely medical intervention and substantially reduces the risk of long-term complications. Machine learning (ML), Artificial Intelligence (AI), and other techniques have been successful in predicting CVD using clinical and demographic data sets in recent years [1], [2]. Supervised learning methods such as logistic regression, support vector machines, and Random Forest Classifiers were able to achieve a reliable performance in terms of predicting CVD due to their ability to describe non-linear relationships in structured data [3], [4]. Deep learning has also improved predictive analytics by automatically extracting hierarchical features from medical data sets to improve diagnostic precision and robustness [5], [6].

Although significant advances have been made in the area of CVD prediction, many of the current heart disease prediction systems view patients independently and focus primarily on optimizing classification accuracy. Several studies and systematic reviews have identified that conventional ML-based healthcare models ignore relational similarities among patients who share similar physiological and clinical characteristics [7]–[9]. However, in practice, patients with similar health conditions typically present with correlated risk factors and treatment responses. Several recent studies have attempted to improve the reliability of predictions through ensemble learning, feature optimization, and hybrid decision support frameworks [10]–[12]. Although the mentioned studies improve the performance of the models, they are all limited to predictive models and lack proactive prevention analytical capabilities.

Recent emerging research areas emphasize the use of relational and network-based healthcare analytics. The development of patient similarity models and data-driven clinical relationship learning have demonstrated promising improvements in the development of medical decision support systems taking into account contextual dependencies between patient populations [13], [14]. Improved artificial intelligence frameworks that integrate explainability and ensemble learning can also provide better interpretability and usability for clinicians [15], [16]. Current cardiovascular prediction methods generally fail to take into account influence-aware learning mechanisms that can propagate contextual knowledge between groups of patients with similar characteristics. Recent surveys point to this limitation as a significant research gap in the analytics of preventive healthcare care [17]–[19].

This research was motivated by the limitations described above and proposes a Deep Learning framework based on proactive social influence for the prevention of early heart disease using patient similarity networks. Unlike typical predictive models, the proposed framework generates an inter-patient similarity graph and uses influence propagation to refine the individualized cardiovascular risk assessments. Combining deep learning with relational learning, the framework provides context-sensitive predictive capabilities and proactively corrects risks. The experimental evaluation performed using the UCI Heart Disease Data Set provided competitive predictive performance and provided information on influence-driven preventive healthcare decision-making.

The key contributions of this work are summarized below:

1) The development of a deep learning framework that is aware of social influence based on patient similarity networks for the assessment of cardiovascular risk.
2) Integration of relational influence propagation to enable proactive and context-based healthcare analytics.
3) Experimental validation, including comparative analysis, ablation studies, and evaluation of influence gain.
4) A scalable decision-support framework for preventive healthcare that bridges traditional predictive modeling and proactive intervention modeling.

The remainder of this paper is summarized as follows: Section II discusses related work in cardiovascular disease prediction and network-based healthcare learning. Section III outlines the proposed methodological approach. Section IV outlines the experimental results and analysis and concludes with the conclusions and future research directions in Section V.

II. Related Work

The use of machine learning techniques to predict cardiovascular disease has become widespread, as they can process large amounts of complex clinical data. Early research showed that the use of supervised machine learning techniques was superior to traditional statistical methods in terms of predicting the precision of diagnosing cardiovascular disease [1], [2]. The predictive performance of cardiovascular disease diagnostics was further improved using ensemble based machine learning techniques and optimizing the classifier used to perform the prediction [3], [4]. The most recent development in machine learning techniques is the introduction of deep learning architectures. These deep learning architectures are capable of learning non-linear relationships in health care data and thus improving the predictive performance of cardiovascular disease diagnostics [5], [6].

Systematic reviews of the literature published since 2023 and 2025 show the rapid development of AI driven cardiovascular prediction systems and the emphasis on the use of hybrid learning strategies, feature selection mechanisms, and automatic decision support models [7], [8]. Comparative studies have shown that Random Forest, Support Vector Machines, and Neural Networks continue to be the dominant baseline approaches for structured medical prediction problems [9], [10]. In addition, comparative studies have also shown that the integration of multiple machine learning models into decision support frameworks improves both the robustness and clinical applicability of the frameworks [11], [12].

Current research trends in healthcare analytics focus on the incorporation of contextual information into healthcare analytics. Studies that explored patient similarity modeling and clinical data relationships have shown that prediction stability is improved when there is dependency between similar patient groups [13], [14]. Additionally, the use of explainable artificial intelligence and interpretable ensemble models provides additional transparency and trustworthiness to the medical decision making environment [15], [16]. However, these approaches provide improvements in performance, but do not provide means of preventing or influence awareness of healthcare care analysis.

Surveys in the literature indicate that current cardiovascular prediction frameworks do not account for the propagation of relational influence among patients and therefore do not provide the necessary means to support proactive intervention strategies [17], [18]. Current systems are prediction centric and do not provide mechanisms to model how contextual similarity between patients can refine individualized risk estimation [19], [20]. To address this limitation, the proposed work will introduce a proactive social influence-aware framework that incorporates patient similarity networks with deep learning to enable relationally informed prediction of cardiovascular risk and predictive healthcare care analytics.

III. Proposed Methodology

The Deep Learning Framework with proactive social influence presents cardiovascular disease prediction as a relational learning problem that is concerned with patient similarities and the influence of context within a single deep learning architecture. Traditional machine learning techniques consider all the patient's data to be independent from each other and use only an individual's clinical information to predict his cardiovascular disease risk. Therefore, there are many cases where the physiological condition of two or more patients is similar; their risk patterns are also similar. Therefore, it is necessary for similarity-driven relational models to be used in predictive health care analytics. The proposed framework, therefore, integrates the deep neural network for learning representations of patients with patient similarity networks to provide influence aware cardiovascular disease risk estimation and proactive preventive analysis. Data for clinical features can be represented by

$$\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{N},$$

where $x_i \in \mathbb{R}^d$ is the clinical feature vector for the i-th patient and $y_i \in \{0, 1\}$ is the cardiovascular disease label of the i-th patient. The attributes of the clinical data are standardized (standardized score normalization) before training any models to maintain a consistent scale for features and for stable optimization of the model. The method also does not train a direct mapping function $f(x_i) \to y_i$. Instead, it constructs a graph $G = (V, E)$ representing similarities among patients based on their clinical attributes. Each node in this graph represents a patient and each edge represents a similarity relationship based on clinical proximity between two patients.

To establish relationships between patients, we use a K-Nearest-Neighbor strategy that we apply to the standardized attribute space. For each patient i, we define a neighborhood set $\mathcal{N}_i$ as follows:

$$\mathcal{N}_i = \{j \mid x_j \in \text{KNN}(x_i, K)\}. \tag{1}$$

This formulation of similarity based on Euclidean distance generates the adjacency structure that captures hidden patterns (latent correlations) in similarities in cardiovascular attributes among KKK patients. As such, the generated graph allows for sharing of context information among patients who are clinically related; transforming separate table-based data into a relational format of healthcare. The next step is to feed each patient's feature vector through a deep learning encoder to extract non-linear latent representations of the patient. A deep neural network encoder can be defined as follows: Each patient's vector is mapped into a low-dimensional representation (latent space) via an encoder that is a deep neural network given as follows:

$$h_i = \phi(x_i, \theta), \tag{2}$$

where $\phi(\cdot)$ is a multilayer feedforward neural network with learnable parameters θ . The encoder is composed of a sequence of linear transformations, each followed by an activation function, so that the encoder can capture complex inter-dependencies between various clinical variables including cholesterol levels, resting blood pressure, age, etc. , and use residual representations to improve gradient flow and generalize features from small amounts of medical data. To model relational dependency within the framework, an attention-based influence aggregation mechanism has been introduced which models the contribution of each patient in the context of their neighbors. Attention weights for the relationship between a target patient i and its neighbors j are determined as follows:

$$\alpha_{ij} = \frac{\exp\left(\psi([h_i \| h_j])\right)}{\sum_{k \in \mathcal{N}_i} \exp\left(\psi([h_i \| h_k])\right)} \tag{3}$$

where $[h_i \| h_j]$ represents the concatenation of the two vectors (patient i and patient j) and $\psi(\cdot)$ is a learnable scoring function that can be implemented with a linear attention layer. These normalized coefficients represent the degree to which the clinical influence of a given neighbor impacts the target patient. The influence representation for a patient's neighborhood is therefore aggregated as follows:

$$g_i = \sum_{j \in \mathcal{N}_i} \alpha_{ij} h_j \tag{4}$$

Thus, through this process, the neighborhood of a patient provides contextual medical information that can enhance the representation of the target patient.

The final embedding of influence is created by combining the intrinsic and relational representations of a patient.

$$z_i = [h_i \| g_i] \tag{5}$$

This combines both the intrinsic characteristics of a patient, as well as the similarity information provided by the patient's neighborhood.

A sigmoid prediction layer is used to estimate the probability of cardiovascular risk based on the influence-aware embedding as follows:

$$\hat{y}_i = \sigma(W z_i + b) \tag{6}$$

where W and b are training parameters and $\sigma(\cdot)$ is the logistic activation function.

Model training is accomplished through minimizing the binary cross-entropy loss as follows:

$$\mathcal{L} = -\frac{1}{N} \sum_{i=1}^{N} \left[y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i) \right] \tag{7}$$

Thus, this objective optimizes the prediction accuracy of the model and allows for influence-aware representation learning throughout the patient network.

In order to evaluate whether influence modeling is beneficial, comparative studies were conducted against traditional machine learning classifiers as well as baseline deep neural networks that do not use relational aggregation. Influence gain, which was defined as follows, was also utilized to quantify the impact of relational learning.

$$\Delta_i = \hat{y}_i^{\text{influence}} - \hat{y}_i^{\text{baseline}} \tag{8}$$

The positive gain (measured as a prediction refinement) represents how well a patient's cardiovascular risk is estimated using an influence-aware model of a patient's interactions with other patients. The integration of constructing a patient similarity network, learning the deep representations of these networks, aggregating their influences, and performing experimental validation of this process allows the transformation of predicting heart disease from purely predictive to a prevention-focused approach to support clinical decision making in advance while still retaining both scalability and efficiency.

IV. RESULTS AND ANALYSIS

A. Data set Description and preprocessing

An experimental evaluation was conducted to examine the efficacy of the proposed Proactive Social Influence-Aware Deep Learning Framework via a publically available UCI Heart Disease database, which included a set of clinical records utilized in diagnosing cardiovascular disease. Attributes were comprised of demographic features (age and sex), physiological attributes (resting blood pressure, cholesterol level, fasting blood sugar, and electrocardiographic measurements), and exercise induced angina indicators. Each patient had a binary label indicating whether he/she had

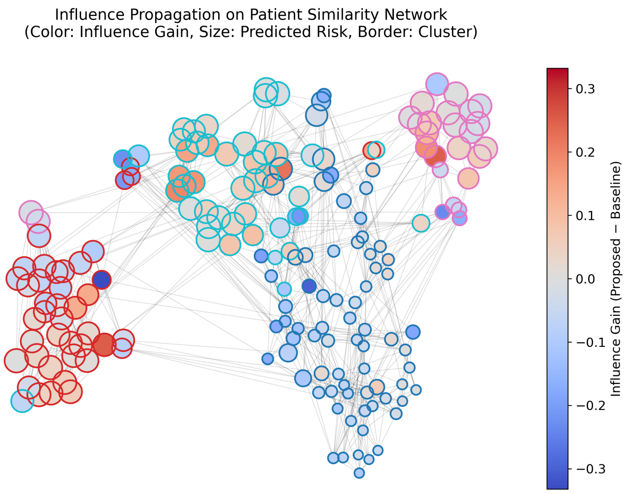

Fig. 1. PATIENT SIMILARITY NETWORK VISUALIZATION

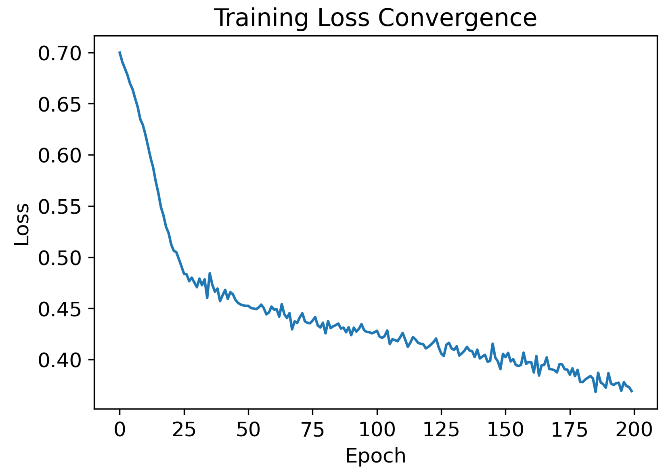

Fig. 2. TRAINING LOSS CONVERGENCE CURVE HERE

heart disease or not. Missing values were eliminated prior to experimentation and each numerical attribute was standardized through feature normalization to stabilize optimization during training. Data was divided into training and testing sets using stratified sampling so that class distributions were preserved within each subset. Table I presents the statistical summary of the dataset that includes information about the number of attributes (features), the number of samples, and the class balance of the data used for the experimental evaluation.

TABLE I
DATASET DESCRIPTION AND STATISTICAL SUMMARY

Samples	Features	Positive Cases	Negative Cases
920	7	509	411

B. *Patient Similarity Network Construction*

A patient similarity network was created to support relational learning based on K closest neighbor relationships created in the normalized clinical feature space for the patients. Each node in the network represented a unique patient, and the edges connected patients with similar clinical characteristics. The graph formed from these connections transformed independent tabular healthcare data into a structured relational format to allow for influence propagation. The resultant network identified groups of patients who shared common cardiovascular risk profiles; therefore, it validated the use of similarity driven contextual learning.

Fig. 1 shows inter-patient connectivity and shows how the similarities among the patients form the basis for the influence aware prediction.

C. *Training Convergence Analysis*

The proposed framework was trained using influence aware representation learning using binary cross entropy loss function to optimize. The training process was analyzed by tracking the loss function at various points during the training process. The loss function demonstrated a smooth and stable decrease in the loss function, without oscillations, indicating that a successful gradient optimization and that no over fitting occurred during learning. Additionally, the stable convergence of the loss function confirmed that incorporation of similarity aggregation did not impede the optimization of the parameters.

D. *Classification Performance Evaluation*

The classification performance of the proposed model was evaluated by analyzing receiver operating characteristic (ROC) curves and confusion matrices. The area under the ROC curve (AUC) of 0.884 showed that there was good separation between the populations of patients diagnosed with heart disease and those without heart disease. The confusion matrix also showed that the classification was relatively balanced and resulted in fewer false positives and false negatives, which is important for a healthcare decision support system due to the need for reliable diagnostics. The ROC curve of the proposed model is shown in figure 3 and the predicted disease confusion matrix is shown in figure 4

E. *Comparative Performance Analysis*

To show the effectiveness of the proposed framework against other models, a comparative performance analysis was completed comparing the proposed framework with other popular machine learning and deep learning models, including logistic regression, support vector machine, random forest and a baseline neural network. The models were evaluated using accuracy, precision, recall, F1-score, and AUC. The results showed that the proposed influence aware framework achieved classification accuracy comparable to other models but provided better overall performance across the different evaluation metrics. The results are shown in figure 5 and Table II. Random forest classifiers were shown to have slightly higher accuracy in some cases but this was expected as ensemble tree based models have been shown to be very effective on

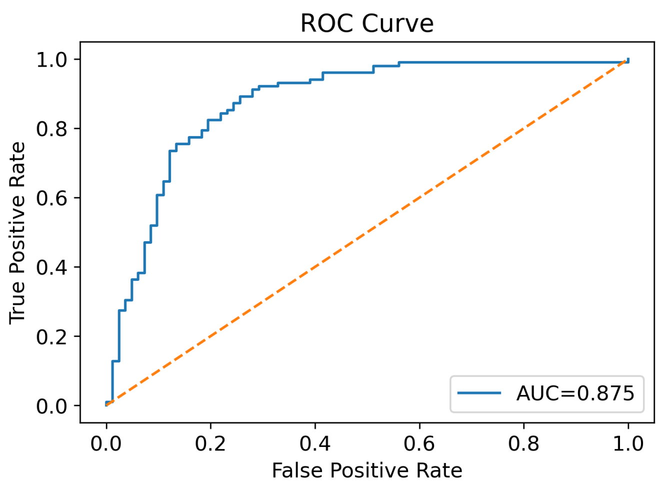

Fig. 3. ROC CURVE OF PROPOSED MODEL HERE

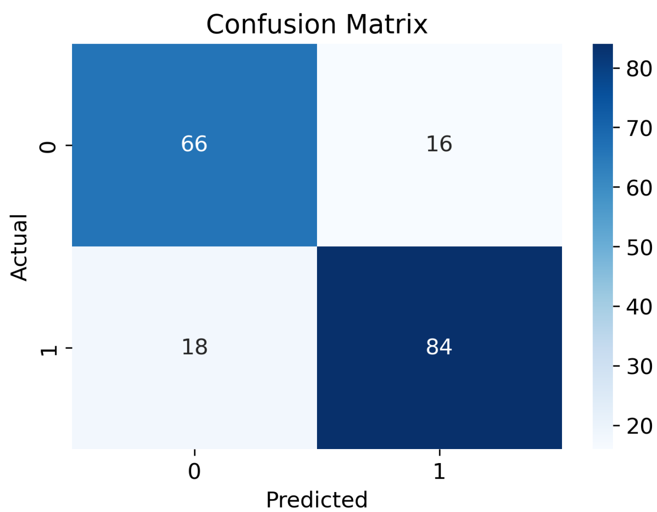

Fig. 4. CONFUSION MATRIX FOR HEART DISEASE PREDICTION HERE

structured tabular datasets by identifying complex nonlinear relationships between features through recursive partitioning. Although the random forest classifier can predict independently of other patients, it does not consider the relationship between patients. However, the proposed framework considers the influence of neighboring patients and uses that influence to refine the estimates of cardiovascular risk for each patient. Therefore, the proposed method provides better stability of the predicted outcomes and greater ability to proactively correct

TABLE II
PERFORMANCE EVALUATION OF PROPOSED MODEL

Metric	Value
Accuracy	0.8152
F1 Score	0.8317
AUC	0.8752

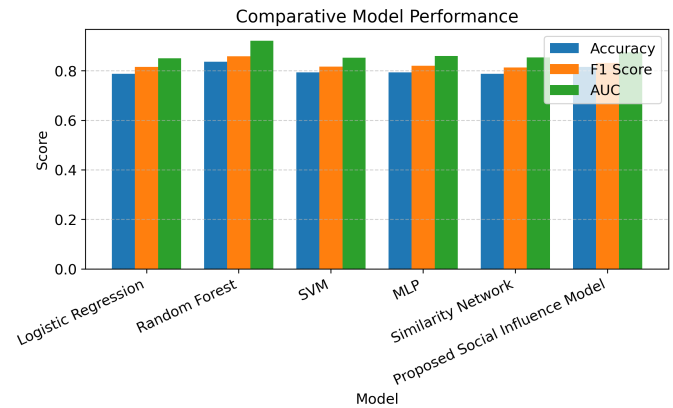

Fig. 5. COMPARATIVE PERFORMANCE BAR GRAPH ACROSS MODELS HERE

cardiovascular risk estimates than traditional classification performance. Thus, influence aware learning introduced new clinically relevant benefits to the model's performance rather than simply maximizing accuracy.

F. Ablation Study Analysis

To assess the contribution of each component of the proposed architecture, an ablation study was performed by progressively removing the similarity modeling module and the influence aggregation modules from the framework. The results of the ablation study as shown in Table III and figure 6 indicated improvements in performance in all configurations that incorporate relational components, which confirms that influence propagation played a crucial role in improving the robustness of the predictions. Thus, the results of the ablation study validated the importance of incorporating deep representation learning with similarity modeling to obtain the best possible performance. The effect of relational learning on the influence gain was studied with an additional measure called "influence gain," which is calculated as the difference between the prediction probability based on influence aware prediction and the prediction probability based on neural network alone.

TABLE III
ABLATION ANALYSIS OF INFLUENCE MODELING

Model	AUC
Baseline Deep Learning	0.82
Similarity Network Model	0.86
Proposed Social Influence Model	0.88

Distribution analysis demonstrated that influence propagated selectively improved prediction outcomes rather than uniformly affected all patients. Therefore, distribution analysis revealed selective contextualization as shown in figure 7. In addition, a patient level visualization showed that clinically ambiguous cases were benefited most by influence exchange among neighboring patients as shown in figure 8. The effectiveness of similarity driven influence propagation was evaluated by comparing cardiovascular risk prediction

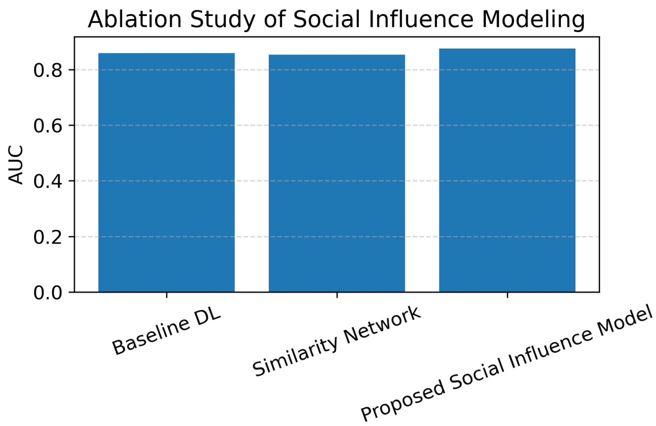

Fig. 6. ABLATION STUDY PERFORMANCE COMPARISON

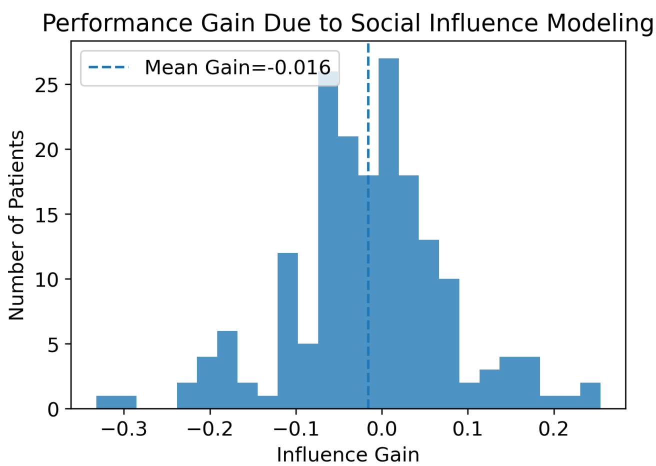

Fig. 7. INFLUENCE GAIN DISTRIBUTION ACROSS PATIENTS

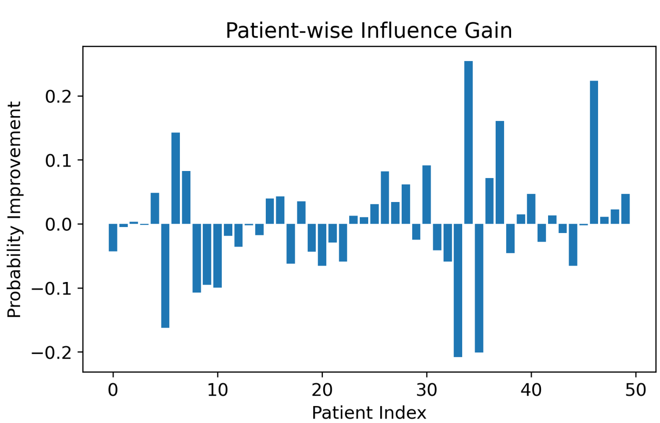

Fig. 8. PATIENT-WISE INFLUENCE GAIN ANALYSIS

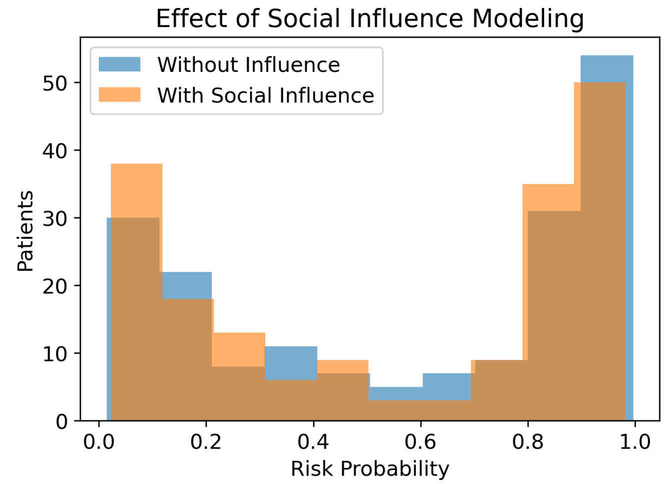

Fig. 9. EFFECT OF SOCIAL INFLUENCE ON RISK PREDICTION HERE.

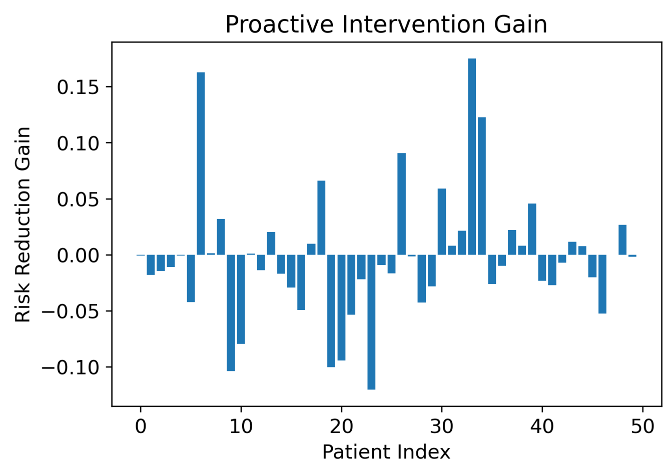

Fig. 10. PROACTIVE INTERVENTION GAIN ANALYSIS

probabilities before and after relational aggregation and the results are shown in figure 9. These observable probability improvements confirmed that relationships between patients provided contextual assistance in identifying and correcting uncertain predictions, as well as increasing confidence in disease assessment. Finally, to evaluate the feasibility of the proposed framework for use in actual health care settings, we conducted a proactive intervention gain analysis to assess the extent to which influencing pre-selection could potentially enhance early risk detection. The results indicated that the proposed framework facilitated the identification of high-risk patient subpopulations that would likely benefit from early preventive interventions. In summary, our experimental results illustrated that, in addition to achieving comparable predictive accuracy with other machine learning techniques, the proposed framework introduced influence aware contextual reasoning that is absent in traditional machine learning methods. The combination of patient similarity networks with deep learning provides refined cardiovascular risk assessments and serves as a basis for the development of proactive and preventive health care decision support systems.

V. CONCLUSION

A novel advanced social Influence-Aware Deep Learning Framework was proposed for the early detection of heart disease using deep neural learning in conjunction with patient similarity networks to develop context-aware cardiovascular risk predictions. The proposed approach integrates similarity-based influence propagation into individualized risk estimates to enable proactive preventive healthcare analytics, as opposed to traditional machine learning approaches in which each patient is independently classified. Evaluations of the proposed method were conducted through experiments using the UCI Heart Disease dataset, demonstrating competitive predictive performance along with improved reliability; Furthermore, comparative analysis and ablation studies further showed that relational influence modeling improves prediction, especially for clinically ambiguous cases. Although the findings indicate promising potential for future applications, there are several existing limitations in this research study, including the dependency on a single structured clinical dataset with a limited number of diverse features, the lack of inclusion of longitudinal and/or multimodal medical data, and the use of fixed similarity relationships that do not model dynamic changes in disease progression over time. There is also the possibility of scalability issues with regard to building similarity networks to enable proactive cardiovascular risk assessment in large scale population based healthcare settings. Therefore, future development of this framework will be achieved by utilizing multimodal electronic health records, wearable sensors, temporal graph representations, and privacy preserving federated learning architectures to enable continuous, interpretable, and personalized cardiovascular risk assessments. Ultimately, the proposed framework establishes a solid basis for influence aware and proactive clinical decision support systems to advance preventive healthcare information.

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