JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

A Fine-Tuned Artificial Neural Networks (FT-ANNs) based Framework for Cardiovascular disease (CVD) Prediction

[1]Mohit Dhiman and [2]Anjali Chaudhary [3]Ved Parkash

[1,2] Department of Compute Engineering State Institute of Engineering and Technology (SIET), Nilokheri, Kurukshetra University, Kurukshetra

Abstract: Cardiovascular diseases (CVDs) remain the leading cause of death and illness worldwide, presenting significant diagnostic challenges due to their complex nature. Recent advancements in artificial intelligence, particularly deep learning (DL) and artificial neural networks (ANNs), offer promising solutions to enhance diagnostic accuracy. This paper presents a fine-tuned ANN framework specifically designed for CVD prediction. By leveraging pre-trained models and optimizing transfer learning techniques, the proposed framework aims to improve early detection and diagnosis of CVDs. This approach not only addresses the limitations of traditional ML and DL models, such as extensive computational resources and overfitting but also ensures clinical relevance and interpretability of the predictions. Our experimental results demonstrate the efficacy of the fine-tuned ANN model in achieving higher accuracy and lower data loss compared to traditional ANN models, thus offering a reliable tool for healthcare professionals in diagnosing and managing CVDs.

Keywords: Deep Learning (DL), cardiovascular disease (CVD), Healthcare, Disease and Artificial neural networks (ANNs)

I. Introduction

Cardiovascular diseases (CVDs) are the leading cause of death and illness worldwide, affecting various parts of the body including the heart, blood vessels, and the circulatory system. The broad term "cardiovascular disease" encompasses multiple conditions that collectively pose a significant threat to public health due to their detrimental impact on heart function [1]. Accurate diagnosis of heart conditions by trained medical professionals is crucial for effective treatment, but there is always a risk of bias and errors in the diagnostic process. Given the complexities involved in diagnosing cardiac issues, extensive research has been dedicated to improving diagnostic accuracy and patient outcomes. The high mortality rate from CVD in areas with limited healthcare resources further underscores the importance of accurate and rapid identification of coronary artery disease. To meet this critical need, researchers are increasingly turning to advanced technologies like Deep Learning (DL).

Deep Learning, a subset of artificial intelligence (AI), employs Artificial Neural Networks (ANNs) with multiple layers of processing to detect complex predictive features in vast datasets, such as medical images [2]. Recent studies have demonstrated that novel DL algorithms may surpass human experts in identifying morphology-dependent diseases like diabetic retinopathy. This breakthrough suggests the potential of using DL for predicting CVD by analyzing retinal images, a rapidly growing area of research. The application of DL to assess CVD risk through retinal images is an emerging field driven by the availability of large datasets and sophisticated computational algorithms. However, the diversity in datasets and methodologies used across studies has resulted in varying prediction outcomes and the identification of different CVD risk factors [3]. This variability highlights the need for standardizing methods and datasets to enhance the reliability and comparability of DL-based predictions [4].

Despite the challenges, the potential of DL in medical diagnosis to transform the prediction and treatment of cardiovascular diseases is immense. By leveraging AI, healthcare professionals can achieve more accurate and unbiased diagnoses, ultimately improving patient outcomes and reducing the global burden of CVD [5]. The aim of this paper is to refine deep learning (DL) algorithms and ensure their applicability across diverse patient populations and clinical settings, thereby translating these technological advancements into tangible health benefits for everyone [6].

II. Related work

Cardiovascular diseases (CVDs) are the leading cause of death and illness worldwide, affecting the heart, blood vessels, and circulation. Accurate diagnosis by medical professionals is crucial but can be prone to bias and error. To improve diagnostic accuracy and outcomes, researchers are increasingly using advanced technologies like Deep Learning (DL) and Machine Learning (ML).

Sreelakshmi et al. [7] aimed to enhance the accuracy and reliability of CVD diagnoses with a hybrid classifier technique using an adaptive voting classifier model, which integrates predictions from classifiers like XGBoost, DT, SVM, KNN, and Random Forest. The model achieved 99.83% accuracy, showing potential for reducing healthcare costs and improving diagnostic capabilities.

Akbar et al. [8] highlighted the importance of ML in clinical diagnostics, focusing on CVD. They introduced a regression-based approach to improve classification accuracy, particularly for small datasets, achieving notable improvements using the Cleveland heart disease dataset.

Perva et al. [9] discussed the importance of early CVD detection and utilized decision trees, k-NN, and Naïve Bayes for prediction. Their study showed promising results, especially for patients with stage 2 or 3 hypertension.

Milind et al. [10] focused on using saturation mutagenesis experiments to predict pathogenicity of missense variants across the proteome with crossprotein transfer models, demonstrating high sensitivity and specificity in identifying disease variants.

Mishra et al. [11] addressed the challenges of managing large volumes of patient data, emphasizing the role of ML in identifying trends and predicting CVD. Using the Cleveland HD dataset, KNN achieved the best recall rate in a multiclass classification of CVD severity.

Ramu and Meghna's [12] research used seven ML classifiers, including Random Forest and SVM, to predict CVD. The Random Forest classifier achieved 94% accuracy, with data visualization illustrating attribute relationships.

Rao et al. [13] focused on using ML for early prediction of heart attacks, highlighting the potential of logistic regression and ANN methods in predicting heart disease from patient records with high accuracy.

Sivakannan et al. [14] emphasized the integration of DL and ML techniques for CVD prediction, highlighting the impact of IoT in improving prediction accuracy. Their method achieved approximately 96% accuracy by combining various classification algorithms with healthcare data.

Sai et al. [15] examined the use of ML and DL algorithms to predict CVD, focusing on risk factors like obesity, hypertension, and cholesterol. Their DL model achieved the highest accuracy at 73.78%.

Jagot and Sheckter [16] developed an explainable deep transfer learning model for predicting illness using high-dimensional genetic data. Their approach outperformed state-of-the-art methods in identifying predictive characteristics and accurately predicting disease risk.

Ahmad et al. [17] proposed a hybrid deep learning model combining CNNs and BiLSTM networks to predict CVD from patient data. Their model achieved 94.507% accuracy, highlighting the potential of advanced DL techniques in early and accurate CVD prediction.

Subramani et al. [18] discussed the integration of IoT in healthcare for CVD prediction, introducing ML models that incorporate various data observation mechanisms to enhance accuracy. Their method achieved nearly 96% accuracy, demonstrating the potential for improved prediction through advanced ML techniques.

III. Proposed Work

Traditional machine learning (ML) and deep learning (DL) models have shown promise in predicting CVD, but they often require extensive computational resources and large, labeled datasets for training. These models involve complex feature engineering and hyperparameter tuning, which can be time-consuming and demand significant expertise. Additionally, they may struggle to generalize to diverse patient populations due to limited training data and overfitting issues. Transfer Learning (TL) offers a potential solution by leveraging pre-trained models from related tasks, thus reducing the need for large, labeled datasets and lowering computational costs. However, the application of TL in CVD prediction is not well-explored or optimized. Key questions remain about selecting appropriate pre-trained models, effective TL strategies, and ensuring interpretability for clinical use. The paper aims to evaluate and develop a fine-tuned artificial neural network (ANN) framework for cardiovascular disease (CVD) prediction. It will focus on adapting pre-trained models to meet the specific requirements of CVD prediction, optimizing transfer learning (TL) techniques to balance accuracy and generalization, and ensuring the clinical relevance and interpretability of model predictions. Fine-tuning is a technique that can significantly improve the early detection and diagnosis of cardiovascular disease (CVD). It involves transforming an already-trained deep learning model to classify individuals as having or not having CVD based on various input characteristics. The process involves selecting a pre-trained model known for learning important features from large datasets, such as image classification. These models have developed a deep understanding of feature hierarchies, making them ideal for adaptation to new tasks.

To adapt the model for CVD prediction, remove the fully connected layers specific to its original task, keep the convolutional base, and add new fully connected layers tailored for CVD disease classification. Freeze the weights of the convolutional layers to prevent them from changing during training on the CVD data. This ensures that the valuable knowledge from the original training remains intact and benefits the CVD prediction task. Train the modified model using CVD-specific data and adjust the weights of the new layers while keeping the convolutional layers unchanged. This allows the model to learn how to link the extracted features to the CVD classification task, using binary labels to indicate the presence or absence of CVD. Fine-tuning for improved accuracy involves gradually unfreezing the upper layers of the pre-trained model and continuing training with a reduced learning rate to adjust the parameters further, aligning the model more closely with the specifics of the heart disease data. This fine-tuning process can enhance the model's predictive accuracy and overall performance. By following these steps, a pre-trained deep learning model can be effectively adapted to predict cardiovascular disease, leveraging the strengths of fine-tuning to improve early detection and diagnosis.

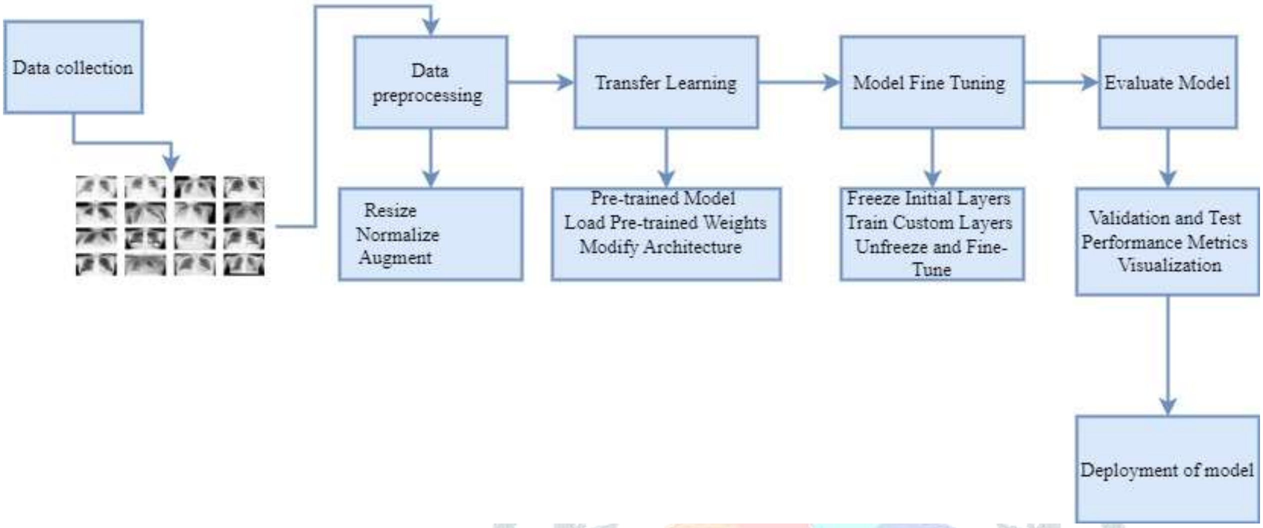

Figure 1 Proposed Framework

The figure1 presents a proposed framework for CVD prediction using deep learning. Here's a detailed explanation of each step:

Data Collection: Collect images or data relevant to the problem you're trying to solve. For example, the images in the figure appear to be related to facial recognition or another computer vision task.

Data Preprocessing:

- Resize: Adjust the size of images to a consistent dimension suitable for the model input.
- Normalize: Scale pixel values to a range (e.g., 0 to 1) to make the training process more stable and faster.
- Augment: Apply random transformations (like rotations, flips, or zooms) to increase the diversity of the training dataset and improve the model's robustness.

Transfer Learning:

Utilize a pre-trained model that has already been trained on a large dataset (e.g., ImageNet) to leverage learned features.

- Pre-trained Model: Load a model that has been previously trained on a related task.
- Load Pre-trained Weights: Use the weights from the pre-trained model as a starting point for your own model.
- Modify Architecture: Adjust the architecture of the pre-trained model to suit your specific task, possibly adding or removing layers.
- Model Fine-Tuning:

- Freeze Initial Layers: Keep the early layers of the pre-trained model fixed, as they usually contain general features.
- Train Custom Layers: Train the newly added layers specific to your task.
- Unfreeze and Fine-Tune: Optionally, unfreeze some of the earlier layers and fine-tune the entire model to improve performance on your specific task.

Evaluate Model:

- Validation and Test: Assess the model's performance using a validation dataset during training and a separate test dataset after training.
- Performance Metrics: Calculate metrics such as accuracy, precision, recall, F1-score, etc., to evaluate the model's performance.
- Visualization: Use visual tools to better understand the model's performance and identify potential issues (e.g., confusion matrices, loss/accuracy plots).

IV. Results and Analysis

We implement the proposed framework using Python on Google Colab, a free cloud-based platform provided by Google. Google Colab facilitates the writing and execution of Python code in a collaborative environment, based on Jupyter Notebooks. It offers a variety of functionalities, including access to GPU and TPU (Tensor Processing Unit) resources, which enhance computational efficiency.

A. Dataset Used

In this dissertation we collect cardiovascular disease (CVD) dataset from Kaggle to analyze the proposed framework. The attributes used in dataset are depicted in table 1 and in figure 1.

Table 1 Attributes used in dataset

Attribute	Value
Resting blood pressure (trestbps)	Trestbps in mm Hg.
Sex	Gender of the patient (e.g., female, male)
Chest pain type (cp)	Type of cp experienced (e.g., asymptomatic, typical angina, non-anginal pain, atypical angina).
Fasting blood sugar (fbs)	Fbs level (1 if > 120 mg/dL, 0 otherwise).
Serum cholesterol (chol)	chol level in mg/dL.
Age	Age of the patient.
Restingrelectro	Resting ECGs detect cardiovascular disease by analyzing heart electrical activity.
Maxheartrate	Maximum Heart Rate (MaxHR).
Exerciseangia	Exercise-induced angina symptoms during activity.
Noofmajorvessels	Number of major vessels (0-3).

Target	Diagnosis of heart disease (0 = no disease, 1 = disease).

B. Performance metrices used:

- Accuracy: Accuracy is a metric used to evaluate the performance of a machine learning model. It is defined as the ratio of the number of correct predictions to the total number of predictions made.
- Data loss: Data loss, often referred to simply as loss, is a metric that measures the difference between the predicted values produced by a machine learning model and the actual values from the dataset. The loss function quantifies how well or poorly the model's predictions align with the true values, with lower values indicating better model performance.

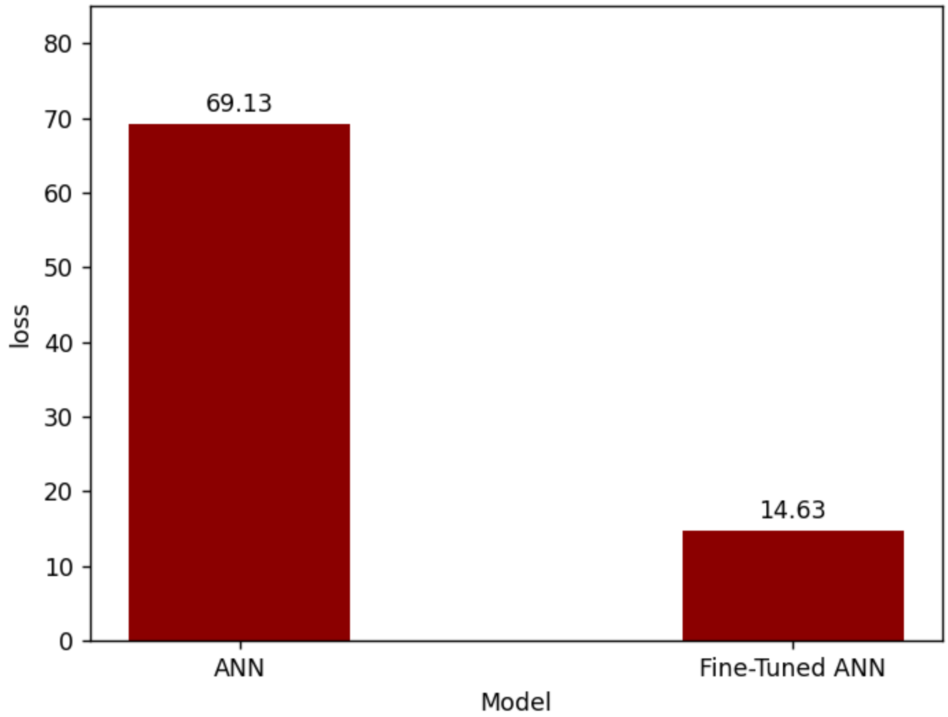

Figure 2 data loss comparison of ANN and Fine-Tuned ANN

Figure 2 shows a detailed comparison of data loss between traditional ANN model and fine-tuned ANN model. The figure intensely determines the substantial reduction in data loss that fine-tuned models achieve in comparison to traditional ANN models. In particular, the traditional ANN model shows a data loss of 69.13, whereas the fine-tuned ANN model exhibits a significantly lower data loss of 14.63. The fine-tuning method, which adjusts the weights of the ANN model to the specific task of predicting cardiovascular disease (CVD), is responsible for this efficacy in reducing data loss.

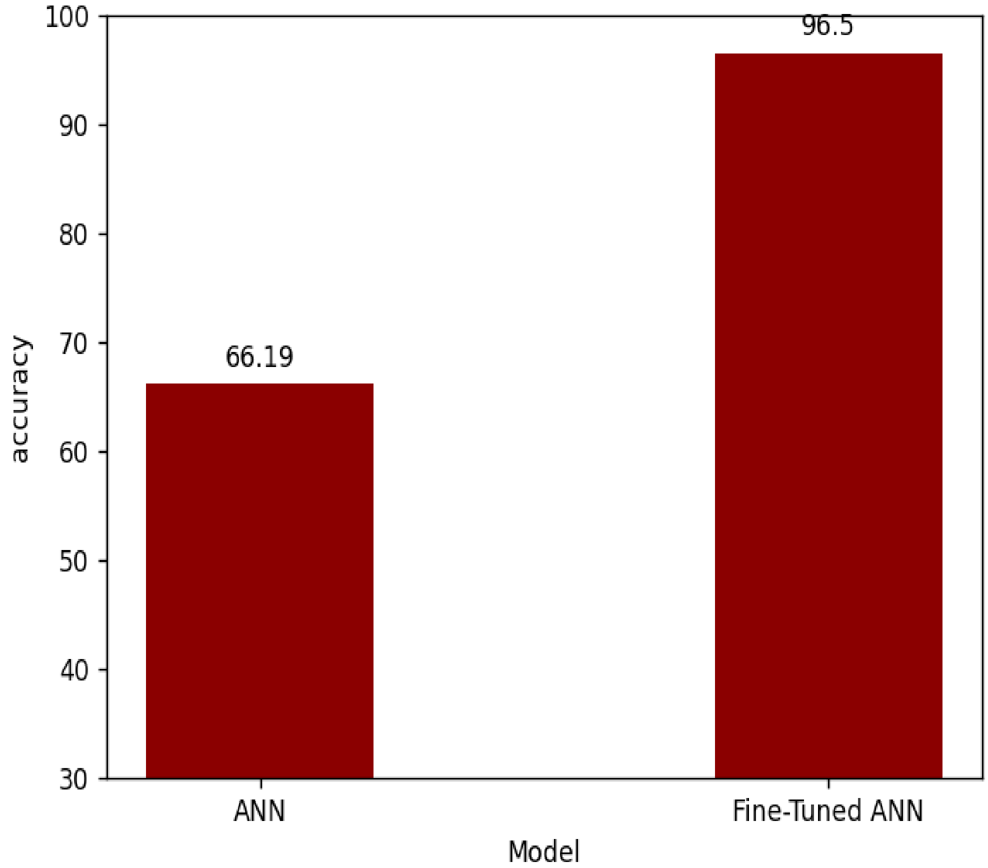

Figure 3 Accuracy comparisons of ANN and Fine-Tuned ANN

Moreover, Figure 3 highlights the accuracy comparison between traditional ANN and fine-tuned ANN models. Specifically, the traditional ANN model achieves an accuracy of 66.19%, while the fine-tuned ANN model reaches an impressive accuracy of 96.5%. This observation underscores the effectiveness of fine-tuning in optimizing the precision of heart disease diagnosis.

V. Conclusion

The fine-tuned ANN framework proposed in this study significantly improves the predictive accuracy and overall performance for diagnosing cardiovascular diseases. By adapting pre-trained models and employing advanced transfer learning techniques, we have addressed key challenges such as overfitting and limited training data. Our results show a substantial reduction in data loss and a marked improvement in accuracy, with the fine-tuned ANN model achieving a data loss of 14.63 compared to 69.13 for the traditional ANN model. Additionally, the accuracy of the fine-tuned ANN model reached an impressive 96.5%, significantly higher than the 66.19% accuracy of the traditional ANN model. These findings highlight the potential of this approach in clinical settings. This framework not only enhances diagnostic precision but also contributes to reducing the global burden of CVDs by enabling more accurate and unbiased diagnoses. Future work will focus on further refining these models and exploring their applicability across diverse patient populations and clinical environments to ensure broad and effective implementation.

References

[1] Karthikeyan, N. K. (2024). A novel attention-based cross-modal TL framework for predicting cardiovascular disease. Computers in Biology and Medicine, 170, 107977.

[2] Qadri, A. M., Hashmi, M. S. A., Raza, A., Zaidi, S. A. J., & ur Rehman, A. (2024).

Heart failure survival prediction using novel TL based probabilistic features. PeerJ Computer Science, 10, e1894.

[3] Hettiarachchi, R., Haputhanthri, U., Herath, K., Kariyawasam, H., Munasinghe, S., Wickramasinghe, K., ... & Edussooriya, C. U. (2021, May). A novel TL-based approach for screening pre-existing heart diseases using synchronized ecg signals and heart sounds. In 2021 IEEE international symposium on circuits and systems (ISCAS) (pp. 15). IEEE.

[4] Jang, J. H., Kim, T. Y., & Yoon, D. (2021). Effectiveness of TL for DL-based electrocardiogram analysis. Healthcare informatics research, 27(1), 19.

[5] Khan, K. N., Khan, F. A., Abid, A., Olmez, T., Dokur, Z., Khandakar, A., ... & Khan, M. S. (2021). DL based classification of unsegmented phonocardiogram spectrograms leveraging TL. Physiological measurement, 42(9), 095003.

[6] Maity, A., Pathak, A., & Saha, G. (2023). TL based heart valve disease classification from Phonocardiogram signal. Biomedical Signal Processing and Control, 85, 104805.

[7] D., Sreelakshmi., P., Prudvi, Teja. (2023). Cardiovascular Disease Prediction Using ML. doi: 10.1109/ISCON57294.2023.10112052

[8] Wasif, Akbar., Qaisar, Shaheen., Mohammad, Hijji., Muhammad, Anwar., Muhammad,

Ayaz. (2023). Probability Based Regression Analysis for the Prediction of Cardiovascular Diseases. Cmc-computers Materials & Continua, doi: 10.32604/cmc.2023.036141

[9] Fejsal, Perva., Harun, Tucakovic., Muhammed, Musanovic., Emine, Yaman. (2022). Prediction of cardiovascular disease. doi: 10.1109/ICAT54566.2022.9811108

[10] Milind, Jagota., Chengzhong, Ye., Carlos, Albors., Ruchir, Rastogi., Nilah, M., Ioannidis., Jun, S., Song. (2023). Cross-protein TL substantially improves disease variant prediction. bioRxiv, doi: 10.1101/2022.11.15.516532

[11] Sarita, Kumari, Mishra., Manjusha, Pandey., Siddharth, Swarup, Rautaray. (2022). ML based Cardiovascular Disease Prediction Using One-vs-one Approach. doi: 10.1109/ICAISS55157.2022.10011022

[12] M, Ramu., P, Sai, Meghana. (2023). Cardiovascular Disease Prediction Using ML

Classifiers. doi: 10.1109/ICACCS57279.2023.10112809

[13] K., Dhananjay, Rao., M., S., D., Kumar., Duvvuru, Akshitha., K., N., Rao. (2022). ML Based Cardiovascular Disease Prediction. doi: 10.1109/ICCPC55978.2022.10072072

[14] Sivakannan, Subramani., Neeraj, Varshney., M., Vijay, Anand., Manzoore, Elahi, M., Soudagar., Lamya, Ahmed, Al-Keridis., Tarun, Kumar, Upadhyay., N., Alshammari., Mohd, Saeed., Kumaran, Subramanian., K., Anbarasu., K., Rohini. (2023). CVD prediction by ML incorporation with DL. Frontiers in Medicine, doi: 10.3389/fmed.2023.1150933

[15] Thirupati, Sai, Eswar, Reddy., Satwik, Reddy, Sripathi., Dhanush, Akula., Suja, Palaniswamy., Subramani, R. (2022). Cardiovascular Disease Prediction using ML and DL. doi: 10.1109/CSITSS57437.2022.10026391

[16] Shazia, Jagot., Clifford, C, Sheckter. (2022). Explainable deep TL model for disease risk prediction using high-dimensional genomic data. PLOS Computational Biology, doi: 10.1371/journal.pcbi.1010328

[17] Ahmad, S., Asghar, M. Z., Alotaibi, F. M., & Alotaibi, Y. D. (2023). Diagnosis of cardiovascular disease using deep learning technique. Soft Computing, 27(13), 8971-8990.

[18] Subramani, S., Varshney, N., Anand, M. V., Soudagar, M. E. M., Al-Keridis, L. A., Upadhyay, T. K., ... & Rohini, K. (2023). Cardiovascular diseases prediction by machine learning incorporation with deep learning. Frontiers in medicine, 10, 1150933.