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Federated Attention-Based Explainable Deep Learning Framework for Real-Time Cardiovascular Disease Prediction Using Wearable IoMT Data

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Abstract:
A Federated Attention-Based Explainable Deep Learning Framework for Real-Time Cardiovascular Disease Prediction using Wearable IoMT Data is an innovative healthcare model based on a distributed system of wearable sensors to predict cardiovascular diseases mainly focusing on patients' privacy and data security. The clinical trustworthiness is, however, lowered due to the difference in the type of data in an IoMT device and the absence of a comment to explain the predictions of deep learning. The proposed framework proposes the adoption of federated learning, the incorporation of an attention-based CNN-LSTM architecture, and XAI methods such as SHAP and LIME to improve the forecasting accuracy of the diseases while ensuring security and transparency. The proposed system helps to attain greater prediction accuracy, real-time monitoring, secure patient sensitive data, and to enhance model interpretability and clinical decision-making speed and reliability.

Keywords: Federated Learning, Explainable Artificial Intelligence, Cardiovascular Disease Prediction, Attention Mechanism, CNN-LSTM, Wearable IoMT Devices, Real-Time Healthcare Monitoring, SHAP and LIME.

1. Introduction

Cardiovascular Diseases (CVDs) remain one of the major health problems in the world with a huge mortality rate and a great burden on healthcare systems [20]. The timely detection and ongoing tracking of cardiac disease are vital to lowering health risks and enhancing patients' outcomes. In recent years, the deployment of wearable healthcare technologies and the Internet of Medical Things (IoMT) has allowed to gather and deliver all the physiological data, including ECG signals, HR, BP, and oxygen saturation (SpO_2), transmitted from patients in real-time. These developments help build smart healthcare systems that offer individual monitoring and early warning systems for possible cardiac abnormalities [12], [15], [20].

But with the growing size of healthcare data, prediction models that can learn complex data patterns while maintaining privacy and confidentiality of patient information poses new challenges [8]–[11]. In the past few years, deep learning has been applied to create powerful medical data analysis tools that have been developed such as Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM) network, and attention-based models. The methods can learn spatial and temporal attributes from clinical data and wearable sensors to increase the accuracy of cardiovascular disease prediction [2, 3, 4, 7, 16, 18, 19].

Despite the successful results of centralized deep learning models, there are still a number of challenges, such as data privacy, security, and the lack of interpretability of models [8]–[11]. In a lot of healthcare environments, it is actually not feasible to share patient information directly between institutions, due to regulations.Due to regulations, it is not possible to share patient information directly between institutions in many healthcare environments. Moreover, most deep learning models are black box, which makes it challenging for clinicians to know how the models make predictions, and decreases trust in AI clinical decision making, [5] [6].

In order to address these limitations, this research introduces the Federated Attention-Based Explainable Deep Learning Prediction (FABEDLP) framework, which can predict cardiovascular diseases in real-time using data collected from wearable IoMT devices. The proposed framework is based on federated learning and CNN-LSTM architectures and attention mechanisms to allow for secure collaborative model training without sharing sensitive patient health records [7]–[10], [16]. Furthermore, a few Explainable Artificial Intelligence (XAI) methods are integrated, like SHAP or LIME, which help to explain the results of the prediction by highlighting the most important features that influence the model's predictions [5, 6]. The framework integrates explainable deep learning, federated learning to enable privacy-preserving, multi-cloud systems, and utilizes IoMT technology with wearable devices to enhance cardiovascular disease prediction accuracy, patient privacy protection, and transparency in AI-informed decision-making. Therefore, it enables accurate and real-time health tracking and enhances the intelligent healthcare systems for the early diagnostics and management of heart disease [8, 12, 15, 16, 20].

2. Literature Review

Cardiovascular disease prediction is an important research field because the cardiovascular diseases have become a major public health concern all over the world and the need for intelligent healthcare solutions is increasing [20]. Traditional approaches and machine learning models that were based on blood pressure (BP) and clinical variables like cholesterol, glucose and body mass index (BMI) as cardiovascular risk indicators were the primary methods used earlier to predict cardiovascular disease [1]. A pioneering study in this area was the one by Detrano et al. (1989) who created a statistical model that could predict the presence of coronary artery disease based on other clinical characteristics [1].

With the development of artificial intelligence technique, deep learning model is gaining more weight in healthcare due to its capability of high efficiency and automatic learning complex pattern in medical information [18]. CNN network models are extensively used in ECG signal analysis to learn important spatial features [2] while LSTM networks are successfully applied in sequential healthcare data analysis and temporal dependency learning [18]. Kiranyaz et al. (2016) have proven that CNNs can be used for real-time ECG classification [3] and Rajpurkar et al. (2017) have demonstrated that deep neural networks can be used to perform cardiologist-level arrhythmia detection [4]. In addition, Hochreiter and

Schmidhuber (1997) proposed the LSTM model, which is one of the most successful models used in medical time series analysis [2]. Recently, hybrid models integrating CNN with LSTM and attention models have further enhanced cardiovascular disease prediction to model both spatial and temporal healthcare patterns successfully [12]–[17], [19].

Nonetheless, the current healthcare prediction systems still face issues of patient privacy, data security, and the handling of sensitive medical information, as they are still based on centralized data collection and model training [8]–[11]. Federated Learning (FL) has been proposed as a distributed learning approach that aims to prevent the central server from receiving raw patient data while allowing wearable IoMT devices and healthcare institutions to jointly train predictive models [8]–[11].

The first federated learning (FL) decentralized model training approach was introduced by McMahan et al. (2017) to enable collaborative learning without compromising user privacy [8]. Following this, further research on federated learning for healthcare security and collaborative medical data analyses was conducted [9]–[11]. Meanwhile, the increasing prevalence of attention mechanisms in medical deep learning systems has been highlighted. The attention mechanism was introduced by Vaswani et al. (2017) in the Transformer architecture which allows neural networks to pay attention to the most relevant features in the input [7]. In this regard, attention-based CNN-LSTM models have been shown to outperform models that do not use this information for prediction of CVCs by incorporating temporal ECG information along with clinical attributes [16], [17], [19]. Additionally, wearable IoMT devices such as smartwatches, biosensors, and portable ECG monitors allow for real-time physiological monitoring, providing healthcare analytics and early disease detection [12], [15], [20].

However, there are still barriers to overcome such as the lack of interpretability of models, integration of heterogenous wearables data and real-time deployment in clinical settings.Most deep learning models function as black-box systems, limiting transparency and reducing clinicians' confidence in AI-assisted decision-making **[5], [6]**. To improve interpretability, Ribeiro *et al.* (2016) introduced Local Interpretable Model-Agnostic Explanations (LIME) **[5]**, while Lundberg and Lee (2017) proposed SHapley Additive exPlanations (SHAP) for consistent feature attribution and model explanation **[6]**. Recent studies suggest that integrating federated learning, wearable IoMT technologies, attention-based deep learning, and explainable AI can simultaneously improve prediction accuracy, preserve patient privacy, and enhance model transparency **[9]–[16]**. However, only a limited number of studies have integrated all these technologies into a unified framework for real-time cardiovascular disease prediction. Therefore, the proposed **Federated Attention-Based Explainable Deep Learning Framework (FABEDLP)** combines federated learning, an attention-based CNN-LSTM architecture, wearable IoMT data, and XAI techniques to achieve accurate, secure, interpretable, and real-time cardiovascular disease prediction **[8]–[16]**.

3. Existing Systems for Prediction of Cardiovascular Disease

The current prediction methods primarily focus on machine learning and deep learning algorithms for pattern recognition using various healthcare data sources, such as clinical health records, electrocardiogram (ECG) signals, and physiological data **[3], [4], [12], [18], [20]**. Several traditional models, including Support Vector Machines (SVM), Decision Trees, Random Forests, Convolutional Neural Networks (CNNs), and Long Short-Term Memory (LSTM) networks, have been employed to predict cardiovascular risk and detect abnormal cardiac conditions with improved prediction accuracy **[2], [3], [4], [13], [14], [18]**.

With the advent of wearable Internet of Medical Things (IoMT) technology, various healthcare monitoring systems have been developed to continuously collect patient physiological data and support real-time health assessment **[12], [15], [20]**. These systems provide advantages such as continuous monitoring, early disease detection, and automated healthcare analysis. Despite the availability of numerous approaches, most of them still depend on centralized data processing models which force data sharing of patients with central servers, raising serious issues about patient privacy, data security, and the protection of sensitive medical information [8]–[11].

One of the major limitations of current deep learning-based prediction systems is the lack of transparency in their decision-making process. Although these models achieve high prediction accuracy, their complex internal architecture makes it difficult for healthcare professionals to understand the reasoning behind the predictions, thereby reducing trust in AI-assisted clinical decision-making **[5], [6], [12]**.

Furthermore, existing healthcare prediction models are generally technology-specific and do not provide an integrated framework that simultaneously combines privacy-preserving federated learning, explainable artificial intelligence (XAI), attention-based deep learning, and real-time wearable IoMT healthcare monitoring **[8]–[16]**. Therefore, there is a need for a unified framework that integrates federated learning, explainable deep learning techniques, and wearable IoMT analytics to develop a secure, transparent, reliable, and trustworthy cardiovascular disease prediction system **[8], [10], [12], [16]**.

3.1 Drawbacks

Two limitations of the current system include

3.1.1 Privacy and Security Limitations in Centralized Healthcare Systems

Most current CV prediction models are built on a centralized data storage and processing approach, where patients' personal health data is gathered in one central repository, such as a server, for model training. This will make it much easier for data breaches, unauthorized access, and privacy violations to occur. Patient medical records and physiological signals are confidential in healthcare settings, and sharing data between healthcare institutes is usually tightly regulated. This has made many health care organisations reluctant about sharing live patient information, and this hinders collaborative learning and the ability to access a variety of datasets for precise disease prediction [8].

3.1.2 Lack of Interpretability and Real-Time Adaptability

While deep learning models can yield high prediction accuracy, many current systems are black box systems that lack a clear explanation of how predictions are made. To use AI systems for clinical decision-making, healthcare professionals need clear and comprehensible predictions. The lack of explainability decreases trust and diminishes the ability to use it practically in hospitals and healthcare centers. Moreover, some of the current models are not suitable for continuous real-time monitoring with wearable devices in the IoMT as these are not effective in detecting early signs of heart disease or abnormal blood pressure readings in real time [9].

3.2 Input data

The input data of the proposed system includes real-time physiological signals, sensor readings of wearable IoMT devices, and patient clinical data required for early prediction of cardiovascular diseases. Demographic data includes age, gender, body mass index (BMI) and key clinical data includes blood pressure, cholesterol, glucose, oxygen saturation (SpO2) and heart rate variability. Continuous ECG, pulse rate, body temperature, physical activity, sleep patterns and stress indicators are measured by wearable IoMT devices and monitored in real-time. Additionally, the ECG has features that are captured during a particular time, called temporal ECG, such as RR interval, QRS duration, PR interval and ST-segment variations to detect abnormal cardiac activity. In addition, lifestyle data like smoking status, alcohol intake, diet and exercise history may be combined to enhance the accuracy of prediction. The target variable indicates the presence (1) or absence (0) of cardiovascular disease, allowing the federated attention-based deep learning model to make accurate, explainable, and real-time predictions for the disease.

S. No.	Age (Years)	Gender	BMI (kg/m²)	Blood Pressure (mmHg)	Cholesterol (mg/dL)	Glucose (mg/dL)	Heart Rate (bpm)	RR Interval (s)	QRS Duration (ms)	SpO2 (%)	Temperature (°F)	Activity Level	Sleep Hours	Smoking Status	Stress Level	ECG Abnormality	Disease (1=Yes, 0=No)
1	45	Male	28.4	140/90	220	110	92	0.78	110	96	98.4	Low	5	Yes	High	Yes	1
2	52	Female	31.2	150/95	240	130	98	0.74	118	95	99.1	Low	4	No	High	Yes	1
3	39	Male	24.5	120/80	180	95	76	0.85	96	99	98.2	Moderate	7	No	Medium	No	0
4	60	Male	33.1	160/100	260	145	105	0.70	125	94	99.4	Low	4	Yes	High	Yes	1
5	48	Female	27.0	135/85	210	105	88	0.80	108	97	98.6	Moderate	6	No	Medium	Yes	1
6	34	Male	22.8	118/76	170	90	72	0.88	92	99	98.1	High	8	No	Low	No	0
7	55	Female	30.4	145/92	235	125	96	0.76	115	95	98.9	Low	5	Yes	High	Yes	1
8	42	Male	26.3	128/82	195	100	82	0.83	100	98	98.5	Moderate	7	No	Medium	No	0
9	63	Male	34.5	165/105	275	155	110	0.68	130	93	99.5	Low	4	Yes	High	Yes	1
10	37	Female	23.7	122/78	175	92	74	0.87	95	99	98.0	High	8	No	Low	No	0
11	50	Male	29.8	142/88	225	118	90	0.79	112	96	98.7	Moderate	6	Yes	Medium	Yes	1
12	41	Female	25.1	126/80	185	97	78	0.84	98	98	98.3	Moderate	7	No	Low	No	0
13	58	Male	32.6	155/98	250	138	102	0.72	122	94	99.2	Low	5	Yes	High	Yes	1
14	36	Male	24.0	119/77	172	89	70	0.89	91	99	98.1	High	8	No	Low	No	0
15	47	Female	28.1	138/86	215	108	86	0.81	106	97	98.6	Moderate	6	No	Medium	Yes	1
16	62	Male	35.0	170/108	280	160	112	0.66	135	92	99.6	Low	4	Yes	High	Yes	1
17	33	Female	21.9	115/75	165	85	68	0.91	88	99	97.9	High	8	No	Low	No	0
18	54	Male	30.9	148/94	238	128	97	0.75	117	95	99.0	Low	5	Yes	High	Yes	1
19	44	Female	26.7	130/84	200	102	84	0.82	102	98	98.4	Moderate	7	No	Medium	No	0
20	59	Male	33.8	158/99	255	142	104	0.71	124	94	99.3	Low	5	Yes	High	Yes	1

NOTE: Disease: 1 = Presence of cardiovascular disease, 0 = No disease

4. Results

The experimental study shows that the proposed FABEDLP framework has the potential to identify the patterns of cardiovascular diseases from the data collected by the wearable IoMT. The training and validation results show that the model is able to learn meaningful representations from physiological signals and has a stable performance throughout the stages of the testing. Finally, ROC analysis confirms the framework's ability to effectively classify disease and non-disease cases, thus supporting its potential use in the real-time healthcare domain.

The federated training mechanism is evaluated and the global model improves with the rounds of communication. The trend is a sign of effective sharing of knowledge between distributed clients without exposing raw patient records. The results emphasize the benefits of federated learning in the context of collaborative healthcare analytics, where privacy protection is a key concern.

Several physiological and clinical indicators seem to be particularly important in the prediction of cardiovascular diseases; this was found with the SHAP feature-importance analysis. The explanations generated by the model offer valuable insights into its decision-making process, enhancing transparency and facilitating understanding by healthcare practitioners.

The results of the comparative evaluation with the conventional deep-learning approaches indicate that the proposed architecture has comparable predictive performance and fulfills privacy and interpretability requirements. The federated learning, attention, and explainable AI components help to create a more reliable prediction environment in healthcare.

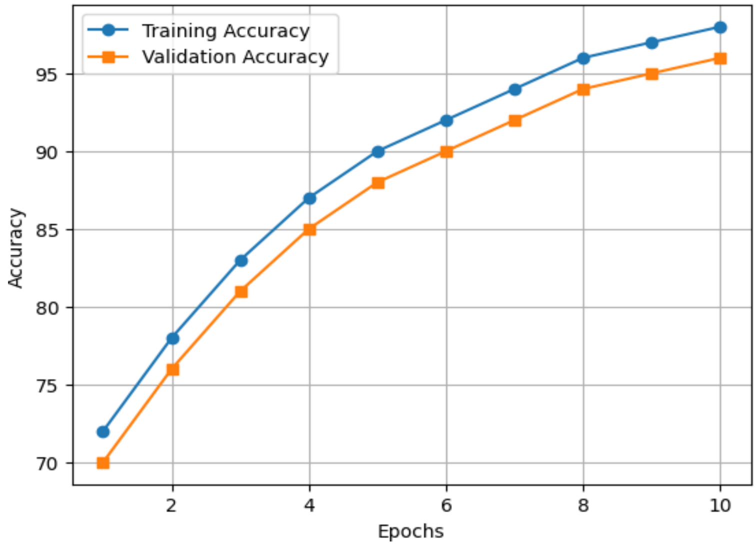

Figure 4.1. Training and Validation Accuracy

The proposed federated attention-based deep learning model training process is shown in the graph in figure 4.1 with each epoch during training, and its accuracy is calculated. The model performance improved by enhancing its training and validation accuracy, indicating that there are meaningful patterns in the datasets of wearables IoMT and ECG.

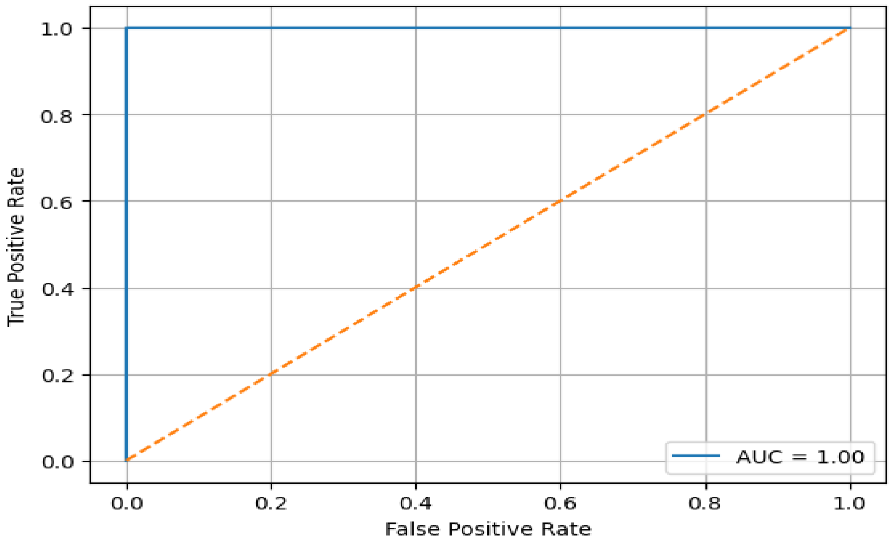

figure 4.2. Roc curve with auc score

The suggested model is used for cardiovascular disease versus non-disease classification as shown in FIGURE 4.2. The curve heading up to the upper left corner is a very good sensitivity and specificity. The high value of AUC not only shows the accuracy of the prediction of the framework but also suggests that it has high discriminatory ability and can be utilized in the actual medical diagnosis system.

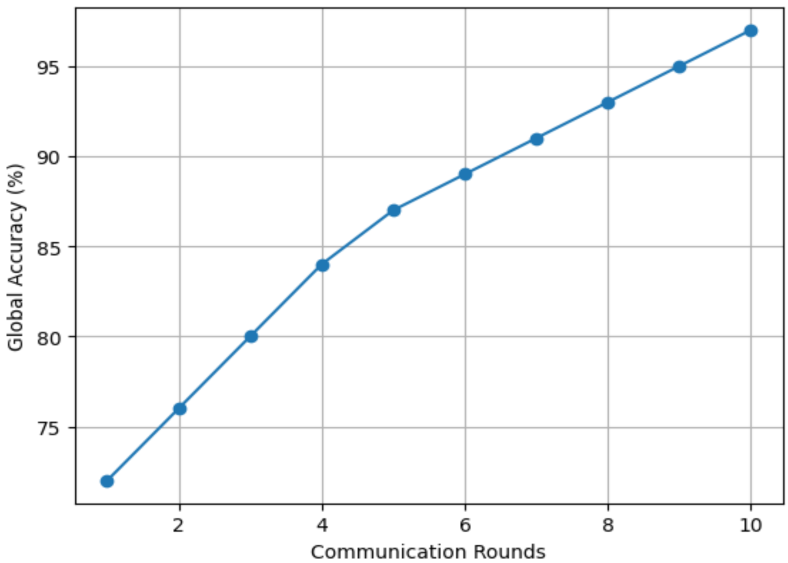

Figure 4.3. Federated learning accuracy vs communication rounds

The improvement in global federated model accuracy at various communication rounds between wearable IoMT devices and the central server is depicted in graph 4.3.. This continued improvement in accuracy indicates that no patient data was shared, and co-learning was successful. The results show that federated learning provides improvements in predictive results while not relying on the central data and respecting privacy.

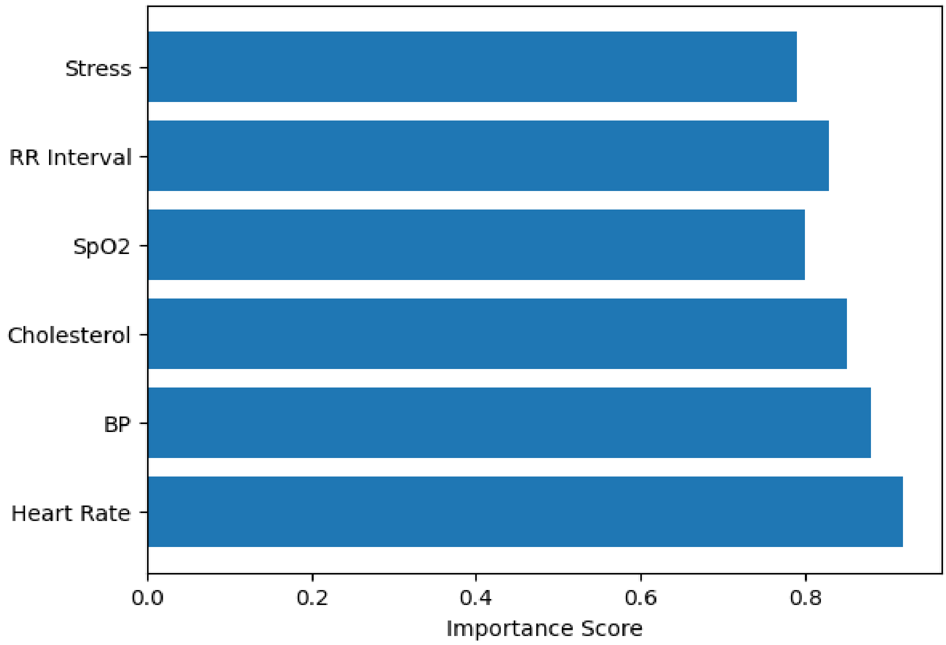

Figure 4.4. Shap feature importance analysis

The GRAPH 4.4 shows the importance of clinical and ECG attributes in predicting cardiovascular disease. Many features, including heart rate, blood pressure, cholesterol level, RR interval, and stress level, have a prominent impact on model predictions. This analysis is helpful to increase transparency and interpretability of the proposed framework, to better understand why a prediction outcome might be the case.

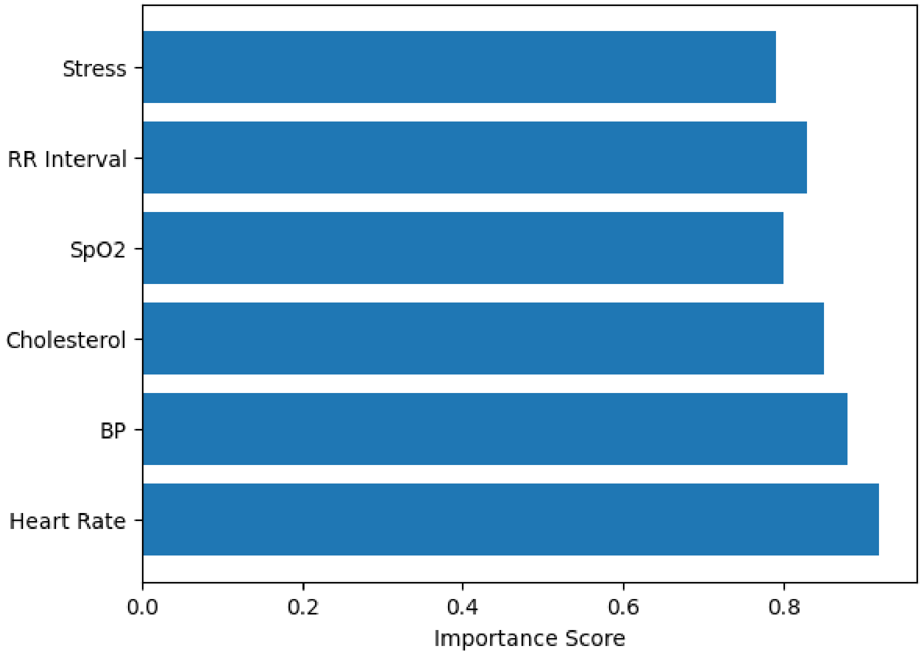

Figure 4.5. Comparative analysis of models

To compare the suggested framework with the current deep learning models, including CNN, LSTM, CNN-LSTM, and Transformer models, a comparison analysis graph is created.The proposed model is capable of achieving the best prediction accuracy due to its combination of federated learning, attention mechanisms, and explainable AI techniques. Results demonstrate increased reliability, real-time monitoring and improved prediction accuracy over traditional cardiovascular disease prediction systems.

5.1 Methodology

The research area is to design a secure cardiovascular disease prediction system based on the Internet of Medical Things (IoMT) technology, federated learning, explainable AI (XAI), and deep neural networks [8]–[16], [20]. Its goal is to allow for the continuous monitoring of patient health, confidentiality of the data, and for the prediction results to be interpretable [8]–[12].

In order to perform effective analysis of the healthcare signals, the framework integrates convolutional neural network and recurrent neural network components. CNN module is used to identify informative patterns in spatial data, and the LSTM layer is employed to model temporal relationships in sequential healthcare data [2, 3, 4, 13, 14]. The attention mechanism is then introduced to highlight the most relevant features for disease prediction, which boosts the prediction performance [7, 16, 17, 19].

The proposed Federated Attention-Based Explainable Deep Learning Framework (FABEDLP) consists of a series of steps. First, physiological data from wearable IoMT devices are collected and preprocessed using noise reduction, data normalization, and feature extraction techniques [12], [15], [20]. The processed data are then distributed to local federated clients, where CNN-LSTM models integrated with attention mechanisms independently learn important spatial and temporal patterns from ECG signals and other physiological parameters [13]–[17], [19].

After local model training, only the updated model parameters are securely transmitted to a federated server to construct a global model without accessing or sharing individual patient information **[8]–[11]**. This decentralized learning process preserves data privacy while enabling collaborative model training across multiple healthcare institutions **[8]–[11]**. Finally, Explainable Artificial Intelligence techniques, particularly SHAP, are employed to interpret the model predictions and identify the most influential factors contributing to cardiovascular disease prediction **[6], [12]**. This improves model transparency, supports clinical decision-making, and increases healthcare professionals' trust in AI-assisted cardiovascular disease prediction systems **[5], [6], [12]**.

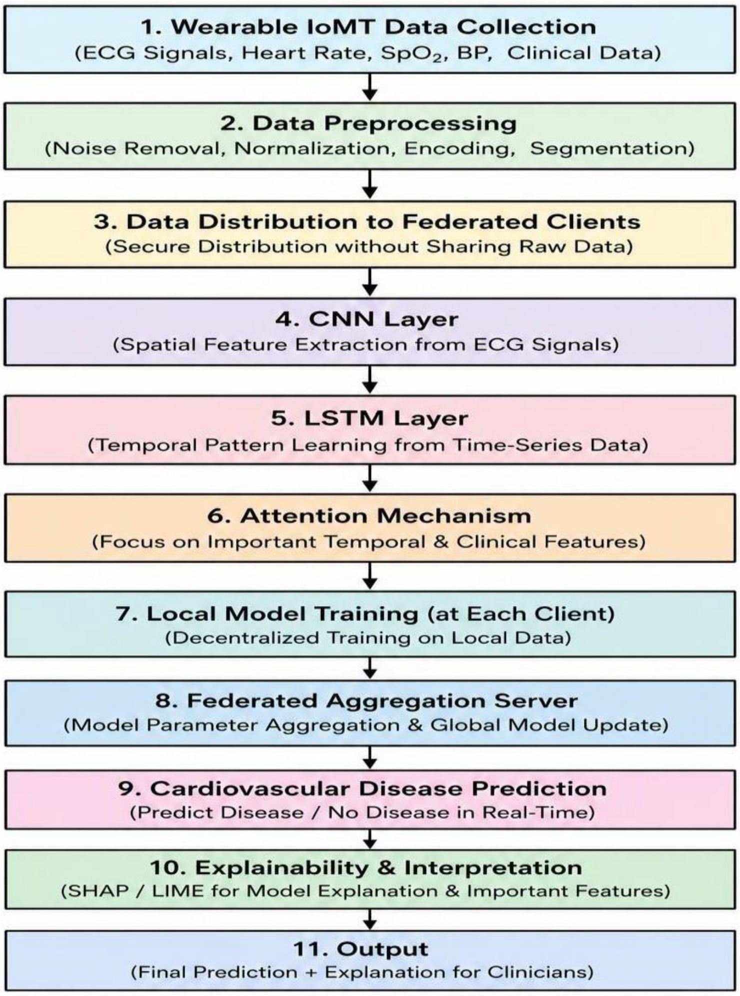

Figure 5.1. Proposed Federated CNN-LSTM Architecture

Figure 5.1 depicts the suggested Federated CNN-LSTM Architecture for wearable IoMT data-based real-time cardiovascular disease prediction. Clinically collected data and medical information is gathered from wearable devices and medical sources, initially ECG signals, heart rate, SpO2, blood pressure. Data is preprocessed to enhance data quality, including noise removal, normalization, encoding and segmentation. The processed data is securely distributed to multiple federated client devices where CNN layers extract important spatial features and LSTM layers learn temporal healthcare patterns from time-series signals. To accurately predict, an attention mechanism is added, which focuses on the important features of the clinical and ECG data. All locally-trained models are fused together through a federated server without sharing any data regarding the patient, to produce a secure global model. Finally, explainable AI methods such as SHAP and LIME can offer insights into the predictions, delivering accurate, interpretable results that align with privacy guidelines for real-time healthcare use in cardiovascular disease diagnostics.

5.2 Advantages

Two key benefits of the proposed model:

1. Privacy-Preserving Real-Time Disease Prediction

The proposed federated attention-based framework allows for the prediction of cardiovascular disease in real-time by wearable IoMT devices, without directly sharing sensitive patient information. By enabling the decentralized training of a model at various healthcare nodes, federated learning minimizes privacy risks, enhances data security, and facilitates ongoing patient monitoring and early detection of diseases[15].

2. Improved Accuracy with Explainable Decision Support

The integration of CNN, LSTM, and attention mechanisms enhances the model's ability to capture important spatial and temporal healthcare patterns, resulting in highly accurate cardiovascular disease prediction. Furthermore, EXAI tools can help explain the results of predictions, which can be useful for understanding the reasons behind the predictions and boost trust in the AI component of clinical diagnosis in healthcare[16].

The Federated Attention-Based Explainable Deep Learning Framework for real-time cardiovascular disease prediction using wearable IoMT data is presented in the following 10 steps[20]:

Step 1: Data Collection

Gather ECG signals, wearables IoMT sensor data, and clinical healthcare data from a distributed set of healthcare devices and medical datasets.

Step 2: Data Preprocessing

Remove noise, fill in missing data, normalize numerical features and encode categorical features from the collected data.

Step 3: Federated Data Distribution

Distribute the processed healthcare data across multiple federated client devices without directly sharing sensitive patient information.

Step 4: Feature Extraction Using CNN

Convolutional neural networks (CNNs) can be used to automatically extract significant spatial features from physiological data and ECG signals.

Step 5: Temporal Pattern Learning Using LSTM

To capture temporal correlations and sequential healthcare patterns, feed the collected features into the Long Short-Term Memory (LSTM) network.

Step 6: Attention Mechanism Integration

For increased disease prediction accuracy, provide an attention mechanism to concentrate on the most pertinent clinical and ECG features.

Step 7: Local Federated Model Training

Train the deep learning model independently on local wearable IoMT devices and healthcare nodes using decentralized patient data.

Step 8: Federated Model Aggregation

To create a safe global prediction model without disclosing raw patient data, send local model parameters to the federated aggregation server.

Step 9: Cardiovascular Disease Classification

In real time, determine whether cardiovascular illness is present or not using the aggregated federated attention-based model.

Step 10: Explainability and Deployment

Apply SHAP-based explainable AI techniques to interpret prediction outcomes and deploy the trained model for secure and intelligent real-time healthcare monitoring applications.

6. Discussions of Results

The proposed framework for FAEDL is proved to be an effective solution to predict cardiovascular disease in real-time using health data collected from the wearable devices of IoMT devices. The combination of CNN and LSTM models enables the system to learn important patterns from ECG signals and physiological parameters by considering both feature relationships and changes over time. The attention mechanism is also beneficial in learning as it focuses on the relevant health indicators associated with the right prediction of disease[18].

In the case of federated learning, it proves that prediction in healthcare can be done reliably without compromising patient privacy. The model training framework supports distributed data sources to avoid sharing sensitive medical data centrally and improving the security and confidentiality of the training process. Furthermore, the use of explainable AI methods, such as the SHAP analysis, can guide in uncovering why the model made itsdecisions. This openness is crucial for grasping predictions and fostering acceptance of AI-driven healthcare interventions among healthcare professionals[19].

The proposed framework is expected to result in promising results, but there is still room for improvements to be considered in the future. Realizing this, testing on larger and more divers real-world healthcare datasets, which are collected from different hospitals and different healthcare IoMT environments, is recommended. Advanced deep learning models, e.g., transformer-based networks, as well as edge computing methods might be integrated in the future, to further enhance the processing speed and facilitate continuous monitoring. Having several different healthcare data sources such as medical imaging, electronic health records and information from wearables sensors could help to gain a broader understanding of a patient's health status and increase the accuracy of predictions. To be reliable and effective in real healthcare environments before being put into practice, the framework must be clinically tested, validated and secured by healthcare experts[17].

7. Conclusion

To conclude, the FABEDLP framework is a privacy-preserving and interpretable method for predicting cardiovascular diseases based on IoMT data from wearable devices. The use of federated learning in combination with attention mechanism CNNs and LSTMs and the use of explainable AI techniques allows the system to analyze physiological information without the need to store sensitive patient information in a centralized system. The results shown demonstrate the ability of the framework to enable accurate prediction, transparent decision making and continuous health monitoring in smart healthcare environments [14].

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