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Federated Knowledge Transfer and Interpretable Decision-Tree Analytics for IoMT Healthcare

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Abstract

As Internet of Medical Things (IoMT) enables continuous healthcare monitoring, it has also created major issues with respect to data privacy, distributed learning, and model interpretability in healthcare organizations. To address these issues, the proposed federated knowledge transfer and interpretable decision-tree analytics for enabling privacy-preserving clinical prediction. This approach makes use of locally learned decision trees to generate clinical decision-path features and federated knowledge transfer on the level of features. The fusion of global-local features makes it even better to make the predictions more reliable by retaining client-specific information. The proposed framework is experimented with MIMIC-III clinical dataset in a distributed IoMT environment. Experimental results show that the accuracy rate is 92.3%, precision rate is 91.8%, recall rate is 92.6%, F1-score is 92.2%, and AUC-ROC value is 0.963.

Keywords: Internet of Medical Things (IoMT), Clinical Decision Support, Decision Tree Analytics, Privacy-Preserving Healthcare, Knowledge Transfer, Explainable Artificial Intelligence (XAI).

1. Introduction

The development of the Internet of Medical Things (IoMT) has changed modern healthcare practices with the continuous monitoring of the patient's health by using the

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interconnection of various medical devices, wearables, and smart monitoring. The increasing amount of information about the physiological process of humans collected by the distributed devices, which creates many possibilities for enabling early diagnosis and personal treatment. Healthcare data is private in nature and is spread out across several hospitals and healthcare organizations, which makes it more difficult to collect the data centrally due to the privacy concerns and increased costs associated with communication. Moreover, sending data to centralized servers from healthcare organizations would create latency and bandwidth issues as well. Therefore, there is a need for intelligent healthcare solutions that support collaboration and learning, and also provide privacy for patients.

Recent research studies have explored the concepts of federated learning, fog-assisted computation, and distributed artificial intelligence technologies, which can be used for solving the problem of preserving patient privacy during the process of healthcare data analytics. Federated learning allows collaborative model training without any exchange of patient data, whereas fog computation will speed up the process by analyzing the healthcare data closer to the IoMT devices. Despite the success that has been realized through the use of such techniques, there are still issues that need to be addressed. Most of the existing systems are based on complex deep learning architectures with poor interpretability, which also result in performance challenges when used in heterogeneous non-IID datasets within healthcare, experience high communication costs during federated learning, and do not provide clear clinical reasoning.

To address these challenges, federated knowledge transfer framework based on interpretable decision-tree analytics in the IoMT healthcare system has been proposed. The proposed framework makes use of hierarchical fog-assisted federated learning, knowledge transfer at feature level, global-local feature fusion, and interpretable decision tree modeling. By integrating communication-efficient aggregation of features along with a transparent decision-tree inference process, the proposed framework enhances collaboration-based learning with explainable clinical decision support. The proposed method has the ability to handle the heterogeneous healthcare settings, minimizing the need for communication and making real-time intelligent healthcare services feasible. An experimental study is performed to illustrate the effectiveness of the proposed framework to enable privacy-aware IoMT healthcare analytics.

2. Related Works

IoMT has revolutionized healthcare in a way that it has allowed patients to be monitored continuously by using connected devices and wearables. This produces huge amounts of physiologic data, which have to be secured, processed, and analyzed in an efficient manner. It has been shown that the IoMT technology has a lot of potentials in providing better patient care but faces issues such as security, scalability, and interoperability [8], [12].

To address these challenges, federated learning has proved to be an efficient distributed learning framework that allows multiple healthcare organizations to train machine learning algorithms without sharing the raw patient information. Such approach ensures patient privacy while performing collaborative medical intelligence operations. Many studies have confirmed that the federated learning provides an efficient way to perform healthcare analytics for multiple organizations while abiding by healthcare data protection standards [2], [10].

To establish further advancements in the real-time healthcare services, there is an emerging method of fog-assisted federated learning that is achieved through moving computation near the IoMT devices. By doing so, communication delays, congestion, and reliance on clouds are minimized, and thus, it is fit for use in time-sensitive healthcare applications such as intensive care monitoring and emergency response systems [3], [11]. Moreover, the communication-efficient federated learning approaches have been adopted through feature-level aggregation and model optimization to minimize transmission costs but still maintain competitive performance [1].

Deep learning methods have demonstrated high predictive performance, their lack of explainability has made them less suitable for deployment in decision-support systems for clinical applications. Consequently, decision tree–based federated learning has become an alternative solution, as it offers clear decision logic, which is more comprehensible to practitioners. Several research works have addressed federated decision tree learning and aggregation strategies to improve the model explainability [4], [5], [6]. In addition, parallel decision tree algorithms have increased the processing speed and inference of large datasets [9]. Another recent development in multimodal learning has been in terms of learning representations from different modalities using contrastive learning and diffusion networks, which facilitates better semantic alignment of features and consistency across different modalities [7].

Despite these advancements, limited research has attempted to integrate knowledge transfer at the feature level, interpretable decision trees, and hierarchical fog-enabled IoMT architecture into a coherent healthcare setting. While most of the studies concentrate on efficient federated learning or interpretable decision tree approaches individually, there is no specific research focus to deal with the issues of data heterogeneity, communication efficiency, real-time analytics, and transparent clinical decision support. To solve these challenges, this research proposes a knowledge transfer framework based on federated learning.

3. Proposed Methodology

A hierarchical fog-assisted federated learning architecture has been proposed for conducting privacy-preserving healthcare data analytics in distributed IoMT settings. As shown in Figure 1, the proposed architecture starts with acquiring the physiological data from the MIMIC-III dataset, and then conducting data preprocessing in order to have standard feature representations for distributed learning.

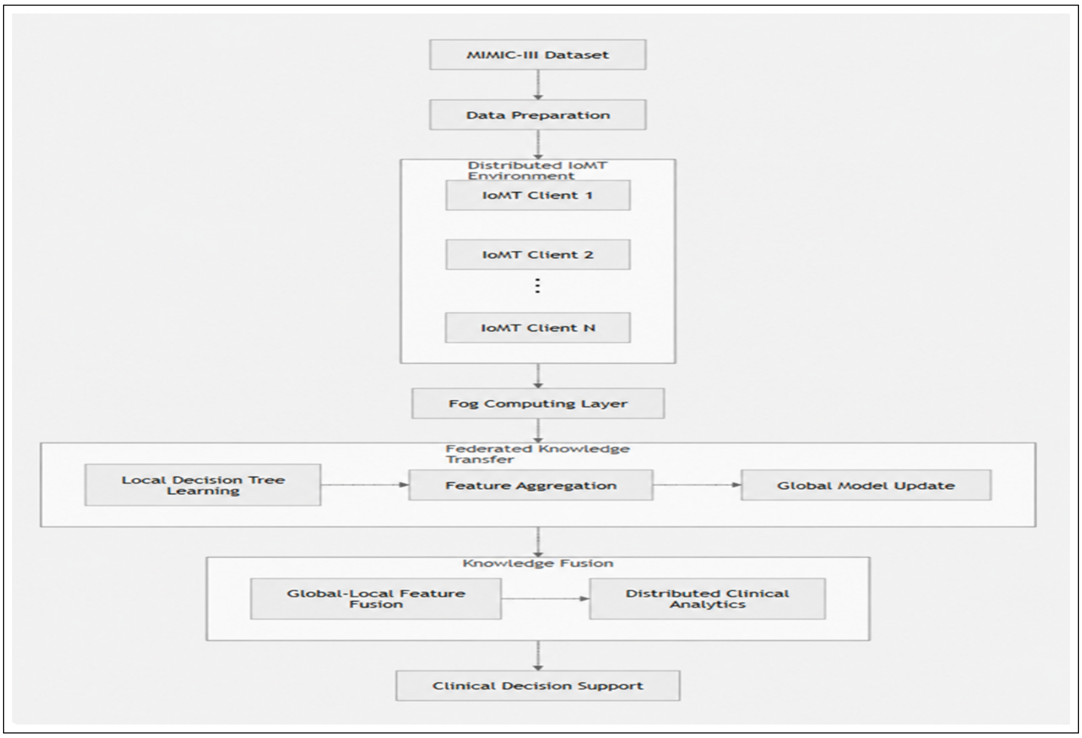

Figure 1. Proposed hierarchical federated learning workflow for IoMT healthcare

These processed features are then distributed among multiple IoMT clients, where decision tree models are built and decision path features are generated at the fog computing layer. Knowledge is collaboratively shared using the federated knowledge transfer framework, which allows for global aggregation of features without revealing the patient information. This is followed by the fusion of global and local feature representations in order to enhance the model generalization without losing the client-specific attributes. The obtained knowledge is finally employed by the distributed clinical decision analytics framework in order to generate understandable predictions.

3.1 Overall Framework

The proposed framework adopts a hierarchical architecture involving IoMT devices, fog computing, federated learning, and interpretable decision tree analysis to provide a secure and efficient healthcare monitoring approach. Figure 1 demonstrates how the procedure starts with collecting the physiological data from the MIMIC-III database [13] and its pre-processing to obtain feature vectors required for the distributed learning process. The resulting features are then assigned to several IoMT clients while the healthcare data stay decentralized.

The management of each IoMT client is solely responsible for the respective clinical records through the local validation of data, standardizing features, and client-wise partitioning of data before training the models. The processed data stay within the respective healthcare institution and undergo local processing to obtain a representative set of features for learning. The local processing ensures consistency of data among the participating clients without leaking any patient information beforehand.

In the fog computing layer, each client builds a local decision-tree model and learns the features of decision paths from the respective healthcare dataset. Instead of sharing all the patients' data, only the learned knowledge is passed on to the federated server using a secure knowledge transfer scheme. In the federated server layer, the aggregated knowledge is used for creating a complete feature representation.

The aggregated global knowledge is further used in conjunction with the representations of features specific to each client using a global-local feature fusion method to provide generalization and preserve the properties of local data at the same time. Afterward, the enhanced feature representation is employed in the distributed clinical decision analytics module for the generation of healthcare predictions. The predictions are finally sent to the clinical decision support system for performing disease assessment.

3.2 Dataset Description

Effective clinical decision-making in IoMT environments requires access to detailed and representative healthcare data. In order to implement the federated learning approach that was suggested in this study, the Medical Information Mart for Intensive Care III (MIMIC-III) [13] database is used as the main data source. It consists of anonymous medical records of ICU patients, covering such aspects as patient demographics, physiological parameters, lab tests, diagnoses, treatments, and medicines. Due to its variety of clinical parameters and large number of patient records, the database is highly suitable for creating secure healthcare analytics.

The Medical Information Mart for Intensive Care III (MIMIC-III) database serves as the main source of data for this research. While the database includes more than 40,000 de-identified electronic medical records of intensive care patients, a subset of 2,000 medical records with all physiological features is chosen following pre-processing and quality assessment. The data includes demographic data, vital signs, laboratory tests, and diagnoses, which act as representative clinical data for distributed learning. The chosen data are split among different IoMT client simulators using 80:20 training-test ratio to mimic decentralized healthcare organizations without any privacy breaches during federated learning.

The selection of clinically relevant physiological features plays a major role when developing reliable prediction models. In this regard, cardiovascular, respiratory, metabolic, and demographic features are extracted from the MIMIC-III database as an indicator of each patient's physiological state. Features used and their units of measure, as well as their clinical relevance, are listed in Table 1. Extracted records are then partitioned into several partitions that belong to different clients and are distributed across geographic locations to resemble different healthcare organizations working together on model development while maintaining the patient data local throughout the entire federated learning process.

Table 1. Selected clinical parameters used for model development

Parameter	Unit	Clinical Significance
Heart Rate	bpm	Cardiac function assessment
Systolic Blood Pressure	mmHg	Cardiovascular status
Diastolic Blood Pressure	mmHg	Vascular resistance
Respiratory Rate	breaths/min	Respiratory function
Body Temperature	°C	Infection and metabolic activity
Oxygen Saturation	%	Blood oxygenation level
Blood Glucose	mg/dL	Metabolic regulation
Age	Years	Demographic risk factor
Gender	Male/Female	Demographic characteristic

3.3 Federated Knowledge Transfer Framework

Privacy-aware collaborative learning demands an efficient way to exchange the knowledge of models without transferring patient data records. The proposed federated knowledge transfer framework is used by the distributed IoMT clients to construct a global model together, while maintaining the data at each respective healthcare institution. Figure 2 illustrates the stages of the proposed framework including local decision tree learning, decision path feature extraction, federated knowledge transfer, global feature aggregation, and global-local feature fusion. The entire learning process is coordinated by a federated server, which aggregates the knowledge features sent from clients without accessing clinical data.

Local learning is conducted independently at each IoMT client with the clinical data assigned to that client. At first, the pre-processed clinical data are employed to learn an interpretable decision-tree model at the fog computing layer. Instead of transmitting the full model or clinical records, only the discriminative decision-path features are selected to represent the locally learned patterns of interest. The learned discriminative features not only save communication cost but also retain clinical information for model collaboration.

Feature level collaboration allows efficient knowledge exchange in heterogeneous healthcare environment. Decision-path features extracted from all clients are safely transferred to the federated server, where the process of weighted aggregation is performed to consolidate the distributed knowledge in one global feature representation. The aggregated feature representation is then merged with the local feature representation in order to enhance model generalizability while retaining the learning properties of each individual client. The resultant feature space is used by the distributed clinical decision analytics component to produce interpretable healthcare predictions for IoMT purposes.

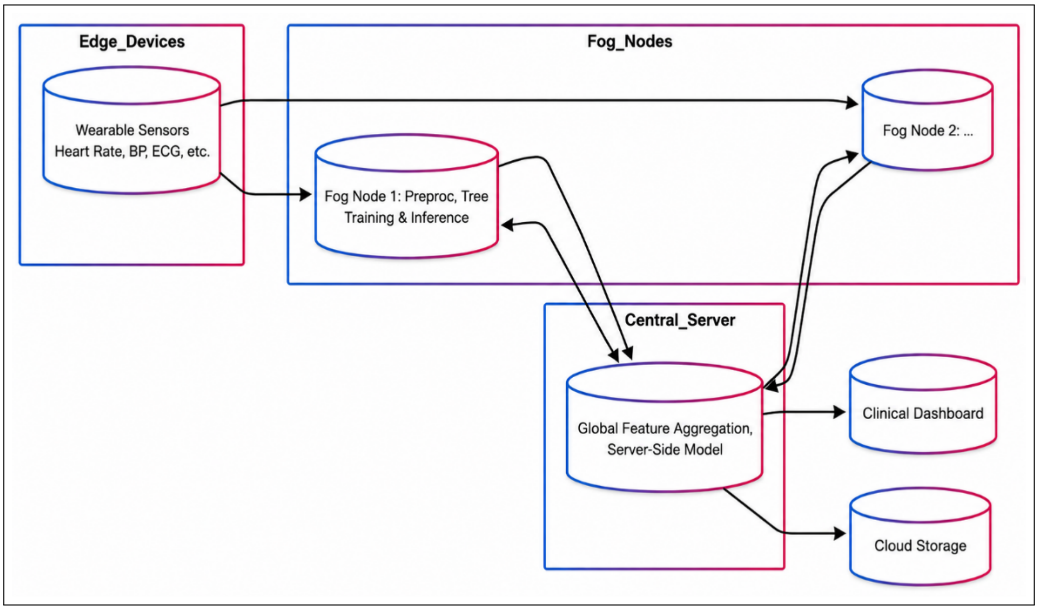

Figure 2. Architecture of the proposed federated knowledge transfer framework

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Algorithm 1: Federated knowledge transfer procedure

Input: Distributed client datasets D= {D, D2 ... Dn}

Output: Global feature representation FG

Refined feature representation FF

1. Initialize local clients and federated server
2. Distribute client datasets to IoMT nodes
3. for each client Ci do
4. Train local decision tree Ti
5. Extract decision-path feature Fi
6. Transmit Fi to federated server
7. end for
8. Aggregate all received features
9. Construct global feature representation FG
10. Fuse FG with local feature FL

11. Generate refined feature FF
12. Perform distributed clinical prediction
13. Return prediction results

3.3.1 Global Feature Aggregation

The federated server combines the feature representations from all the IoMT clients to form an overall global knowledge representation. The above weighting is represented as

$$F_G = \sum_{i=1}^{N} w_i F_i \tag{1}$$

where,

- F_G denotes the aggregated global feature representation,
- F_i represents the feature representation extracted from the i th client,
- w_i is the aggregation weight satisfying

$$\sum_{i=1}^{N} w_i = 1$$

- N denotes the total number of participating clients.

The weight aggregation technique makes sure that the knowledge generated by various healthcare facilities is combined together into a single global representation.

3.3.2 Global–Local Feature Fusion

After performing federated aggregation, the global feature representation is fused with local features in order to preserve both generalized knowledge and knowledge specific to the clients. The feature fusion is formulated as

$$F_F = \alpha F_G + (1 - \alpha) F_L \tag{2}$$

where,

- F_F denotes the refined feature representation,

- F_G is the aggregated global feature representation,
- F_L is the local feature representation,
- α is the fusion coefficient ($0 \leq \alpha \leq 1$).

This adaptive fusion approach enhances the robustness of the distributed learning process with the proper balance between the generalized knowledge and the clinical knowledge obtained locally.

The enhanced feature representation which has been developed based on the proposed federated knowledge transfer framework acts as an input for the distributed clinical decision analytics engine, where the privacy-preserving decision trees are generated.

3.4 Distributed Clinical Decision Analytics

Precise and interpretable predictions play a key role in making healthcare decisions within IoMT environments. The enhanced feature set after global-local feature fusion is then provided to the distributed clinical decision analytics module. In this module, the optimized decision tree model enables patient health assessment and disease prediction. This is possible due to the interpretable nature of the decision tree that provides explicit rules corresponding to each decision.

Distributed inference is used for scaling purposes, while maintaining the computational latency low in all the healthcare organizations. Inferences about patients' clinical conditions are made locally available on the IoMT clients through the new feature representation, without the need to upload personal information to a central server. Fog computing ensures fast inference as it decreases the communication time and enables real-time analysis of the continuously collected physiological data.

The interpretable prediction outcomes are provided at last to the clinical decision support system, which helps to monitor healthcare and support patients medically. The obtained results help clinicians with the patients' health diagnostics to determine the risks and develop treatment strategies without violating the conditions of distributed healthcare security.

4. Results and Discussion

The experimental analysis measure the performance of the federated knowledge transfer framework. The proposed federated knowledge transfer framework is analyzed with the help of MIMIC-III dataset to measure its performance in terms of prediction, communication, computational performance, and interpretation in distributed IoMT healthcare environment. The analysis performed on the proposed federated knowledge transfer framework measures the effect of knowledge transfer at the feature level as well as the fusion of global and local features to improve collaborative model learning without compromising the privacy of patients' data. The results achieved from the analysis prove the practicality of the proposed framework.

4.1 Implementation and Experimental Configuration

In the proposed model, the framework is implemented in Python with Scikit-learn and machine learning libraries. The experiment is carried out on a workstation, whose configuration is an Intel Core i7 processor along with 16GB RAM. The MIMIC-III dataset is distributed among various simulated IoMT clients, which is intended to reflect various distributed healthcare organizations, whereas the fog computing layer takes care of federated communication and knowledge accumulation. The implementation settings adopted for experimental evaluation are summarized in Table 2.

Table 2. Experimental configuration

Parameter	Specification
Dataset	MIMIC-III
Processor	Intel Core^{TM} i7 Processor
Memory (RAM)	16 GB
GPU	NVIDIA GeForce RTX 3060 (12 GB)
Operating System	Windows 11 (64-bit)
Programming Environment	Python 3.11 with Scikit-learn
Training–Testing Split	80:20

4.2 Classification Performance Evaluation

The classification performance ensure that the provided clinical decision support is valid in the distributed IoMT healthcare systems. The performance of the proposed federated knowledge transfer framework will be analyzed based on the MIMIC-III dataset with regard to the framework's performance in predicting clinical outcome in a decentralized setting. The analysis will consider various metrics in measuring the predictive performance of the decision tree model, such as accuracy, precision, recall, and F1-score.

Prediction accuracy is first analyzed using the confusion matrix, where the classification of the correct and incorrect cases is presented. As can be seen from Figure 3, the proposed method recognizes 963 positive and 972 negative clinical data, whereas there are 37 false negatives and 28 false positives in total. The balanced distribution of classification results proves that the proposed federated knowledge transfer process is able to extract clinically meaningful information from distributed data.

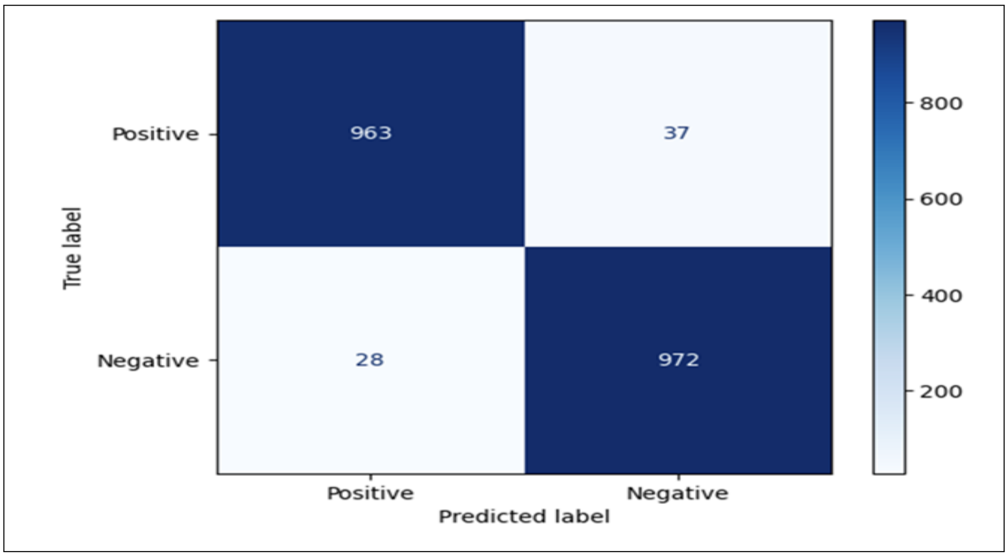

Figure 3. Confusion matrix of the proposed federated knowledge transfer framework

The performance of the proposed approach in terms of its discriminative power is demonstrated using the Receiver Operating Characteristic (ROC) curve. As Figure 4 shown, the analysis of the ROC reveals a high level of separability among the classes, thus proving the efficacy of the feature representations used and of the proposed global-local features fusion method.

Quantitative evaluation of the proposed framework is summarized in Table 3. The obtained performance metrics indicate that the integration of feature-level federated knowledge transfer with interpretable decision-tree analytics enables accurate and consistent clinical prediction while preserving data privacy. These results demonstrate the suitability of the proposed framework for distributed IoMT healthcare

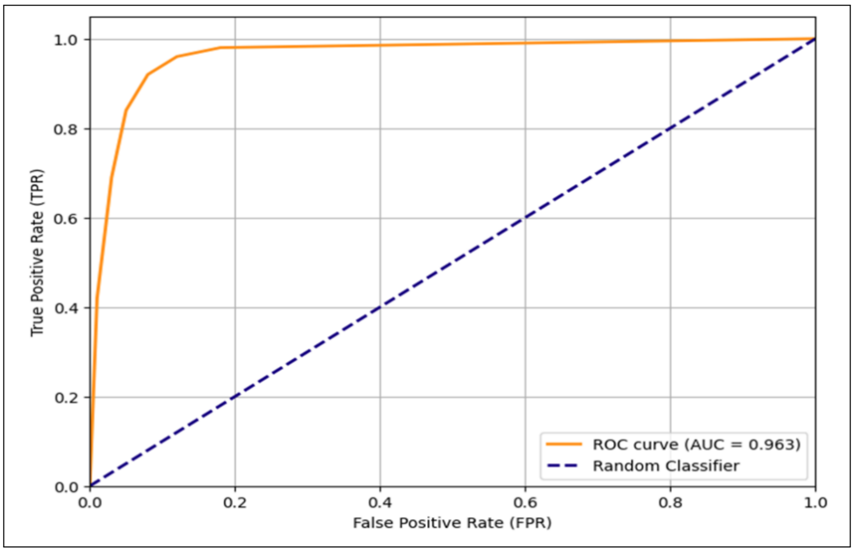

Figure 4. ROC analysis of the federated clinical prediction model

Table 3. Performance evaluation of the proposed framework

Metric	Value (%)
Accuracy	92.3
Precision	91.8
Recall	92.6
F1-Score	92.2

4.3 Discussion

The experimental results represent the proposed federated knowledge transfer framework solves the problems of privacy-preserving clinical prediction in IoMT systems successfully. The combination of feature-level knowledge transfer with interpretable decision tree-based analytics allows for achieving high performance of classification while providing explainability of the decision process. Conventional centralized methods, the framework allows for collaborative learning of models without the need for exchanging confidential patient information, thus ensuring confidentiality of the information among the healthcare facilities involved. Moreover, the nature of the hierarchical federated architecture used, distributed learning is possible without losing predictability of the model. Therefore, the suggested framework would be suitable for use in healthcare settings in real time.

5. Conclusion and Future Work

This research study proposed a federated knowledge transfer and interpretable decision-tree analytics system to address the problem of clinical prediction in an IoMT healthcare environment that maintains patients' privacy. Through the combination of feature-level federated knowledge transfer and interpretable decision tree learning, this framework allows collaborative learning from distributed healthcare organizations without sharing the patient information. The inclusion of the global-local feature fusion will increase the effectiveness of the knowledge representation while keeping the properties of each client. The proposed architecture effectively resolves the problems of data privacy, distributed learning, and model explainability to be used in practical IoMT applications in healthcare. Future research is geared towards developing the framework to support heterogeneous multi-modal healthcare data, adopt an adaptive federated learning approach to enhance learning efficiency, and incorporate techniques of explainable artificial intelligence. Moreover, future efforts will be made to evaluate the framework using various real-time IoMT data and multiple institutions' healthcare environments.

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