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RESEARCH ARTICLE

Breast Cancer Prediction Using Shapely and Game Theory in Federated Learning Environment

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ABSTRACT Breast cancer is a critical health issue affecting the well-being of women. Breast cancer is one of the most common causes of the increase in the mortality rate of women around the world. Early detection of breast cancer can, to some extent, decrease the number of deaths caused and also improve treatment outcomes and patient survival rates. Traditional Machine learning (ML) and Deep learning (DL) approaches have proven to be more successful in predicting breast cancer. In terms of privacy and early detection, Federated Learning (FL), a decentralized ML approach, offers a promising solution for training predictive models on distributed healthcare data while ensuring privacy and security. This paper proposes a novel framework that combines the benefits of integrating Shapley values and game theory concepts with FL for breast cancer prediction. The framework uses Shapley values for feature selection from 30 features of the Wisconsin Diagnostic Breast Cancer (WDBC) dataset from University of California Irvine machine learning repository (UCI ML). The framework also addresses the issue of poor-performing clients by introducing a payoff mechanism based on individual client accuracy. Clients with higher accuracy are given greater influence in the model aggregation process, encouraging client competition and improving the overall model performance. Our framework proves to be promising by achieving a prediction accuracy of 94.73% in the FL environment. The proposed approach provides a privacy-preserving solution for breast cancer prediction in an FL environment, by combining Shapley values and game theory. The results of this study can help in the development of more accurate and robust breast cancer prediction models, contributing to improved patient outcomes and healthcare decision-making.

INDEX TERMS Federated learning, machine learning, Shapley values, game theory, incentive mechanism.

I. INTRODUCTION

Breast cancer is the most prevalent cancer among women worldwide and continues to be a major factor in cancer deaths in women. Reduced quality of life and higher rates of anxiety and depression are linked to breast cancer [1]. It accounts for around 685,000 deaths till 2020, out of the total 2.3 million cases detected [2]. Breast cancer is a form of metastatic cancer that frequently spreads to distant organs such as the bone, liver, lung, and brain [3]. Figure 1 depicts the total number of cancer deaths across all ages and sexes. The figure also indicates that breast cancer takes fourth place in the number of deaths caused around the world. Early detection of breast cancer is crucial for successful treatment and improved outcomes. Several methods are available for the early detection of breast cancer, including self-examinations, clinical breast examinations, mammography, and other imaging techniques. Many investigations are using ML and artificial intelligence (AI) to analyze massive volumes of data and create more precise breast cancer prediction models [4]. These models can include a wide range of variables and increase the accuracy of risk assessment. There has been an increased interest in applying AI in the early detection of breast cancer. ML is one such technology that has enhanced and added techniques for predicting breast cancer [6], [7]. ML has transformed several domains, including healthcare,

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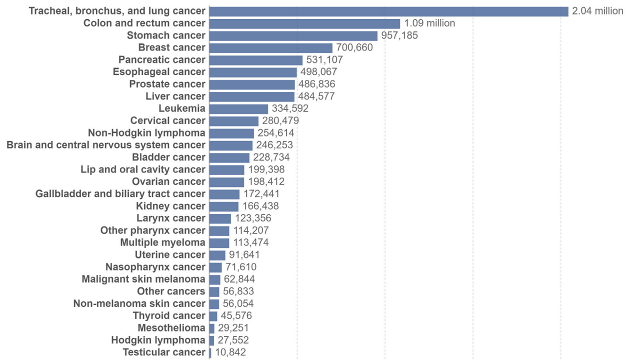

FIGURE 1. Total annual number of deaths from cancers across all ages and both sexes, broken down by cancer type [5].

by facilitating the development of appropriate prediction models [8]. Several ML algorithms like Gated Recurrent Unit Support Vector Machine (GRU-SVM) [9], Linear Regression, Nearest Neighbour Search, Softmax Regression, and Support Vector Machine (SVM) have been successfully deployed in predicting breast cancer [10]. Also, several DL techniques [11] like Feed forward neural network, Deep neural network, and Multilayer Perceptron (MLP), [12] were successfully implemented to predict breast cancer [13].

However, the success of these ML and DL models majorly depends on the availability of large and different datasets for training purposes [14]. In scenarios where sensitive and private data is involved, like medical records or personal data, managing data privacy is very difficult and it is a topic of concern.

FL has emerged as a revolutionary solution for addressing data privacy issues. It allows different clients to collaborate and train the shared model by retaining data at their own location [15], [16]. Though FL proves to be a promising approach for predicting breast cancer [17], it has several significant challenges like data heterogeneity, communication overhead, resource limitations, model heterogeneity, lack of centralized control, security hazards, and difficulties with convergence speed [18].

To address these challenges, this research integrates the concepts of Shapley values and game theory. The Shapley value is one of the concepts from cooperative game theory [19]. Meanwhile, game theory [20], [21] is a branch of mathematics and economics that deals with the way for analyzing and predicting how entities make decisions when their outcomes are dependent on the actions of other entities [22]. This study harnesses Shapley and game theory concepts, where Shapley values are used for feature selection in WBCD and game theory is used for client selection during model aggregation. Shapley values provide a unique feature of interpreting the contribution of each feature in ML models [23]. Game theory is strategically chosen to enhance FL's privacy-preserving aspects. In a collaborative environment where data is distributed across multiple clients, game theory [24] helps incentivize participation and model contribution while addressing privacy concerns associated with centralized approaches. In the context of breast cancer prediction, where interpretability is crucial for clinical acceptance, Shapley's values are more prominent [25]. Similarly, in a collaborative healthcare scenario, where data privacy is paramount, game theory provides a strategic framework to incentivize collaboration without compromising individual privacy. By combining Shapley values and game theory, our approach offers a tailored solution to the challenges presented by breast cancer prediction in an FL environment. The combination of interpretability, privacy preservation, and collaborative optimization positions Shapley values and game theory as the preferred methodologies for achieving meaningful insights while addressing the complexities of healthcare data. The proposed work aims to boost the efficiency of FL in breast cancer prediction, emphasizing both accuracy and data privacy. Figure 2 depicts the framework of FL.

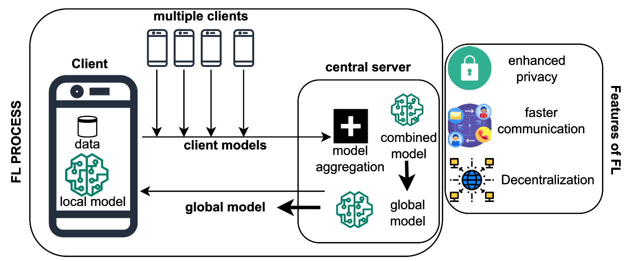

FIGURE 2. Federated learning process.

A. KEY CONTRIBUTIONS

The main contributions of this research are as follows:

- We present details about the implementation of FL and its drawbacks in breast cancer prediction and how Shapley and game theory help in enhancing the performance of FL.
- We propose a methodology that helps in developing a more robust, efficient, and privacy-preserving model that encourages active participation and cooperation among nodes leading to better-performing model quality.

B. PAPER ORGANIZATION

The rest of the paper is organized as follows. Section II provides an overview of related work in FL, Shapley, and game theory applications in healthcare. Section III presents the methodology, describing the feature selection using Shapley values and the game theory-based FL algorithm. Section IV presents the experimental setup, discusses the results obtained, summarizes the findings, and limitations of this research. Section V describes implementation Challenges in Real-World Clinical Settings. Section VI presents the theoretical and business implications of the proposed model. Finally, Section VII gives the conclusion and future directions pertaining to the research.

C. RESEARCH PROBLEM

The primary challenge is to develop a decentralized, game-theoretic FL system for training a binary classification model on a breast cancer dataset. This system should allow multiple clients, each with their data, to train local models. These local models are then aggregated on a server to form a global model. Additionally, the system should employ Shapley additive explanations (SHAP) values to analyze the importance of features from the dataset. The key issues to address include preserving privacy, improving interpretability, and increasing accuracy in breast cancer prediction.

II. BACKGROUND AND RELATED WORK

This research paper focuses on the application of FL, Shapley values, and game theory for breast cancer prediction. The following literature survey provides an overview of related studies and their contributions in the areas of breast cancer prediction, FL, Shapley values, and game theory.

A. BREAST CANCER PREDICTION

Breast cancer is among the leading causes of cancer-related deaths worldwide [26]. Early detection and accurate prediction can lead to timely intervention [27], improving patient outcomes.

The authors in [28] focused on designing a breast cancer prediction system. The authors use the WBCD dataset for experimentation. The potential of the proposed model for accurately predicting breast cancer is evaluated by applying several classification techniques like Logistic Regression (LR), SVM, and K-Nearest Neighbour(KNN). This work achieves a maximum classification accuracy of 99.28% with KNN as a classifier.

The authors in [29] aimed to predict breast cancer using different ML approaches applying demographic, laboratory, and mammographic data. Algorithms like Random Forest(RF), MLP, gradient-boosting trees, and genetic algorithms were used in this study. RF presented higher performance compared to other techniques (accuracy 80%, sensitivity 95%, specificity 80%, and the area under the curve (AUC) 0.56).

The authors in [30] applied five ML algorithms namely SVM, RF, LR, Decision tree (C4.5), and KNN on the WBCD. The objective of this work is to predict breast cancer using ML algorithms and to find out which is the most effective algorithm. According to the results obtained in this work, SVM outperformed all other classifiers and achieved the highest accuracy (97.2%).

The authors in [31] aim to assess the effectiveness of different basic and ensemble ML algorithms in predicting breast cancer. A dataset of 1503 suspected breast cancer cases was extracted from a hospital-based electronic database and used for evaluation. Wrapper-J48, wrapper-SVM, wrapper-Naive Bayes(NB), LR, and correlation-based feature selection methods were used in this work to identify the important risk factors. The performance of basic ML algorithms like NB, Bayesian network, RF, MLP, SVM, C4.5, eXtreme Gradient Boosting (XGBoost), decision tree, and two ensemble algorithms, including Confidence weighted voting and voting techniques were compared in this work to predict breast cancer before and after performing feature selection. They evaluate the performance of these algorithms using relevant metrics and techniques to determine their accuracy and reliability in detecting breast cancer cases. According to the results in the above work, RF presented the best performance before and after performing feature selection with AUC of 0.799 and 0.798.

The authors in [32] contribute to the understanding of ML techniques like SVM, KNN, RF, artificial neural networks (ANNs), and LR for breast cancer prediction. Through a comparative study, the authors offer valuable insights into the performance and effectiveness of different algorithms. The results of this work reveal that the ANNs obtained the highest accuracy of 98.57%.

The above survey reveals that though several studies highlighted the effectiveness of various ML algorithms for breast cancer prediction, there remains a lack of focus on the integration of decentralized data sources, preserving patient privacy, and interpretability of these algorithms.

B. FEDERATED LEARNING

FL is the new dawn of AI. The increase in Internet of Things (IoT) devices and the increasing importance of data privacy and security led to the exploration of decentralized learning methods. In 2016, Google researchers introduced the concept of FL as a solution to these challenges [40], [41], [42]. FL allows distributed learning without the transferring of raw data between the client and server thereby improving the privacy of the data [43], [44], [45]. FL can use large amounts of data on remote devices [46], [47]. It is majorly implemented in places where privacy is very important [48], especially in the medical field [49]. Table 1 is the summary of the existing works.

The following steps brief the working of FL:

1) Initialization: A central server creates a global model depending on the dataset available.
2) This global model is then shared with participating devices or clients.
3) The models are trained on clients' data locally.
4) The trained models are sent back to the server.
5) The models sent from each client are aggregated on the server side using aggregation algorithms.
6) The server sends the new updated global model to the client and this process repeats till the optimal model is created.

The authors in [33] aims to provide an overview of FL, a distributed ML approach. This survey covers various topics of FL, which include its definition, principles, algorithms, applications, and respective challenges. The study dives into the basic concepts of FL, such as FL optimization, and several privacy-preserving mechanisms. The advantages and

TABLE 1. Summary of the literature review.

Ref. no.	Key Concept	Key Findings	Open Issues
[28]	Breast cancer prediction system; WBCD; LR, SVM, KNN	Highlighted effectiveness of KNN as a classifier in breast cancer prediction	No privacy protection measures
[31]	Effectiveness of ML algorithms; Hospital-based electronic database; NB, RF	RF showed the best performance	No privacy protection measures, computational cost, and time complexity calculation
[32]	ML techniques for breast cancer prediction; SVM, KNN, RF, ANNs, LR	ANNs obtained the highest accuracy	Lack of privacy protection measures
[33]	Overview of FL	Introduction to principles, algorithms, and challenges of FL	Need more explanation of FL in healthcare
[34]	Security in FL in healthcare	Blockchain-based FL system to protect against poisoning attacks	The computation cost is expensive
[35]	Federated transfer learning in healthcare; Wearable devices	"FedHealth" approach for accurate healthcare recommendations	The work can be expanded for other datasets with more evaluation metrics
[36]	Shapley values for feature selection	Advantages and challenges of Shapley values	Less exploration on the medical datasets
[37]	Shapley values in ML	Importance of Shapley values in ML	Less exploration on the medical datasets
[38]	Game theory in cloud computing	Game-theoretic method for cyber-threat information sharing	Scope of game theory for healthcare sector less explored
[39]	FL and Shapley value	Client selection in FL with Shapley value	Number of clients used in implementation is minimum

disadvantages of FL and its applications in various domains are also discussed in this paper.

The authors in [18] offer a comprehensive overview of FL, discussing the challenges, methods, and future directions. It serves as a valuable resource for researchers, practitioners, and policymakers interested in understanding and advancing FL techniques and applications.

The authors in [50] present the high-level design of FL, outlining the architectural components and their interactions. This work also highlights the key challenges encountered during the development process and provides solutions to address these challenges.

The authors in [34] focus on enhancing the security and privacy of FL in healthcare systems, which are currently susceptible to adversarial attacks. A blockchain-based FL system, combined with Secure Multi-Party Computation is introduced in this work in order to protect against poisoning attacks. The local models from clients are scrutinized through an encrypted inference process. The models that are poisoned are identified and removed. and after verification, the local models are aggregated on a blockchain node.

The authors in [35] introduce "FedHealth", a novel federated transfer learning approach that is designed for wearable healthcare. This framework addresses two primary challenges, lack of personalization in models trained solely on the cloud and the difficulty in aggregating isolated user data without breaching privacy and security. Through the combination of FL and TL, the FedHealth approach ensures accurate and personalized healthcare recommendations from wearable devices. The efficiency of the approach was proved through wearable activity recognition tests and a Parkinson's disease diagnosis application.

The studies in [18], [33], [34], [35], [50] are relevant to our work as they also use FL, but the proposed approach enhances FL performance by integrating Shapley values for feature selection and a payoff mechanism for model aggregation. The proposed approach addresses the limitations of the blockchain-based FL system in [34] and the "FedHealth" approach in [35] by integrating Shapley values and a payoff mechanism. The majority of the mentioned works emphasized boosting the performance and privacy of FL. However, game theory has been used less to improve the performance of global models. The proposed approach uses FL, Shapley values, and game theory for breast cancer prediction improving model performance and ensuring data privacy.

TABLE 2. Comparative analysis of studies in Sections II-B, II-C, and II-D.

Section	Study	Description/Key Findings	Accuracy	Privacy	Security
2.2	[21]	Comprehensive overview of FL	-	Emphasized	Emphasized
	[38]	Challenges, methods of FL	-	-	-
	[39]	High-level design of FL	-	-	-
	[22]	Blockchain-based FL system	-	High	High
	[23]	FL and TL for wearables	High	High	-
2.3	[24]	Feature selection with Shapley	-	-	-
	[25]	Shapley values in ML	-	-	-
	[41]	Hybrid ReliefF & Shapley	Over 80%	-	-
2.4	[26]	Cyber-threat sharing in cloud	-	-	Enhanced
	[45]	Game-theoretical FL setup	Over 90%	High	-

C. SHAPLEY VALUES

Shapley (1953) introduced Shapley values, a cooperative game theory concept, to quantify the contribution of each feature in a prediction model. It provides insights into feature importance and helps interpret the model's decision-making process [51].

When referring to the survey related to Shapley values, the authors in [36] use Shapley values for feature selection. The theoretical background and methodology of Shapley values are presented in this work. The advantages of Shapley like interpretation ability and fairness are discussed in this work along with the challenges and drawbacks.

The authors in [37] focus on the Shapley value in the context of ML. In ML, Shapley values are needed to measure the importance of the individual features in the predictive model. Several practical aspects of Shapley values like computational complexity, approximation methods, and potential applications in different ML tasks are also addressed.

The authors in [52] introduce a feature selection approach that uses a filter-wrapper technique which is a combination of ReliefF and Shapley Value. The proposed method using ReliefF and Shapley value was used to select the most prominent features, which were later applied in the classifiers; SVM, RF, and NB. The efficiency of the dataset is tested on five different medical datasets from the UCI repository namely the WBCD dataset, Parkinson's dataset, heart disease, statlog, and hepatitis datasets. The overall accuracy for all models exceeded 80%. Though Shapley values are considered to be important in understanding feature importance in models, their implementation in healthcare datasets like breast cancer datasets along with FL is not thoroughly explored. This is due to the following reasons:

1) Shapley values can be computationally expensive to compute, particularly for large datasets.
2) The interpretation of Shapley values can be complex, especially for non-linear models.
3) There is a lack of standardized methods for implementing Shapley values in FL.

D. GAME THEORY

Osborne and Rubinstein (1994) introduced the concept of game theory, which analyzes strategic interactions among multiple agents or players. It provides a mathematical framework to model and understand decision-making in competitive scenarios [53], [54], [55]. Table 2 is the comparative analysis of studies in sections II-B, II-C, and II-D.

The authors in [38] focus on the application of game theory to address the problem of cyber-threat information sharing in cloud computing technology. The main contribution of the article is the development of a game-theoretic method that incentivizes information sharing by aligning the interests of the entities involved. The authors discuss the formulation of the game model, including the definition of strategies, payoffs, and the decision-making process for each entity.

The authors in [56] introduced a game-theoretical setup where multiple stakeholders are optimized for their interests while privacy is ensured using FL. The approach called a non-interactive verifiable privacy-preserving FL aggregation scheme is explained in the work. The approach is tested on the COVID dataset and achieves good accuracy results of more than 90%. The implementation of game theory in cloud computing and other sectors is evident, but its application and implementation to healthcare models, especially in breast cancer prediction are less explored.

E. FEDERATED LEARNING WITH SHAPLEY VALUES AND GAME THEORY

The authors in [57] proposed a federated Shapley value that encapsulates the favorable properties of Shapley value without incurring extra communication cost and is also able to capture the effect of participation order on data value.

TABLE 3. Synthesis of the literature review.

Section	Key Findings	Relevance to Current Work
Breast Cancer Prediction	Several ML algorithms applied. Different data sets were used.	Concentrated on evaluation metrics but the need for decentralized data and interpretability was noted.
Federated Learning	Introduction due to IoT and privacy. Principles, algorithms, applications, challenges, and privacy mechanisms of FL are discussed.	Preservation of data privacy, especially in healthcare.
Shapley Values	Measures contribution of features.	Provides interpretability and fairness in ML.
Game Theory	Addresses decision-making in competitive scenarios.	Application in optimizing processes, such as in cloud computing.
FL with Shapley Values and Game Theory	Combination for evaluating data provider contributions in FL and client selection.	Achieving data privacy, interpretability, fairness, and accurate predictions.

The authors in [39] resolved the problems about the Federated Relevant Client Selection (FRCS) like selecting the appropriate client and detecting the client that has the relevant data. A principled approach is developed when FL, Shapley value, and cooperative game theory are used together.

The authors in [58] proposed a contribution index, a new Shapley value-based metric for evaluating the contribution of each data provider for the joint model trained by FL. Directly calculating the contribution index takes time, though, because several joint models with various combinations of data sets must be trained and assessed. Two gradient-based approaches are suggested to address this issue.

The authors in [59] propose an energy-efficient FL scheme based on two-stage game theories. The payoff function incorporates both the energy expenditure and the individual vehicle's contribution ensuring equal remuneration using Shapley value through a collaborative game. Later, for optimized federated worker selection, a hedonic game is used. The results show that the scheme improves energy efficiency by 68.8%.

F. RESEARCH GAP

The current literature on breast cancer prediction has not explored the integration of decentralized data sources, which highlights the need for leveraging FL in order to ensure data privacy in healthcare. Though the potential of Shapley values in understanding model features is identified, their application with FL remains less explored. Similarly, the use of game theory in healthcare models, particularly in breast cancer prediction, is much limited. A significant gap exists in the convergence of FL, Shapley values, and game theory for enhancing accuracy, fairness, interpretability, and data privacy in the domain of breast cancer prediction.

III. METHODOLOGY

In this section, we outline the methodology of our research, which focuses on the integration of Shapley, game theory, and FL for breast cancer classification. We describe the dataset used, use of shapley in feature selection, and the game-theoretic FL framework.

TABLE 4. Description of features in the dataset.

S.No.	Column Name	Datatype
1	radius(mean)	float64
2	texture(mean)	float64
3	texture(worst)	float64
4	texture(error)	float64
5	perimeter(mean)	float64
6	perimeter(worst)	float64
7	perimeter(error)	float64
8	area(mean)	float64
9	area(worst)	float64
10	area(error)	float64
11	smoothness(mean)	float64
12	smoothness(worst)	float64
13	smoothness(error)	float64
14	compactness(mean)	float64
15	compactness(worst)	float64
16	compactness(error)	float64
17	concavity(mean)	float64
18	concavity(worst)	float64
19	concavity(error)	float64
20	concave points(mean)	float64
21	concave points(worst)	float64
22	concave points(error)	float64
23	symmetry(mean)	float64
24	symmetry(worst)	float64
25	symmetry(error)	float64
26	fractal dimension(mean)	float64
27	fractal dimension(worst)	float64
28	fractal dimension(error)	float64
29	radius(worst)	float64
30	radius(error)	float64
31	target	int64

A. DATASET

Breast Cancer dataset which is used in the proposed work is available publicly for breast cancer classification tasks [60]. It contains 30 features that are extracted from the digital images of breast mass, such as texture, radius, and area using the Fine Needle Aspiration (FNA) method. Table 4 describes the features and their data types. The dataset also contains the corresponding binary label that indicates the presence of malignant or benign tumors [61].

The FNA method is used as a diagnostic procedure in which a small sample of cells is collected from a breast mass using a thin needle. The sample is then examined under a microscope to detect any abnormalities or signs of cancer [62]. To analyze the sample, features are computed from a digitized image of FNA. These features describe the characteristics of the cell nuclei present in the image.

There are about 569 samples of which 212 samples belong to the Malignant class and the remaining 357 belong to the Benign class.

Mean, standard error and worst values were computed for each image. Table 5 explains the basic details of the dataset. There are 10 features for each of these categories, and a total of 30 features were computed for each image [63].

B. SHAPLEY VALUES FOR FEATURE SELECTION

The proposed framework uses Shapely values for feature selection. In this study, we used the SHAP library to compute the SHAP values for each feature in our dataset. The objective is to extract these SHAP values and analyze if they accurately reflect the relationships and contributions of each feature to the model's predictions. SHAP values are designed to distribute the contribution of each feature fairly to the overall prediction.

Data and Model: We used the breast cancer dataset provided by the load_breast_cancer function from *sklearn. datasets*. We choose the gradient boosting framework, XGBoost, which has been shown to be effective in both classification and regression tasks. The XGBoost model is trained on the entire dataset.

Computing SHAP Values: On training the model, we initialized an explainer object using the *shap.Explainer()* method and then computed the SHAP values for our dataset. The output, *shap_values*, gives the contribution of each feature to every prediction in comparison to the mean prediction for the dataset. The Shapley value for each feature is computed using the Equation (1).

$$\phi_j(\hat{f}) = \sum_{S \subseteq \{1,\ldots,p\} \setminus \{j\}} \frac{|S|!(p-|S|-1)!}{p!}[\text{val}(S \cup \{j\}) - \text{val}(S)] \tag{1}$$

where:

- $\phi_j(\hat{f})$ is the Shapley value of the j-th feature.
- S is a subset of the features used in the model.
- p is the number of features.
- $\text{val}(S)$ is the prediction for feature values in set S that are marginalized over features that are not included in set S.

Analysis of Feature Importance: To understand the overall importance of each feature, we averaged the absolute SHAP values over all samples. Features with higher mean absolute SHAP values have a greater impact on model output. We then ranked the features based on their importance and selected the top 10. For each feature, the mean absolute Shapley values are calculated using Equation (2).

$$\text{mean\_shap\_values} = \frac{1}{n}\sum_{i=1}^{n}|\text{shap\_values}[i]| \tag{2}$$

Equation (2) is detailed as follows:

- **mean_shap_values:** This represents the mean or average SHAP values for a given set of features.
- n**:** This denotes the number of instances in your dataset.
- **shap_values**$[i]$**:** This refers to the SHAP values for the i-th observation or instance.
- $|$**shap_values**$[i]|$**:** The absolute value is taken for each individual SHAP value.
- $\sum_{i=1}^{n}|$**shap_values**$[i]|$**:** This part of the equation calculates the sum of the absolute SHAP values across all observations.
- $\frac{1}{n}\sum_{i=1}^{n}|$**shap_values**$[i]|$**:** Finally, the sum is divided by the number of observations (n), obtaining the mean SHAP value.

Feature Selection: Based on the ranked features, we selected the top 10 features for further analysis. By focusing on the most influential features, we aim to build more interpretable models.

The top 10 features with the highest Shapley values are selected using Equation (3). The top 10 features with the highest Shapley values are identified and listed in Table 6. Table 6 gives names and the Shapley values of the top ten features.

$$\begin{aligned} &\text{top\_features} \\ &\quad = \text{feature\_importance['feature'].head(10).tolist()} \end{aligned} \tag{3}$$

Equation (3) can be explained as follows:

- **top_features:** This represents a list of the top 10 features based on their importance.
- **feature_importance['feature']:** This refers to the feature importance values for each feature in a dataset.
- **.head**(10)**:** The head(10) method is applied to select the top 10 features based on their importance.
- **.tolist**()**:** The tolist() method converts the selected top 10 features into a list.

TABLE 5. Dataset details.

Aspect	Details	
	Value	Description
Classes	2	Malignant and Benign
Samples per class	212-Malignant, 357-Benign	569 total samples
Feature dimensionality	30	mean, standard error, and worst values of features

A new data frame is now created with only the top 10 features that are selected based on the Shapley values. Figure 3 is the pictorial representation of the feature importance that is calculated using Shapley values.

1) COMPUTATIONAL COMPLEXITY ANALYSIS

Equation (1) demonstrates that computing the SHAP value for a given feature involves considering all possible subsets of features. This inherently suggests an exponential time

Algorithm 1 Shapley Feature Selection Using XG-Boost

1: Import necessary libraries: pandas, numpy, xgboost, shap, matplotlib
2: Load the breast cancer dataset into a pandas DataFrame (data) with features and target variable
3: Split the dataset into features (X) and target variable (y)
4: Train an XGBoost model (model) on the dataset
5: Use SHAP values to determine feature importance
6: Generate a summary plot of SHAP values
7: Save the summary plot to a PDF file
8: Extract mean SHAP values for each feature
9: Create a DataFrame with feature names and their mean SHAP values
10: Sort features by SHAP values in descending order
11: Print the top 10 features by SHAP values
12: Select the top 10 features and create a new DataFrame with only those features
13: Split the dataset into training and testing sets

TABLE 6. Shapley values of top 10 features.

Feature Name	Shapley Values
area error	1.034378
worst concave points	0.978121
worst area	0.964640
mean concave points	0.914735
worst concavity	0.819696
worst perimeter	0.772261
worst texture	0.767155
worst radius	0.585028
mean texture	0.494641
compactness error	0.409219

complexity, as the number of subsets grows exponentially with the number of features. Consequently, the feature selection method employed in our approach can become computationally impractical when dealing with a large number of features.

To address this issue, it is crucial to explore and implement optimization strategies. These may include approximation techniques such as sampling methods that estimate SHAP values without evaluating all subsets or leveraging parallel computation to distribute the computational load. Future work could focus on developing more efficient algorithms that retain the accuracy of SHAP values while reducing computational overhead.

2) JUSTIFICATION FOR USING SHAP VALUES

Despite the computational inefficiency of SHAP values, we chose them for feature selection due to their interpretability and transparency, consistent measure of feature importance, ability to handle feature interactions, robustness in FL environments, superior empirical performance, and feasibility with optimization techniques. These benefits

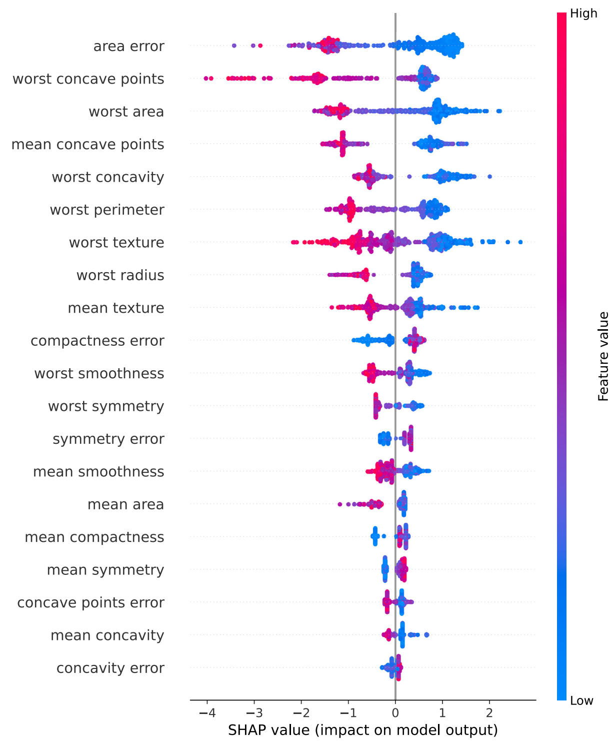

FIGURE 3. Feature selection using shapley values.

outweigh the computational cost, leading to a more effective and trustworthy breast cancer prediction model.

C. DATASET PARTITIONING

The dataset is split into training and testing sets using the train_test_split() function. Initially, the dataset is divided into a temporary training set and a testing set. By specifying a test_size parameter of 0.2 and setting a consistent random_state of 42, we ensured the following distribution:

- Testing Set: Approximately 20% of the total dataset, amounting to 114 samples.
- Temporary Training Set: The remaining 80%, consisting of 455 samples.

To fine-tune our model parameters and prevent overfitting, we further partitioned the temporary training set into a final training set and a validation set:

- Validation Set: This constituted 25% of the temporary training set, which is approximately 114 samples.
- Final Training Set: The residual 75% of the temporary set, resulting in around 341 samples.

In summary, the dataset is partitioned as follows:

- Training set: 60% (341 samples)
- Validation set: 20% (114 samples)
- Testing set: 20% (114 samples)

D. MULTI-LAYER PERCEPTRON

An MLP classifier is a type of feedforward ANN used for classification tasks. Figure 5 discusses the architecture of

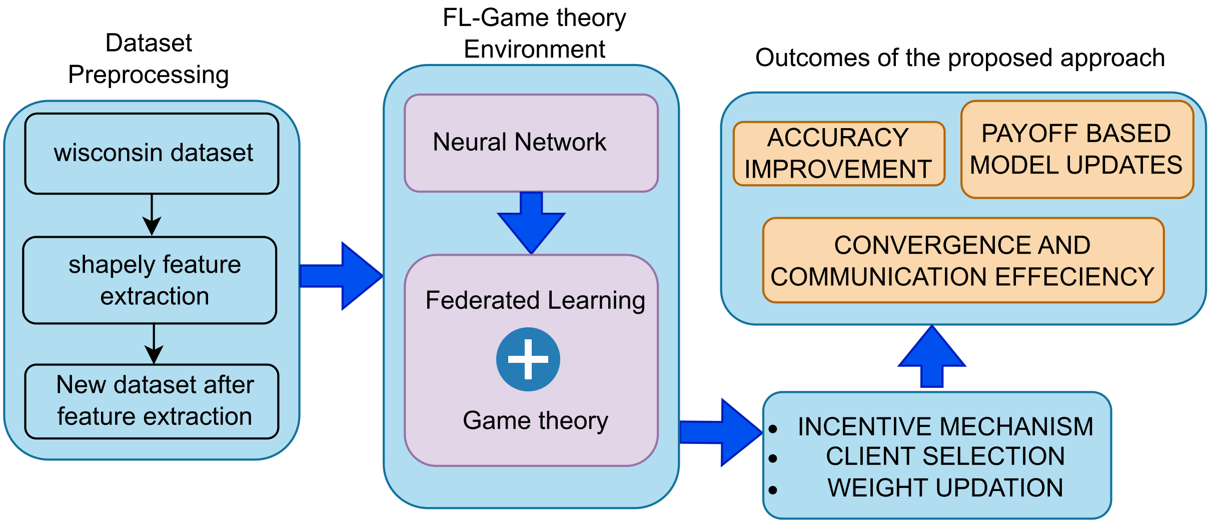

FIGURE 4. Block diagram of the proposed model.

TABLE 7. Configuration of the multilayer perceptron (MLP).

Layer	Configuration
Input Layer	Input Nodes
Hidden Layer 1	64 nodes with ReLU activation
Hidden Layer 2	32 nodes with ReLU activation
Output Layer	1 node with Sigmoid activation

the neural network model. The "multi-layer" refers to the network that consists of multiple layers of neurons between the input and the output layers [64]. In our experiment, two hidden layer MLP is used. Table 7 shows the layers of the MLP model. The following are the layers of MLP:

1) Input layer
2) Dense layer with 64 neurons and ReLU activation.
3) Dense layer with 32 neurons and ReLU activation.
4) Dense layer with 1 neuron and sigmoid activation.

E. GAME-THEORETIC FEDERATED LEARNING FRAMEWORK

Our research leverages the principles of game theory to enhance the performance and convergence of FL models. In the proposed framework, we consider a scenario where multiple clients possess breast cancer data and aim to collaboratively train a model while preserving data privacy [65], [66]. Each client acts as a strategic player and makes decisions regarding their participation during the training process [67], [68]. By introducing payoff functions, we incentivize the clients to optimize their local models. Figure 6 refers to the outline of the game theoretic FL approach.

1) CLIENT TRAINING

The following steps are followed for client training.

a: INITIALIZATION

Every client is initialized with the global model which is an MLP model in our experiment.

b: LOCAL TRAINING

In the experiment, each client model is trained on its respective data subset for a fixed number of epochs.

c: EVALUATION

The models are evaluated using the test set to calculate their accuracy. The accuracy values are then used to calculate client payoffs. The payoff for each client in game-theoretic FL is calculated as the difference between their accuracy and the mean accuracy of all clients. The payoff calculation is as in Equation (4).

$$\text{payoff} = \text{client\_accuracies}[i] - \left(\frac{1}{\text{num\_clients}} \sum_{j=1}^{\text{num\_clients}} \text{client\_accuracies}[j] \right) \tag{4}$$

Equation (4) can be explained as follows:

- payoff**:** This represents a variable that will store the calculated payoff.
- client_accuracies[i]**:** This term represents the accuracy of a specific client, indexed by i.
- $\frac{1}{\text{num\_clients}} \sum_{j=1}^{\text{num\_clients}} \text{client\_accuracies}[j]$**:** This part calculates the average accuracy across all clients.

In Equation (4), client accuracy is the accuracy of a single client model on the test set. The mean accuracy of all the clients on the test set is calculated. The difference between the accuracy of a client model and the mean accuracy of all clients is calculated to find out the payoff values. The resulting values which are the payoff of the client model, can be positive, negative, or zero.

2) MODEL AGGREGATION STRATEGY

The following steps are followed for model aggregation.

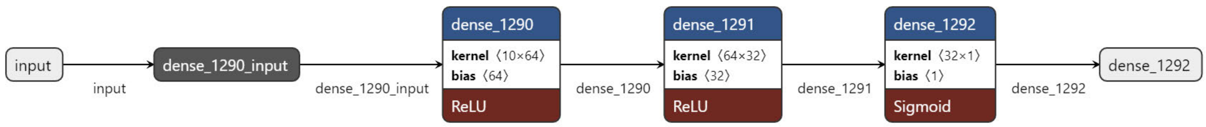

FIGURE 5. Model architecture.

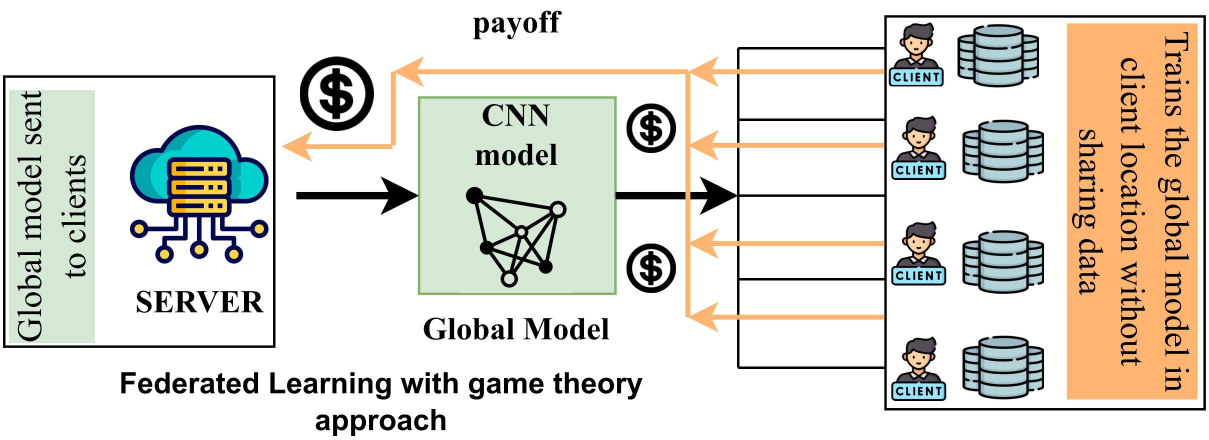

FIGURE 6. Game theoretic federated learning approach.

a: CLIENT SELECTION

After the calculation of the client payoff, the clients are selected based on the payoff of each client. Clients with higher payoffs are selected for the global model update. The number of clients to select is a hyperparameter that is determined in advance. Here we are selecting 10 clients. Equation (5) explains the client selection criteria.

$$S = \{i : \text{Payoff}_i \geq \text{Payoff}_j, \forall j \neq i\} \tag{5}$$

Equation (5) can be described as follows:

- S**:** This represents a set that will be defined based on the condition specified.
- $\{i : \textbf{Payoff}_i \geq \textbf{Payoff}_j, \forall j \neq i\}$**:** This set comprehension notation implies that the set S contains all elements i for which the payoff (Payoff_i) is greater than or equal to the payoff of every other element j in the set, where j is not equal to i.
- $\textbf{Payoff}_i$**:** This represents the payoff associated with the element i.
- $\textbf{Payoff}_j$**:** This represents the payoff associated with the element j.

Here, S represents the set of selected clients, Payoff_i is the payoff of the client i, and j represents all other clients. This Equation (5) implies that a client i is selected (i is included in the set S) if its payoff is greater than or equal to the payoff of every other client j.

b: WEIGHT CALCULATION

In the experiment, the payoff values are applied in adjusting the weights of each client model in the weight update step. By applying the payoff in weight calculation, the proposed work aims to give more weight to the models of clients that are selected.

The weights are calculated using the payoff values obtained from Equation (4). Each client's weight is determined based on its payoff, which reflects its performance in the game. The higher the payoff, the greater the role of the client's model during aggregation. The update of the weights in each layer of the local model is calculated using Equation (6).

$$W_{updated} = W_{current} + \text{lr} \times \text{Payoff}_i \tag{6}$$

Here, W_updated represents the updated layer weights. W_current represents the current layer weights, lr is a hyperparameter that controls the step size for updating the weights, Payoff_i is the payoff of the client i. The lr × Payoff_i term provides the direction and magnitude for the weight updates. Higher payoff results in larger updates to the weights. The weights are normalized to sum up to 1.

c: GLOBAL MODEL AGGREGATION

The central server aggregates the models from selected clients to create a new global model. The aggregation process uses weighted averaging method. Equation (7) is to calculate the updated weights for the global model are as follows:

$$\text{Global Weights} = \sum_{i=1}^{k} \text{Weight}_i \times \text{Local Model Weights}_i \tag{7}$$

where k is the number of selected clients Weight_i is the normalized payoff of the client i, and Local Model Weights_i represents the weights of the local model for client i.

d: CLIENT MODEL UPDATE

The global model is updated and the new global model is distributed to the clients and this process is repeated till the best global model is achieved.

Every client in this game-theoretic FL setting plays a game where the objective is to maximize their own payoff. The ''game'' here is the learning process, and the ''players'' (clients) update their strategies (models) based on their payoffs (reward function). This process aligns most closely with concepts from cooperative game theory where players (clients) receive payoffs (based on their model's performance), and the best-performing players are selected to contribute to the collective goal (improving the global model).

In standard FL, the weights are typically calculated based on a simple averaging scheme. Each client's weight is equal, and the model updates from all clients are averaged equally during the aggregation process [69]. This equal weighting assumes that all clients are equally reliable and contribute equally to the learning process.

Game-theoretic FL considers the strategic interactions which is to assign weights to clients in the aggregation phase based on their relative contribution or utility, thus optimizing the global model and encouraging individual clients to provide high-quality data and models [70]. On the other hand, standard FL focuses on collaborative learning and assumes equal contributions from all clients. The complete process of the proposed framework is explained step by step in Algorithm 2. This approach can improve the overall performance of the global model by giving more importance to the contributions of the clients with better performance. Also, the impact of poor-performing clients is reduced. This can lead to better convergence and more accurate global models in FL scenarios. Figure 4 is the block diagram of the proposed model.

Algorithm 2 Proposed Framework Algorithm

```
Input: Training data X_train, y_train, Test data X_test, y_test, Validation data
       X_val, y_val, Number of clients num_clients, Number of epochs
       num_epochs, Batch size batch_size, Learning rate lr
Output: Global model G
Initialize global model G_0;
for t = 1 to num_epochs do
    for i = 1 to num_clients do
        Initialize client model G_i with G_{t-1};
        Select subset of data DT_i ⊂ X_train, y_train;
        Train client model G_i on DT_i for num_epochs epochs;
        Evaluate client model G_i on test set X_test, y_test, compute
        metrics;
        Compute payoff π_i = accuracy of model_i - mean accuracy of
        all models;
        Update client model G_i based on π_i;
    end
    select top performing clients;
    Calculate weights for aggregation based on payoffs and normalize
    to 1;
    Aggregate client models using computed weights to form a new
    global model G_t;
    for i = 1 to num_clients do
        Update G_i's weights based on their respective π_i;
        Update the global model G_t with the updated G_i's weights;
    end
    Evaluate new global model G_t on X_test, y_test;
end
```

TABLE 8. Constants in the experiment.

Constant	Value
Number of Clients	10
Number of Epochs	10
Client Epochs	10
Learning Rates	0.1
Batch Sizes	32

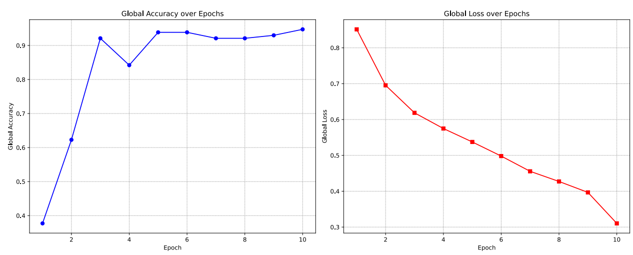

FIGURE 7. Accuracy and loss results of the proposed approach.

IV. RESULTS AND DISCUSSION

This section discusses the experimental results and key findings of the proposed framework.

A. EXPERIMENTAL SETUP

The experiments were carried out on a laptop with an Intel(R) Core(TM) i5-6200U CPU, 250 GB memory, and two NVIDIA GeForce RTX 2070 Super GPUs with 4 GB DRAM each. We used Keras version 2.4.3 and TensorFlow version 2.3.0 for simulating the FL. The proposed work enhances the communication performance of FL.

B. PERFORMANCE OF THE PROPOSED APPROACH

In our work, we implemented a game-theoretic FL algorithm that uses a neural network model. The experiments are conducted with a dataset that contains test, train, and validation samples. The algorithm selected 10 clients out of 20 clients and each client has its own local model. The models were trained for 10 epochs and a batch size of 32. The learning rate (lr) was set to 0.1. We evaluated the performance of the algorithm by calculating the global accuracy of the aggregated models. Table 8 refers to the constants used in the experiment.

Through the analysis of the results, the model demonstrated significant progress in its learning capability. Starting from an accuracy of 0.37719 in the first epoch, it reached an accuracy close to 0.947 by the tenth epoch. Similarly, the global loss observed a consistent decline over the ten epochs, indicating the model's efficient learning and adaptability to

TABLE 9. Accuracy and loss values of the proposed approach.

Epoch	Accuracy	Loss
1	0.37719	0.85154
2	0.62281	0.69543
3	0.92105	0.61870
4	0.84211	0.57491
5	0.93860	0.53743
6	0.93860	0.49807
7	0.92105	0.45558
8	0.92105	0.42724
9	0.92982	0.39677
10	0.94737	0.31034

TABLE 10. Other evaluation metrics of the proposed approach.

Epoch	Precision	Recall	F1-Score	ROC-AUC
1	0.39434	0.39032	0.39189	0.67491
2	0.63964	0.64100	0.64032	0.75438
3	0.93421	0.93156	0.93281	0.85431
4	0.85977	0.86123	0.86050	0.87891
5	0.95455	0.95161	0.95308	0.92037
6	0.95283	0.95423	0.95353	0.94211
7	0.93182	0.93281	0.93231	0.96154
8	0.93182	0.93281	0.93231	0.97031
9	0.93976	0.94323	0.94149	0.98127
10	0.95283	0.95423	0.95353	0.98974

the data. The process suggests that the model effectively captured the underlying patterns in the dataset, leading to improved accuracy and reduced loss with each epoch.

In addition to the loss and accuracy values, we evaluated other performance metrics such as precision, recall, F1-score, and ROC-AUC curve. Table 10 gives the values of the other performance metrics. The equations for other evaluation metrics like precision, recall, F1-score are represented in equations (8), (9), (10). The ROC-AUC curve is shown in the Figure 8

1) PRECISION

Precision measures the proportion of correctly predicted positive instances out of the total predicted positive instances. Equation (8) is used to calculate the precision values.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \times 100 \quad (8)$$

2) RECALL

Recall measures the proportion of correctly predicted positive instances out of the total actual positive instances. Equation (9) is used to calculate the recall values.

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \times 100 \quad (9)$$

3) F1 SCORE

The F1 score is the harmonic mean of precision and recall. It provides a single metric to balance between precision and recall. Equation (10) represents the calculation of the F1 score.

$$\text{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (10)$$

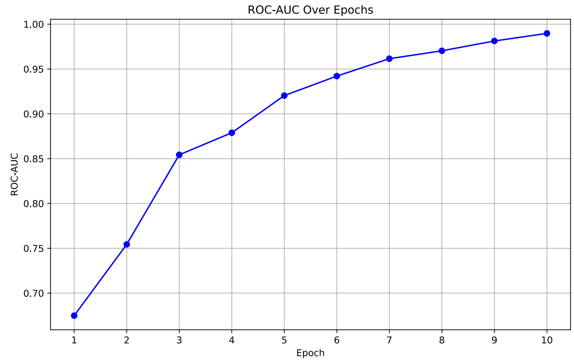

FIGURE 8. ROC-AUC curve analysis.

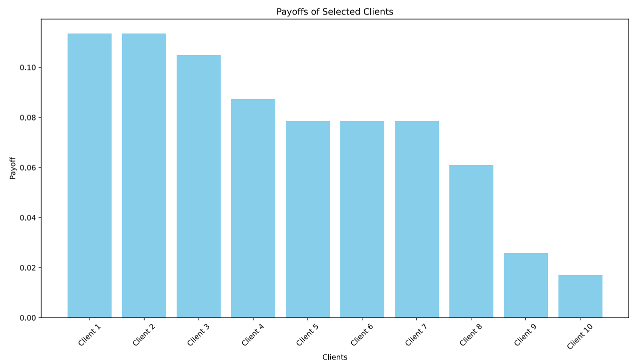

FIGURE 9. Payoff values of each client.

We also tracked the payoff values for every client throughout the process. Figure 9 gives the graphical representation of the payoff values of each client. Once the training is completed, the accuracy of each client on the test set is calculated and then the payoff is computed for each client. This payoff calculation is based on the individual accuracy and the mean accuracy of all the clients. If a client's model has higher accuracy than the average accuracy of all client models, then its payoff will be positive, which indicates that the client has made a positive contribution to the global model. If a client's model has lower accuracy than the average accuracy, then its payoff will be negative, indicating that the client has made a negative contribution to the global model. Figure 9 indicates the payoff values.

Figure 7 discusses the accuracy and loss results of the proposed approach. The proposed approach shows a higher accuracy of 94.47%. Table 9 gives accuracy, loss values in each epoch of the experiment.

C. PERFORMANCE ACROSS DATASETS AND HYPERPARAMETER SETTINGS

In an effort to validate the robustness of our proposed methodology, game-theoretic FL, we have conducted additional experiments using three more diverse datasets namely:

1) Ship-detection dataset-https://www.kaggle.com/datasets/andrewmvd/ship-detection
2) Sonar dataset-https://archive.ics.uci.edu/dataset/151/connectionist+bench+sonar+mines+vs+rocks
3) Forest Fire dataset-https://www.kaggle.com/datasets/alik05/forest-fire-dataset

For the Ship-detection dataset, the model demonstrated an upward trend in accuracy, initiating from 80.47% in the first round and reaching a peak of 93.13% by the eighth round. The corresponding loss exhibited a general decline, implying model optimization with consecutive rounds.

In the case of the Sonar dataset, a more pronounced improvement was evident. The model accuracy leaped from an initial 38.09% to an impressive 88.09% by the tenth round. This continual improvement resonates with the decrement in loss values, signifying the model's adeptness in adapting and learning from this dataset.

Lastly, the Forest Fire dataset displayed consistent enhancement in model accuracy throughout the rounds, starting from 82.44% and culminating at 96.01% in the final round. The loss values corroborate this observation, revealing a downward trend with few fluctuations.

These results show the model's versatility and efficacy across diverse datasets. The consistent improvement in accuracy, along with diminishing loss values, reveals the model's potential for broader applications. In Figure 10 we visualized the performance of our model across different training scenarios. The scenarios are differentiated based on two parameters: batch size (BS) and learning rate (Lr). The scenarios under consideration were "BS = 32, Lr = 0.01", "BS = 32, Lr = 0.001", "BS = 16, Lr = 0.01", and "BS = 16, Lr = 0.001", "BS = 16, Lr = 0.1". We considered the number of epochs as 10.

In addition to the above results we also evaluated the total communication cost and total time consumed for both the approaches namely game theoretic FL and FL. The values are depicted in Table 12. The total communication cost of the game theoretic FL approach is 77.34375 Kilo Bytes(KB) while 100 KB for the FL approach. Similarly, the time consumed for the game-theoretic FL approach is 27.940 seconds while it is 40.467 seconds.

D. PERFORMANCE COMPARISON WITH OTHER MODELS

As a part of our experiment, we also implemented a few test cases where we implemented both FL and game-theoretic FL with and without Shapley feature selection. Figure 11 gives the accuracy and loss values when using FL without game theory for the same feature-selected dataset using Shapley values.

Figure 12 represents the graph for the accuracy and loss values of the both FL and game theoretic FL without the Shapley feature selection. This is evaluated with all the 30 features of the original dataset. Graph (a) in Figure 12 shows the accuracy values for game theoretic FL without feature selection. Graph (b) in Figure 12 shows the loss values for game theoretic FL without feature selection. Graph (c) in

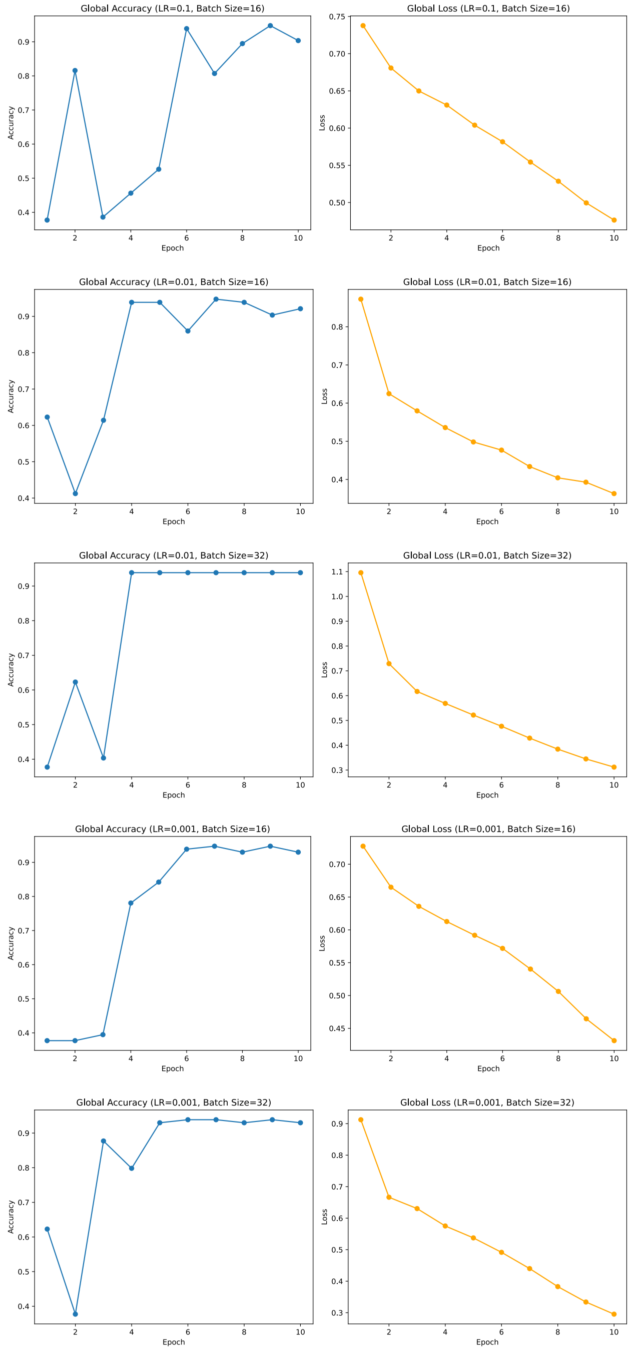

FIGURE 10. Performance of our model across different training scenarios.

Figure 12 shows the accuracy values for FL without feature selection. Graph (d) in Figure 12 shows the loss values for FL without feature selection.

E. PERFORMANCE COMPARISON WITH OTHER PREVIOUS WORKS

This section presents the comparative analysis of the performance of the suggested method on the breast cancer dataset with other models. A convolutional neural networks

TABLE 11. Performance metrics across different datasets over ten rounds.

Dataset	Round									
	1	2	3	4	5	6	7	8	9	10
Accuracy(%)										
Ship-detection	80.47	88.88	89.05	91.12	87.12	92.06	89.27	93.13	89.48	91.63
Sonar	38.09	61.90	66.66	69.04	73.80	73.80	78.51	80.95	85.71	88.09
Forest Fire	82.44	88.82	90.69	91.22	91.75	93.61	94.41	94.68	95.21	96.01
Loss										
Ship-detection	1.16	0.38	0.47	0.39	0.54	0.32	0.44	0.30	0.43	0.20
Sonar	0.69	0.69	0.61	0.59	0.57	0.55	0.53	0.50	0.48	0.46
Forest Fire	1.37	0.36	0.50	0.42	0.38	0.18	0.23	0.32	0.30	0.26

TABLE 12. Communication cost and time.

	Game theoretic FL	FL
Communication Cost (Kilo Bytes)	77.34375 KB	100 KB
Time consumed (seconds)	27.94029402732849s	40.46735453605652s

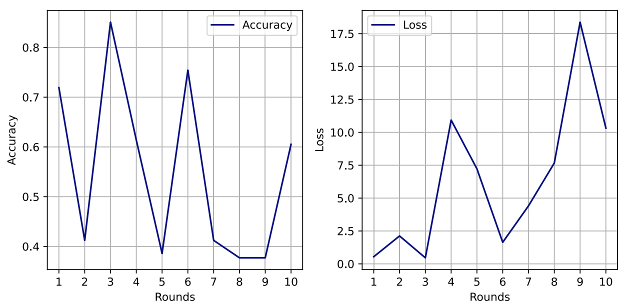

FIGURE 11. Accuracy and loss results FL implementation.

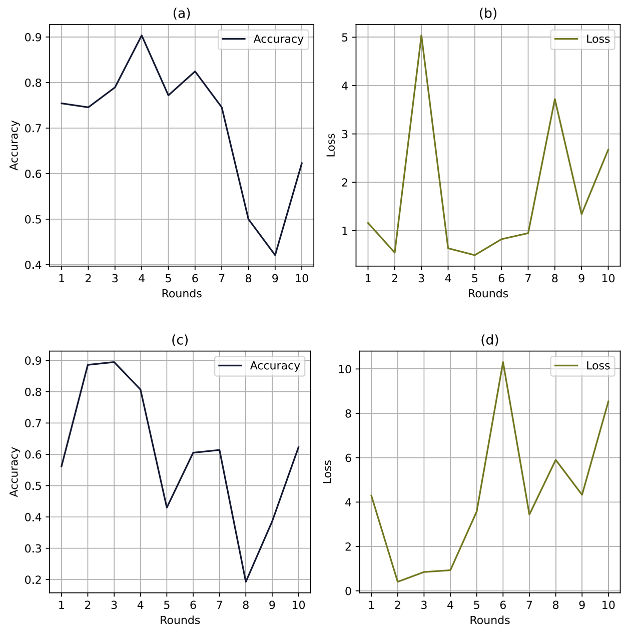

FIGURE 12. Accuracy and loss values of both FL and game theoretic FL without Shapley feature selection.

(CNN)-based approach for the detection of breast cancer in invasive ductal carcinoma tissue regions using whole slide images (WSI) in [71] showed an accuracy of 83%. In [72], the regular ML methods like NB and KNN showed accuracy results of 81.84% and 89.85% respectively. An FL experiment based on breast cancer histopathological dataset (BreakHis) in [73] achieved an accuracy of 86.48%. In [74] a new technique called TL was experimented on a dataset from Mammographic Image Analysis-Society which achieved an accuracy of 86.48% using the Ensemble methods. According to authors in [75], the DenseNet method showed an accuracy of 89.56%. Similarly, the PSO-FL+E-RNN (Particle Swarm Optimization, FL, Efficient Recurrent Neural Network), DHOA-FL+E-RNN(Deer Hunting Optimization Algorithm,FL,Efficient Recurrent Neural Network), and DA-FL+E-RNN(Dragonfly Algorithm,FL, Efficient Recurrent Neural Network) in [74] showed an accuracy of 89.93%, 89.91%, and 91.95% respectively. In comparison to all the previous works, the proposed work achieved a higher accuracy of 94.73%. Table 13 refers to the comparison of accuracies of different algorithms in detecting Breast cancer.

TABLE 13. Accuracies of different algorithms in detecting breast cancer.

Algorithm	Accuracy(%)
CNN [72]	83.00
Ensemble [75], [77]	86.48
NB [73]	81.84
KNN [73]	89.85
DenseNet [76]	89.56
PSO-FL+E-RNN [75]	89.93
DHOA-FL+E-RNN [75]	89.91
DA-FL+E-RNN [75]	91.95
Proposed work	94.73

F. DISCUSSION

In this section, we dive into a comprehensive discussion of the results obtained from our breast cancer prediction model using Shapley values and game theory within the FL environment. The results obtained from the experiments demonstrate the effectiveness of our approach. The algorithm successfully used the distributed nature of the clients to improve the overall accuracy of the global model.

The proposed model combines the concepts of Shapley values, FL, and game theory. While the Shapley values are used for feature selection, game theory is used to optimize the FL process. Since breast cancer prediction deals with sensitive data and needs to be predicted as early as possible with less computational and communication overhead, we used a combination of the three concepts. Shapley values will help in showing the relative impact of every feature on the overall output. In healthcare data where privacy plays a major role FL is a good option to be adopted and game theory plays an important role in optimizing the performance of FL.

1) ASSUMPTIONS AND PREREQUISITES FOR APPLYING SHAPELY AND GAME THEORY TO BREAST CANCER PREDICTION

In discussing the assumptions and prerequisites of our breast cancer prediction model, we assume homogeneous distribution of breast cancer data among participating clients. This assumption is pivotal in collaborative learning environment, where a balanced representation of various types and stages of breast cancer across decentralized datasets facilitates effective model generalization. The success of our game-theoretic FL approach relies on the prerequisite of a collaborative and trustworthy environment. Trust among participants is much needed for encouraging active participation, as clients must willingly share model updates and engage in the reward-based mechanism introduced by game theory. Additionally, we assume feature independence, as a key consideration for Shapley values. While this assumption simplifies the interpretability of feature contributions, we acknowledge the potential existence of dependencies among features.

2) KEY FINDINGS

The key findings and contributions of our work can be summarized as follows:

Accuracy Improvement: The global accuracy achieved by the algorithm indicates that the collaborative training process led to better generalization compared to a single model trained on the entire dataset. The iterative nature of the algorithm, with clients updating their models based on their individual payoffs, resulted in the aggregation of diverse models, which helped in capturing a broader range of patterns and achieving higher accuracy.

Payoff-based Model Updates: The use of payoffs to update the weights of each client's model introduced a game-theoretic aspect to the FL process. Clients with higher accuracy relative to the mean accuracy were rewarded with larger weight updates, allowing their models to contribute more significantly to the global model. This incentivized clients to strive for higher accuracy and promote the overall improvement of the global model.

Convergence and Communication Efficiency: Using local models and selective weight updates based on payoffs reduced the amount of communication required between the clients and the server. This resulted in improved communication efficiency and faster convergence compared to traditional FL approaches where all client models are updated uniformly at each iteration. The game-theoretic approach ensured that models converged towards a better global model while minimizing communication costs.

3) LIMITATIONS

Firstly, the integration of game theory and Shapley values introduces computational overhead, posing scalability challenges for larger datasets and real-time applications. Privacy concerns arise despite the use of FL, as the incorporation of game theory and Shapley values may introduce new vulnerabilities. Additionally, our proposed model is static and does not capture dynamic changes in feature importance, limiting its adaptability to evolving breast cancer research. The feature selection process using Shapley values may not generalize well to broader datasets and diverse patient populations. To address this, employing more diverse and comprehensive datasets, covering different subtypes, stages, imaging modalities, and data quality, alongside methods like bootstrapping and cross-validation, could enhance model robustness. The complexity of DL models in the FL framework can pose several challenges for clinicians, such as lack of interpretability, vulnerability to adversarial attacks, and data poisoning. Furthermore, fairness issues in client selection during FL pose a significant challenge, affecting incentives for contributing clients. Unfairness can manifest at various stages, including client selection, model optimization, and incentive distribution. Effectively addressing these fairness-related concerns is crucial to maintain client engagement and overall success in FL training. Various Fairness-Aware Federated Learning (FAFL) approaches have been proposed to tackle these challenges and promote fairness in FL [77].

V. IMPLEMENTATION CHALLENGES AND STRATEGIES IN REAL-WORLD CLINICAL SETTINGS

This section describes the implementation challenges of our model and strategies for implementing the model when applied to real-world clinical settings.

A. CHALLENGES

1) SCALABILITY

The scalability of a model is dependent on the volume and variety of healthcare data used by various organizations. To build a universally scaled model, variations in disease subtypes, treatment procedures, and patient demographics may provide obstacles [78]. Network capacity problems may arise when clients and the central server transfer large amounts of data. This is especially important when working with large datasets, and optimizing the efficiency of data transfer should be considered.

2) COMPUTATIONAL REQUIREMENTS
FL demands substantial computational resources due to the iterative nature of model training and the need for data processing and aggregation across distributed clients, particularly in healthcare settings where data privacy and regulatory compliance are critical [79]. Scalability relies on robust computational infrastructure to handle large volumes of heterogeneous healthcare data efficiently, from processing gradients locally to aggregating model updates centrally. Approaches that aim to minimize computation costs, facilitate local processing, and reduce the computational footprint of FL models are needed to address this challenge.

3) DATA HETEROGENEITY
Data heterogeneity in FL, particularly in healthcare settings, can lead to several challenges. These include performance degradation of FL algorithms, statistical and model heterogeneity, and impacts on the prediction performance of federated models [80]. Strategies like weighted average for data quantity skew, weighted loss, and batch normalization averaging for label distribution skew have been proposed to address these issues. However, these may not completely resolve the challenges, indicating a need for further research in handling data heterogeneity in FL within healthcare.

4) COMMUNICATION OVERHEAD
Communication overhead is one of the major bottlenecks for FL. Since the communication cost is much greater than the computation cost when several edge devices are sending their model parameters to the central server [81]. The communication cost is very high in the training process, which results in low training efficiency for FL and makes it ineffective in the application of FL in the practical medical field. Therefore, proper FL optimization algorithms are needed to reduce communication costs by optimizing client selection and model compression.

5) SECURITY AND PRIVACY THREATS
Security and privacy threats are counted as major challenges related to FL. In comparison with traditional privacy-protecting computing technologies, FL is characterized by revealing certain parameters and assuming that these data do not reveal sensitive information [78]. In FL, there are still some hidden threats, like parameter leaks and attacks by malicious operations. It is therefore crucial that this communication be encrypted to ensure its privacy and security. In addition, Differential Privacy or Homomorphic Encryption techniques can also be applied to ensure privacy. Differential Privacy ensures that the inclusion or exclusion of a single data point does not significantly affect the outcome of the analysis, thereby protecting individual privacy. Homomorphic Encryption allows computations to be performed on encrypted data without needing to decrypt it first, thus maintaining data confidentiality throughout the computation process [82].

6) COMPUTATIONAL EFFICIENCY
The FL model's computing efficiency in the DL models is complex. The model's inference speed, especially in real-time applications is affected by the model's complexity. Some clients can also have restrictions related to memory and computing capacity [83]. To address this challenge, computer engineers need to monitor and optimize resource management using different strategies and tools, like load balancing, fault tolerance, caching, and edge computing.

7) TRADE-OFF BETWEEN EFFICIENCY AND PRIVACY
Using Secure Multi-Computation (SMPC) and Differential Privacy boosts the privacy protection capability in FL, however, such protection comes with a trade-off between cost and efficiency. Using SMPC, clients are to encrypt the parameters of the models before sending them back to the central server, therefore additional computational resources are required for encryption which will compromise the efficiency of training the model. With Differential Privacy, noise is added to the model and data, hence some accuracy is lost. Therefore finding a suitable trade-off between SMPC and Differential Privacy is an open challenge in FL.

8) SYSTEMS HETEROGENEITY
Federated network involves different and a variety of devices that have different storage, computational, and communication capabilities. These devices have variations in hardware, network connectivity, and power supply and these lead to differences. In a federated network, each device may be unreliable and it is common for an edge device to drop out from the network due to connectivity or energy constraints [84]. So, fault tolerance is very important as the devices in the network may drop even before the training is completed. Therefore, FL methods need to be developed in such a way that they anticipate a low amount of participation, they tolerate the heterogeneous hardware. Asynchronous communication, active device sampling, and fault tolerance are some of the techniques that are needed to handle the heterogeneous systems in FL environment.

9) ETHICAL AND SOCIETAL CONSIDERATIONS
A significant volume of high-quality medical data is the most important requirement for improving FL applications in the healthcare domain. However, given the sensitive nature of health information, security and privacy issues about healthcare data have recently given rise to widespread ethical and legal concerns. To preserve patient privacy, it is morally and legally necessary to assemble and transmit this sensitive data. New regulations that regulate data exchange while protecting user security and privacy have been passed by the majority of healthcare facilities, national laws, and regulatory agencies, such as the Health Insurance Portability and Accountability Act (HIPAA) and the General Data Protection Regulation (GDPR) [85]. Owing to data protection and ethical issues involved with data sharing in healthcare,

this overhead will easily become a technical problem and typically necessitates a time-consuming approval process.

B. STRATEGIES FOR REAL-WORLD IMPLEMENTATION

The implementation challenges in real-world clinical settings for FL encompass various aspects, including scalability, data heterogeneity, communication overhead, security and privacy threats, computational efficiency, trade-offs between efficiency and privacy, systems heterogeneity, and ethical and societal considerations. Strategies to address these challenges and implement in real world clinical settings are as follows:

- Scalability: Implement data preprocessing techniques and utilize data compression and optimization algorithms.
- Computational Requirements: Optimization strategies like federated optimization algorithms, edge computing, and model compression techniques can be implemented to solve the problems with computational requirements.
- Data Heterogeneity: Develop adaptive FL algorithms and explore advanced techniques like weighted averaging and batch normalization.
- Communication Overhead: Design efficient FL optimization algorithms and prioritize client selection and model compression.
- Security and Privacy Threats: Ensure robust encryption methods and implement secure communication protocols.
- Computational Efficiency: Employ resource management strategies and utilize edge computing.
- Trade-off Between Efficiency and Privacy: Explore adaptive mechanisms and investigate trade-offs between privacy protection and computational efficiency.
- Systems Heterogeneity: Develop FL methods to accommodate diverse hardware and network configurations.
- Ethical and Societal Considerations: Adhere to regulatory frameworks and implement transparent data exchange processes.

VI. THEORETICAL AND BUSINESS IMPLICATIONS

This section gives a clear and distinct emphasis on the significance and implications of our research.

A. CONTRIBUTIONS TO THEORIES

Bridge between Cooperative Game Theory and FL: By integrating Shapley values with game theory in an FL environment, our research establishes a theoretical bridge between cooperative game theory principles and the decentralized nature of FL. Cooperative game theory traditionally focuses on the cooperative behavior of agents, while FL operates in a decentralized manner. Our work demonstrates how cooperative behavior can be incentivized and quantified in an FL setting, thus enriching the theoretical understanding of both fields.

Quantification of Individual Client Contributions: Theoretical contributions extend to understanding how individual client contributions can be quantified and optimized within a decentralized FL system. Game theory provides a rigorous framework for attributing contributions to each client, enabling a deeper understanding of their impact on model training and performance. This quantification enhances the theoretical foundation of FL by elucidating the dynamics of decentralized collaboration.

Importance of Features in a Collaborative Environment: Our research sheds light on the importance of features within a collaborative environment. By leveraging Shapley values, we explore how features influence the collaborative learning process in FL. This theoretical exploration contributes to a deeper understanding of feature importance in decentralized settings, thereby advancing the theoretical underpinnings of FL methodologies.

1) THEORETICAL LIMITATIONS OR CHALLENGES:

While our theoretical framework offers significant advancements, there are potential limitations and challenges to consider:

Complexity of Shapley Value Calculations: One challenge lies in the computational complexity associated with calculating Shapley values, particularly in large-scale FL systems with numerous clients and features. Addressing this challenge may require the development of efficient algorithms or approximation techniques to compute Shapley values within practical time constraints.

Assumptions of Cooperative Behavior: Another theoretical limitation pertains to the assumptions of cooperative behavior inherent in game theory models. In real-world FL scenarios, clients may exhibit varying levels of cooperation or conflicting interests, which can impact the efficacy of collaborative learning. Future research could explore more nuanced game-theoretic models that account for such complexities.

2) ADDRESSING THEORETICAL CHALLENGES

To address these theoretical challenges, future research endeavors could focus on:

Algorithmic Optimization: Developing efficient algorithms for computing Shapley values in FL settings to mitigate computational complexity while ensuring accurate attribution of contributions.

Behavioral Modeling: Integrating behavioral economics principles to model client behavior more realistically, accounting for factors such as incentives, trust, and strategic interactions among clients.

B. CONTRIBUTIONS TO BUSINESS

From a commercial perspective, this work holds great promise for healthcare and its associated industries. This work can change the method of sharing and analyzing medical data reduce privacy concerns and enable collaborative research through multiple institutions. In addition, the use of game theory and Shapley values ensures that clients or institutions are motivated in a manner consistent with a common goal that encourages active and beneficial participation. This leads to faster and more efficient model training and can make patient outcomes more better. Such a model can serve as a blueprint for companies outside of healthcare, showing how data can be used collaboratively without centralization and suggesting new business models that focus on decentralized data sharing and analysis.

VII. CONCLUSION

The proposed methodology implements a game-theoretic approach to FL, where multiple clients train their local models on their own data and update them based on a payoff scheme. The breast cancer dataset is used for feature selection, and the top 10 features are selected for training the client models. A simple neural network architecture is used as the base model for each client, and their performance on a validation set is evaluated. The accuracy of each client's model on the test set is used to calculate their payoff, which is then used to update their local models. The performance of the overall FL approach is evaluated based on the accuracy achieved on the test set.

A. FUTURE DIRECTIONS

This subsection explains the possible recommendations for future research.

1) OPTIMIZATION TECHNIQUES

As a part of future work, more sophisticated payoff schemes and optimization techniques to improve the efficiency and scalability of the proposed methodology can be explored. Several other nature or bio-inspired algorithms can also be explored to optimize FL performance.

2) DATASET AND HYPERPARAMETER EXPLORATION

The proposed model performed experiment using different dataset and hyperparameter settings. The methodology can be further extended to other datasets and different hyperparameter settings, to assess the generalizability of the proposed approach.

3) PRIVACY PRESERVATION

The concept of FL provides a basic framework for privacy-preserving model learning, which allows participants to collaboratively train a global model using their respective datasets. However, there is no privacy guarantee in the basic framework. To protect data privacy, privacy-preserving mechanisms like differential privacy and blockchain can be incorporated to strengthen data protection [86].

4) INCREASE IN THE PARTICIPANT NUMBERS

The proposed model is implemented using 10 clients. The experiment can be conducted with a larger number of participants to validate the findings across broader contexts and larger populations.

5) INTEGRATING ADVANCED TECHNIQUES

We plan to explore the integration of deep learning architectures, such as CNNs or RNNs, within the FL framework. Additionally, ensemble methods, which combine predictions from multiple models, could be used to enhance the robustness and generalization of FL models.

6) APPLICATIONS TO DIVERSE HEALTHCARE PREDICTION TASKS

We can extend the application of our framework to address a wide range of healthcare prediction tasks, including but not limited to cardiovascular disease risk assessment, diabetic complications prediction, and infectious disease outbreak forecasting. These tasks often involve heterogeneous datasets, stringent privacy requirements, and complex data distributions, posing significant challenges for traditional centralized approaches.

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