Multiparty Secure Broad Learning System for Privacy Preserving
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Abstract—Multiparty learning is an indispensable technique to improve the learning performance via integrating data from multiple parties. Unfortunately, directly integrating multiparty data could not meet the privacy-preserving requirements, which then induces the development of privacy-preserving machine learning (PPML), a key research task in multiparty learning. Despite this, the existing PPML methods generally cannot simultaneously meet multiple requirements, such as security, accuracy, efficiency, and application scope. To deal with the aforementioned problems, in this article, we present a new PPML method based on the secure multiparty interactive protocol, namely, the multiparty secure broad learning system (MSBLS) and derive its security analysis. To be specific, the proposed method employs the interactive protocol and random mapping to generate the mapped features of data, and then uses efficient broad learning to train the neural network classifier. To the best of our knowledge, this is the first attempt for privacy computing method that jointly combines secure multiparty computing and neural network. Theoretically, this method can ensure that the accuracy of the model will not be reduced due to encryption, and the calculation speed is very fast. Three classical datasets are adopted to verify our conclusion.

Index Terms—Broad learning system (BLS), privacy preserving, secure multiparty computing (SMC), security analysis.

DATA classification is a classical data analysis task, which is widely used in various fields. With the development of machine learning, various supervised neural network classifiers are proposed, along which the classification performance is significantly improved. On this basis, some attempts have been made to consider the task requirements in specific scenarios, in which privacy preserving is an invaluable requirement in recent years. Take the medical scene as an example. Medical image classification is a typical task in medical data analysis [1]. However, the data samples of a single medical institution may not meet the needs of data analysis tasks [2]. For example, the data of tumor hospitals are mostly related to tumors. Due to the lack of data of other diseases, the trained classifier may diagnose nontumor patients as tumor patients; on the contrary, there are few various tumor data samples in general hospitals. It is a challenging issue to train a classifier from the relatively small number of high-dimensional image data. In addition to the need for cooperation between specialized hospitals and general hospitals, small hospitals also need data help from large hospitals. A simple but effective strategy for addressing the issue is to integrate multiparty data from different medical image owners.

Unfortunately, directly integrating multiparty data could not meet the privacy-preserving requirements. Medical data often contain patient identity information and health data, which belong to personal privacy information. If each medical institution directly fuses its patients’ information for data analysis, the process will inevitably leak the private data to other medical institutions or the third-party server responsible for computing, which is extremely unsafe. Therefore, privacy-preserving machine learning (PPML) [3] becomes a key research task in medical image analysis. Compared with the traditional machine learning methods, PPML needs to consider security and communication cost. This means that it needs to find a balance between security, communication cost, and model performance. More complex encryption methods may improve the security of data and reduce the performance of the model.

The broad learning system (BLS) is a neural network model without deep structure [4], [5]. BLS first generates a series of the mapped features by a large number of random transformations on the original data, then activates the random linear combination of the mapped features to obtain a series of enhancement features, and finally combines the

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mapped features and the enhancement features as the coefficient matrix of linear equations, the output class labels as a nonhomogeneous term and calculates the weight coefficient (the solution of linear equations) through the approximate calculation method of pseudo inverse. The difference between BLS and deep neural network is that the deep neural network adjusts the weight coefficient through multiple iterations, so that the output result approximates the objective function. This process usually requires a long calculation time. BLS only needs to calculate the mapped features and the enhancement features once and obtains the weight coefficients through a fast pseudo inverse approximation method. Although BLS will get some features with low contribution, it does not need to iterate repeatedly, so the consumption of computing resources is not high. In recent years, this method has been widely developed [6], [7], [8] and used for solving various problems [9], [10], [11].

PPML is a cross-field involving machine learning and information security. Among them, cryptography is the theoretical cornerstone of information security. This means that ideal PPML needs to give full play to the advantages of machine learning in application and get the security guarantee of cryptography in theory. However, the focuses of these two areas are different. The former focuses more on the field of machine learning and application efficiency, while the latter focuses more on theory and security. Therefore, building a bridge between these two fields is a very important work. Although many efforts have been made on studying this problem, on the whole, most of the research works only focus on application and efficiency, such as federal learning. The starting point of this article is to find a way to closely combine these two fields. From the perspective of information security, this article constructs an appropriate secure multiparty protocol to provide security protection for the clients involved in computing and achieve the security goal of the algorithm. From the perspective of machine learning, this article uses the efficient BLS (broad neural network) to train the machine learning model. Theoretically, BLS can approach any bounded function on any compact set, and its function is similar to that of a deep neural network. Based on the above, we use random feature mapping to combine the secure multiparty protocol and BLS. Among them, randomness protects the security of data from the perspective of information security, and the feature mapping can be used as the input information of BLS. Experiments show that this method will not lose the performance of the model on the premise of protecting data security. In addition, we analyze the security of this method, that is, the parties involved in the calculation cannot obtain the privacy data of other parties.

In this article, we draw on the research idea of secure multiparty computing (SMC) to design the privacy computing framework. SMC is a solution given by Yao for the millionaire problem in 1982 [12]. The millionaire problem refers to two millionaires, Alice and Bob, who want to compare the amount of their wealth values without disclosing their assets. That is, Alice holds an integer $a$ and Bob holds an integer $b$. They want to compare the relationship between the magnitudes of $a$ and $b$ without disclosing their data. Yao’s solution is to design an interactive protocol. Alice and Bob strictly follow the protocol steps to encrypt, transmit, decrypt, and compare the data, and finally compare the size relationship of the two numbers without disclosing private information. Since then, this interactive protocol-based method has been extended to more general computing tasks to calculate the results of various agreed functions.

Aiming at the difficulties of the PPML method, this article designs multiparty secure BLS (MSBLS) to implement privacy computing based on the technical characteristics of BLS and SMC. Specifically, the main ideas of this article are as follows.

First, this article encrypts data with the help of the generation process of the mapped features of BLS. BLS extracts a random linear combination of the original features of data to generate the mapped features. We take random linear combination as the encryption process of data, so as to ensure the security of data. However, this is not a simple and direct task. We use the random coefficient matrix as the secret key, but different clients need to encrypt their own data with the same secret key to ensure that the mapped features are not chaotic (see Section IV-D for detailed reasons). However, the shared secret key is likely to cause the disclosure of private data. Therefore, this article designs an interactive protocol for encrypting data. This protocol can use the same secret key to encrypt the data of two clients and generate the mapped features. Afterward, we simplify the generation process of the mapped features into a matrix form. The advantage of this method is that it can simplify the process of interactive protocol and make the protocol easier to be extended to different application scenarios. In the next part, we analyze the security and communication cost of the computing process of the interactive protocol. The analysis results show that the protocol can guarantee the data security of two clients under the semi-honest model. In the end, MSBLS cleverly embeds the mapped features generated above into BLS and calculates model parameters. In order to verify the experimental performance of MSBLS, we conduct experiments on three classical data sets and simulate different actual scenarios. This includes the case where the number of data samples is unbalanced and the case where the distribution of data labels is nonuniform (see Section VI-A for a detailed description). Experiments show that even in extremely difficult scene tasks, compared with BLS, MSBLS can still protect the data security without losing the performance of the model. As a comparison, the current popular FedProx [13] algorithm and the BLS-based federal learning method FCL-BL [14] both lose a certain amount of prediction accuracy. This means that MSBLS can simultaneously meet the requirements of security and model performance.

In summary, the main contributions of this article are as follows.

1) According to the requirements of PPML, this article proposes the MSBLS method, which inherits the advantages of SMC and BLS. That is, we design an interactive protocol to encrypt the data of the two clients and generate the mapped features and use the mapped features to calculate the machine learning model parameters.
2) This article simplifies the generation of the mapped features in BLS, making the process of interactive protocol more concise.

3) This article gradually analyzes whether the data received by each client and server can recover the original data. The security analysis results show that the amount of information they hold is not enough to recover the original data.

The remainder of this article is as follows. Section II introduces several commonly used PPML methods and points out the advantages of MSBLS. Section III introduces the neural network classifier, namely, BLS used in this article. Section IV describes the MSBLS method in detail, including the problems to be solved, the simplified way of BLS, and the specific solutions to the problems. Section V analyzes the security and communication cost of the proposed scheme. Section VI designs the experimental process and analyzes the experimental results. Section VII discusses the limitations of the MSBLS method and suggests several possible solutions. Section VIII summarizes the work of this article and discusses the possible future research work.

II. RELATED WORK

To solve the problems of security and computing efficiency in the process of privacy computing, many efforts have been made in developing different solutions from different perspectives [15], [16]. Among them, differential privacy [17], homomorphic encryption [18], federated learning [19], [20], [21], and SMC [12] are the fastest-growing methods.

The concept of differential privacy was first proposed by Microsoft in 2006 [22]. The differential privacy method protects the real value of sensitive data by adding noise to the data and uses the corresponding method to obtain the real value in the query process [17]. The advantage and disadvantages of this method coexist. Although adding noise protects the security of data, it also destroys the original characteristics of data to a certain extent. Therefore, there is no ideal differential privacy algorithm that can equilibrate the relationship between security, computational efficiency, and query accuracy.

Homomorphic encryption was proposed by Rivest et al. in 1978 [18]. In 2009, Gentry [23] improved homomorphic encryption to obtain fully homomorphic encryption. The method of homomorphic encryption is to find a mapping function to encrypt the data, and then use the encrypted data for analysis, which ensures that the analysis result is the same as that obtained by directly using the original data for analysis. However, the efficiency of fully homomorphic encryption is low, and the encrypted data can only use addition and multiplication (the use of square root operation or other operations will lead to inconsistent results), so homomorphic encryption can only be applied to simple data analysis methods such as linear model [24], [25], [26].

Federal learning is a PPML framework proposed by Google in 2016 [19], [20], [21]. In recent years, it has been widely studied and applied to various tasks [14], [27], [28], [29], [30], [31], [32]. In 2017, McMahan et al. [33] proposed FedAvg. Its basic steps are as follows: first, the central server sends the initial model parameters (global model parameters) to each client, then each client trains the local model parameters with local data, and then sends the updated model parameters to the central server for aggregation to obtain new global model parameters. The above steps are repeated iteratively until the global model parameters converge. In 2020, Li et al. [13] generalized and reparameterized FedAvg to obtain FedProx. Despite the success, there is a lack of the relevant literature for proving the security of federal learning. Moreover, although federated learning only transmits model parameters rather than the original data, there are literature that use the model parameters of federated learning to restore the original data [34], [35].

SMC is a privacy protection computing method proposed by Yao for the millionaire problem in 1982 [12]. For a group of participants participating in the calculation, each participant has its own private data and does not trust other participants or any third party. On this premise, SMC constructs an interactive protocol to calculate a target result from multiparty data. The main difficulty of the SMC protocol is to construct corresponding protocols for different tasks. In 2014, Bost et al. [36] constructed three SMC protocols for classification problems, which are, respectively, used to realize the privacy constraints of hyperplane decision problem, medium vector Bayesian problem, and decision tree problem. Cock et al. [37] proposed another decision tree privacy protection protocol in 2018. In 2020, Pan et al. [38] proposed a joint feature selection algorithm based on the SMC interactive protocol. Despite the long-term development, the SMC methods can only be applied to the traditional linear machine learning models. Presently, there is still a lack of neural network-based models with privacy preserving for SMC.

In this article, we propose a new PPML framework called MSBLS. Specifically, we construct a neural network classifier based on SMC, which inherits the powerful fitting ability of BLS with the secure computing ability of SMC to form an efficient and secure privacy computing framework. It is especially suitable for integrating multiparty image data with preserving privacy.

In general, a complete PPML method is designed as follows. First, it encrypts the data in the local client, and then transmits the encrypted data to the central server. Finally, the central server conducts model training according to the algorithm design. Compared with the above methods, the proposed MSBLS method has the following advantages.

1) Compared with differential privacy, MSBLS can make full use of the original data information and has higher security. It can meet the needs of security, computing efficiency, and query accuracy.

2) Compared with homomorphic encryption, MSBLS can achieve the same effect of homomorphic encryption, but it will not be constrained by homomorphic addition and multiplication. In other words, MSBLS can be applied to a wider range of classification tasks, and the computational efficiency is very high.

3) Compared with federated learning, MSBLS also uses a neural network as the classifier for model training, which can make full use of the advantages of machine learning
methods. The difference is that MSBLS does not require a large number of iterations, so it can reduce the computing time. In addition, MSBLS provides security analysis, which theoretically ensures the data security of the client participating in the calculation.

4) Compared with other SMC methods, MSBLS is not limited to the traditional linear machine learning methods but uses the neural network method with stronger classification and generalization ability as the classifier.

III. BROAD LEARNING SYSTEM

BLS is a neural network model for supervised machine learning without deep structure. Compared with the traditional deep neural network, BLS uses the transverse broad structure to establish the model framework and does not require an iterative updating procedure to achieve a very good training effect. In this section, we will introduce the basic structure of BLS.

As shown in Fig. 1, first, BLS uses a set of random feature maps to generate n mapped features of data samples $X \in \mathbb{R}^{N \times d}$, that is

$$Z_i = \phi(XW_{ij} + \beta_{ij}), \quad i = 1, 2, \ldots, n$$  \hspace{1em} (1)

where $N$ and $d$ are the number and dimension of data samples, $d_z$ is the dimension of each mapped feature, $W_{ij} \in \mathbb{R}^{d_z \times d_h}$ is the randomly generated weight matrix, and $\beta_{ij} \in \mathbb{R}^{N \times d_z}$ is the randomly generated bias matrix with the same row, that is, for each $i$, $\beta_{ij}(j, :) = \beta_{ij}(1, :), \forall j = 1, 2, \ldots, N$.

Then, BLS uses a set of nonlinear activation functions to act on the mapped features $Z^n$ to generate m enhancement features, that is

$$H_j = \xi(Z^nW_{hj} + \beta_{hj}), \quad j = 1, 2, \ldots, m$$  \hspace{1em} (2)

where $W_{hj} \in \mathbb{R}^{m_h \times d_h}$ is the randomly generated weight matrix, $\beta_{hj} \in \mathbb{R}^{N \times m_h}$ is the randomly generated bias matrix with the same row, and $d_h$ is the dimension of each enhancement feature. The activation function $\xi(\cdot)$ can be set as the commonly used tangent function or sigmoid function.

Finally, BLS maps the concatenation of the mapped features and the enhancement features to the predicted output label vector $\hat{Y} \in \mathbb{R}^{N \times d_y}$ by means of a learnable weight matrix $W_n^m \in \mathbb{R}^{(d_t + m_h) \times d_y}$ as follows:

$$\hat{Y} = [Z_1|Z_2|\ldots|Z_n|H_1|H_2|\ldots|H_m]W_n^m$$

$$= [Z^n|H^n]W_n^m$$

$$= AW_n^m$$  \hspace{1em} (3)

where $d_y$ is the dimension of the output label vectors. And in the training procedure, $W_n^m$ can be solved by the approximate solution method of matrix pseudo inverse, that is

$$W_n^m = A^+Y$$  \hspace{1em} (4)

where

$$A^+ = \lim_{\lambda \to 0} \left(\lambda I + AA^T\right)^{-1} A^T$$  \hspace{1em} (5)

where $Y \in \mathbb{R}^{N \times d_y}$ is the ground-truth class label matrix with each row being a one-hot vector representing the ground-truth class label of the corresponding sample. For other calculation details of BLS, readers can read [4] and [5].

IV. PROPOSED METHOD

In this section, first, we describe the privacy computing problems that need to be solved. Second, we briefly summarize the MSBLS framework proposed in this article. Third, we simplify the generation of the mapped features in BLS. Fourth, we analyze in detail the necessity for different clients to use the same secret key and propose an interactive protocol to solve this problem. Finally, we describe the proposed MSBLS method.

A. Problem Statement

In this section, we assume that two clients hold privacy data and randomly generate some secret keys. A third-party server assists the calculation. To protect data security, all unencrypted private data and secret keys cannot leave the client. The purpose of the method we designed is to calculate the mapped features in (1) required by BLS under the above premise, and finally calculate the parameters of the machine learning model of the neural network classifier.

B. Overview of the MSBLS Framework

In this article, we propose a privacy-preserving multiparty machine learning method. It is very efficient and suitable for a variety of scenarios, which does not lose the information of data features while ensuring data security. Specifically, we use the SMC protocol to protect the input data of the BLS and calculate the mapped feature of the data in a secure computing environment. The computing idea of the protocol is shown in Fig. 2. In theory, the protocol can ensure that the trained machine learning model has the same performance as the machine learning model trained by direct fusion data. And, the experimental results confirm this conclusion. Moreover, different from homomorphic encryption, this method only needs a few computing resources and the training speed is very fast.

First, MSBLS performs feature fusion on the input data of the two clients while preserving privacy. Specifically, MSBLS uses a third-party server to assist two clients in multiple rounds of interactive communication. The purpose of this process is to encrypt data and generate the mapped features. It is worth mentioning that neither two clients nor the third-party server
can recover data that does not belong to them in this process. Then, in order to mine the nonlinear features of the data, similar to BLS, MSBLS activates the mapped feature to generate the enhancement feature. In this process, the original data will not be used, so the privacy of the data is preserved. Finally, the mapped features and the enhancement features are concatenated to form a feature matrix, a linear mapping is established between the feature matrix and labels, and the model parameters are solved by calculating the pseudo inverse of the matrix.

Theoretically, this encryption method will not lose the intrinsic information of the original data, so it can ensure that the trained model can generate the same results as applying the classical BLS on the direct fusion data, and our experiments on three classical image classification datasets confirm the above theoretical analysis. In addition, we analyze that in this process, the two clients providing data and the third-party server assisting the computation cannot recover the original data that does not belong to them. Moreover, the number of communications required by this method to process data of any scale is constant (12 times), which means that it is difficult to recover data through statistical law (law of large numbers). Finally, the method uses BLS as the neural network classifier, and its training speed is much faster than that of the deep neural network, which ensures the high efficiency of the method.

C. Simplification of BLS

The MSBLS designed in this article needs to send encryption features to achieve privacy computing. Since a large number of mapped features need to be calculated in (1), this process needs to be simplified to facilitate the design of interactive protocols.

In theory, the activation function \( \varphi(\cdot) \) has no specific requirements in (1). In this article, in order to simplify the model and reduce the number of communications, we use linear function as \( \varphi(\cdot) \). In addition, functions, such as the convolution function and nonlinear function, can also be used. Since \( \varphi(\cdot) \) is a linear function, (1) can be rewritten as follows:

\[
Z'' = \begin{bmatrix} Z_1 | Z_2 | \ldots | Z_n \end{bmatrix} \\
= \left[ \varphi(\mathbf{XW}_{c1} + \mathbf{\beta}_{c1}) \varphi(\mathbf{XW}_{c2} + \mathbf{\beta}_{c2}) \ldots \bigg| \varphi(\mathbf{XW}_{cn} + \mathbf{\beta}_{cn}) \right] \\
= \varphi \left( \begin{bmatrix} \mathbf{X} & \mathbf{1}^N \times 1 \end{bmatrix} \begin{bmatrix} \mathbf{W}_{c1} \mathbf{W}_{c2} \ldots \mathbf{W}_{cn} \end{bmatrix} + \begin{bmatrix} \mathbf{\beta}_{c1} \mathbf{\beta}_{c2} \ldots \mathbf{\beta}_{cn} \end{bmatrix} \right) \\
= \varphi \left( \begin{bmatrix} \mathbf{W}_{c1} & \mathbf{W}_{c2} \ldots \mathbf{W}_{cn} \end{bmatrix} + \begin{bmatrix} \mathbf{\beta}_{c1} & \mathbf{\beta}_{c2} \ldots \mathbf{\beta}_{cn} \end{bmatrix} \right)
\]
\[
\begin{aligned}
\phi \left( X^{N \times 1} \right) & = \phi \left( W_{1} W_{2} \cdots W_{n} \right) \\
& = \phi \left( \bar{X} \times W \right)
\end{aligned}
\]  

where \( X^{N \times 1} \) is a column vector of dimension \( N \) with all elements being 1, and \( \bar{X} = [X^{N \times 1}] \in \mathbb{R}^{N \times (d+1)} \). Since \( W_{i}, i = 1, 2, \ldots, n \), are random matrices and \( \beta_{i}(1,:), i = 1, 2, \ldots, n \), are random vectors, they can be written in the form of random matrix
\[
W = \begin{bmatrix}
W_{1} & W_{2} & \cdots & W_{n} \\
\beta_{1}(1,:) & \beta_{2}(1,:) & \cdots & \beta_{n}(1,:)
\end{bmatrix} \in \mathbb{R}^{(d+1) \times ndz}.
\]  

Without loss of generality, the random matrix \( W \) can be expressed by the product of two random matrices \( W_{0} \in \mathbb{R}^{(d+1) \times ndz} \) and \( W_{1} \in \mathbb{R}^{ndz \times ndz} \) (refer to Section V for the necessity of this step), that is
\[
Z' = \phi \left( X W_{0} W_{1} \right).
\]  

In addition, the goal of \((6)-(8)\) is to make the interactive protocol in Algorithm 1 (as will be described later) more concise and easy to read and greatly reduce the number of communications. Readers can change \( \phi(\cdot) \) into a nonlinear function according to their own needs. On this basis, the protocol in Algorithm 1 is still applicable.

D. Privacy Preserving via Random Mapping

In this section, we will introduce the privacy-preserving part of MSBLS in detail.

Assume that we need to encrypt the data from two clients A and B, and then integrate and analyze ciphertext. In addition, there is a third-party server to assist the calculation. The implementation of data encryption generally needs a secret key. A common key encryption method is to encrypt data by using random mapping (secret key). However, if the data encrypted by random mapping is directly used in training machine learning models, it may cause performance loss, that is, the original features are largely damaged by the random mapping. Therefore, we need to make random mapping as part of model training, which seems contradictory, but in fact, this is not an impossible work. For example, the deep neural network will use the random initial weight coefficient, the evolutionary algorithm will use the random initial population, and some clustering algorithms will carry out the random initial classification of samples. However, the aforementioned randomness is only regarded as initialization which will be updated in the later steps and hence cannot be considered as data encryption. In this article, we use the random mapping of BLS to achieve this purpose. Specifically, according to the previous description, BLS uses random mapping to generate the mapped features of data. From the perspective of data security, this process can be regarded as encrypting data. Therefore, using BLS can integrate data encryption and model training, and avoid the loss of model performance caused by encryption. However, it is not a trivial task. Specifically, if clients A and B directly use a set of confidential random mapping to encrypt data and aggregate the results as the mapped features

in \((1)\), the feature extraction methods of the two clients will be inconsistent.

1) If A and B hold the same samples, using different random mappings will generate different mapped features, which is obviously not conducive to the subsequent model training.

2) If A and B hold different samples, using different random mappings may generate the same mapped features, such as \((1, 2, 3) \times (2, 1, 0)^{\top} = (2, 2, 1) \times (0.5, 0.5, 2)^{\top}\), which is obviously not conducive to the subsequent model training.

3) Generally, we hope that in the data sample space, the data distribution of the same label will be concentrated as much as possible, and the data distribution of different labels will be dispersed as much as possible. However, if two clients use different random mappings to generate the mapped features and jointly participate in the next operation, the mapped features of different labels may significantly overlap, and the mapped features of the same label may be distributed in multiple centralized areas. As shown in Fig. 4, this will seriously affect the training of model parameters.

On the contrary, if clients A and B use the same random mapping to encrypt the data, respectively, it is equivalent to that they have obtained each other’s secret key (random mapping), which is extremely unsafe for the security of the data. To sum up, assume that client A holds data \( X_{A} \in \mathbb{R}^{N_{A} \times d} \) and the labels of data \( Y_{A} \in \mathbb{R}^{N_{A} \times d_{y}} \), and client B holds data \( X_{B} \in \mathbb{R}^{N_{B} \times d} \) and the labels of data \( Y_{B} \in \mathbb{R}^{N_{B} \times d_{y}} \), with \( N_{A} \) and \( N_{B} \) being the number of samples of clients A and B, and \( N = N_{A} + N_{B}, d_{y} \) being the dimension of the output label vectors. We use the following methods for data encryption and feature extraction:

![Fig. 4. Disadvantages of using different random mappings.](image-url)
\[
Z^* = \varphi(\bar{X}W_0W_1) \\
= \varphi\left(\left[\begin{array}{c} \bar{X}_A \\ \bar{X}_B \end{array}\right] \times \left[\begin{array}{c} W_A \\ W_B \end{array}\right] \times W_1 \right) \\
= \varphi\left(\left[\begin{array}{c} \bar{X}_A W_A \\ \bar{X}_A W_B \\ \bar{X}_B W_A \\ \bar{X}_B W_B \end{array}\right] \times W_1 \right) \\
\tag{9}
\]

where \( \bar{X}_A = [X_A \ 1^{N_A \times 1}] \in \mathbb{R}^{N_A \times (d+1)} \) and \( \bar{X}_B = [X_B \ 1^{N_B \times 1}] \in \mathbb{R}^{N_B \times (d+1)} \) are the augmented matrices of \( X_A \) and \( X_B \), respectively, \( W_A \in \mathbb{R}^{(d+1) \times (nd_d/2)} \) and \( W_B \in \mathbb{R}^{(d+1) \times (nd_d/2)} \) are two random matrices, and \( W_1 \in \mathbb{R}^{nd_d \times nd_d} \).

In order to calculate the mapped features using (9), it is necessary to calculate four block matrices \( \bar{X}_A W_A, \bar{X}_A W_B, \bar{X}_B W_A, \) and \( \bar{X}_B W_B \).

First, the random matrices \( W_A \) and \( W_B \) are generated by clients A and B, respectively, and therefore \( \bar{X}_A W_A \) and \( \bar{X}_B W_B \) can be directly calculated by the two clients, respectively. Furthermore, in order to calculate \( \bar{X}_A W_B \) and \( \bar{X}_B W_A \) in a secure environment, a third-party server needs to be introduced to assist the calculation. The interactive protocol framework for calculating \( \bar{X}_A W_B \) is illustrated in Fig. 2. After generating the four block matrices, the mapped features are generated by the third-party server.

For clarity, Algorithm 1 summarizes the detailed generation process of complete data encryption and the mapped features, where \( R_A \in \mathbb{R}^{N_A \times (d+1)} \), \( R_B \in \mathbb{R}^{(d+1) \times (nd_d/2)} \), and \( R_B \in \mathbb{R}^{(d+1) \times (nd_d/2)} \) are three intermediate variables for encryption, and \( E_1 \in \mathbb{R}^{N_A \times (nd_d/2)} \) and \( E_2 \in \mathbb{R}^{N_A \times (nd_d/2)} \) are two encrypted intermediate variables.

**Algorithm 1** Data Encryption and Mapped Feature Generation Procedures of MSBLS

**Input:** Data: Client A: \( X_A \), Client B: \( X_B \), feature mappings: \( \varphi \), number of mapped features: \( n \), dimension of mapped features: \( d_z \).

1: Third-party server do
2: Generate random matrices \( R_A, R_B, R_B \), send \( R_A \) to A, and send \( R_B, R_B \) to B;
3: Client A do
4: Let \( \bar{X}_A = [X_A \ 1^{N_A \times 1}] \), and calculate \( X_A^* = \bar{X}_A + R_A \), and send \( X_A^* \) to B;
5: Client B do
6: Generate random matrix \( W_B \), calculate \( W_B^* = W_B + R_B \), \( E_1 = X_A^* W_B + R_B \), and send \( W_B^*, E_1 \) to A;
7: Client A do
8: Calculate \( E_2 = E_1 - R_A W_B^* = \bar{X}_B W_B - R_B - R_A R_B \), and send \( E_2 \) to Server;
9: Third-party server do
10: Calculate \( E_2 - R_B + R_A R_B = \bar{X}_A W_B \);
11: Repeat the above steps to calculate \( \bar{X}_B W_A \) in the same interactive way;
12: Client A do
13: Calculate \( \bar{X}_A W_A \) and send it to Server;
14: Client B do
15: Calculate \( \bar{X}_B W_B \) and send it to Server;
16: Third-party server do
17: Generate random matrix \( W_1 \), calculate \( Z^* \) using Eq. (9).

**Output:** Mapped features \( Z^* \).

**Algorithm 2** MSBLS

**Input:** Data: Client A: \( [X_A, Y_A] \), Client B: \( [X_B, Y_A] \), feature mappings: \( \varphi, \xi \), number of mapped features: \( n \), dimension of mapped features: \( d_z \), number of enhancement features: \( m \), dimension of enhancement features: \( d_h \).

Calculate the mapped features \( Z^* \) via Algorithm 1;
Client A do
Send \( Y_A \) to Server;
Client B do
Send \( Y_B \) to Server;
Third-party server do
Let \( Y = \begin{bmatrix} Y_A \\ Y_B \end{bmatrix} \);
for \( j = 1 \) to \( m \) do
Generate random matrices \( W_{hj}, \beta_{hj} \);
Calculate \( H_j = \xi(Z^* W_{hj}, \beta_{hj}) \);
end for
Calculate \( W_{mn} \) using Eqs. (3)-(5).

**Output:** Weight matrix \( W_{mn} \).

V. ANALYSIS

A. Security Analysis

In this section, we analyze the security of the protocol in Algorithm 1, that is, Protocol 1. Specifically, we consider the data security in the semi-honest model. That is, the three parties (one server and two clients) involved in the calculation strictly implement Protocol 1, but they will infer the nonheld private data as much as possible according to the information they hold. In addition, we propose the following two assumptions.

1) **Hypothesis 1:** There is a secure channel between two of the three parties, that is, the data sent by the three parties will not be intercepted.
2) Hypothesis 2: Two of the three parties will not collude with each other and share private data.

Security Objective: On the premise of disclosing the mapped features, client A cannot obtain or recover data $X_B$ and $W_B$, client B cannot obtain or recover data $X_A$ and $W_A$, and the third-party server cannot obtain or recover $X_A$, $X_B$, $W_A$, and $W_B$.

Security Analysis: In line 4, client B receives $X_B^*$, but because client B does not hold the matrix $R_A$, it cannot recover $X_A$.

In line 6, client A receives $W_B^*$ and $E_1$, but since client A does not hold matrices $R_B$ and $R_B$, it cannot recover $W_B$ and $X_A^*W_B$.

In line 8, client A obtains $E_2$ through equation $E_2 = E_1 - R_AW_B^*$, which is equivalent to $X_AW_B + R_b - R_AR_B$. Therefore, $X_A$, $R_A$, and $E_2$ are known quantities to client A but $R_B$ and $R_b$ are unknown quantities to client A, so it cannot recover $W_B$.

In line 10, the third-party server obtains $X_AW_B$ through equation $E_2 - R_b + R_bR_B$. But $W_B$ is an unknown quantity to the third-party server, so it cannot recover $X_A$.

Line 11 is the same as the above analysis.

In lines 13 and 15, the third-party server holds the real values of the four product matrices $X_AW_A$, $X_AW_B$, $X_BW_A$, and $X_BW_B$, but using this information to recover the data $X_A$ and $X_B$ is an infeasible task. Specifically, the task is to solve a system of nonlinear equations of order $(N_A + N_B + n) \times d$ with $(N_A + N_B + n) \times d$ unknowns, which cannot be solved in polynomial time.

In line 17, the third-party server multiplies matrix $\begin{bmatrix} X_AW_A & X_AW_B \\ X_BW_A & X_BW_B \end{bmatrix}$ right by a random matrix $W_1$. Since $W_1$ is a nonpublic secret key, both clients A and B cannot recover matrix $\begin{bmatrix} X_AW_A & X_AW_B \\ X_BW_A & X_BW_B \end{bmatrix}$ using $Z^n$.

It should be noted that in the parameter training process of the whole Algorithm 2, Protocol 1 only runs once, and the corresponding data will only be transmitted once, which means that in theory, the data cannot be approximately recovered through the law of large numbers.

According to the above analysis, in the whole protocol procedure, neither client B nor the third-party server can recover the privacy data $X_A$ of client A. The same is true for $X_B$. Therefore, Protocol 1 is secure.

B. Communication Cost

In this section, we calculate the communication cost required to encrypt the data in Algorithm 1. To simplify the analysis process, we consider each element of the matrix as a character and express the communication cost in terms of the number of characters transmitted. The number of characters to be transmitted at each step in Algorithm 1 is listed in Table I.

| Steps | Number of characters transmitted |
|-------|-------------------------------|
| Line 2 | $N_A \times (d + 1) + 2(d + 1 + N_A + N_B) \times nd_c$ |
| Line 4 | $N_A \times (d + 1)$ |
| Line 6 | $(d + 1) \times nd_c + N_A \times nd_c$ |
| Line 8 | $N_A \times nd_c$ |
| Line 11 | Similar to lines 2 to 8: $2N_B \times (d + 1) + (2d + 2 + 3N_B) \times nd_c$ |
| Line 13 | $N_A \times nd_c$ |
| Line 15 | $N_B \times nd_c$ |

where $d$ denotes the dimension of the original features of the data, $N_A + N_B$ denotes the number of samples of the data, and $nd_c$ denotes the dimension of the generated mapped features. Comparing the generated mapped features $Z^n \in \mathbb{R}^{(N_A + N_B) \times nd_c}$ with the data $\begin{bmatrix} X_A & X_B \end{bmatrix} \in \mathbb{R}^{(N_A + N_B) \times d}$, it can be seen that the communication cost consumed by the encryption process in Algorithm 1 is of the same order of magnitude as the original data, which is acceptable.

VI. EXPERIMENTS

In this section, we verify the effectiveness of the proposed algorithm through experiments.

A. Datasets Description and Experimental Scenario

In order to make the experimental results more convincing, this article uses three classical image classification datasets, namely, Norb, MNIST, and Fashion.

1) The Norb dataset [39] samples the 3-D images of 50 toys at different heights, angles, and brightness. The images are divided into five categories: a) animals; b) humans; c) aircraft; d) trucks; and e) cars. The training set contains 24 300 images of 25 toys, while the testing set contains 24 300 images of another 25 toys.

2) The MNIST [40] handwritten numeral image dataset contains 70 000 scanned images of handwritten numerals [0, 1, ..., 9], each of which is a grayscale image of size $28 \times 28$. Among them, 60 000 samples are used as the training set, and the other 10 000 samples are used as the testing set.

3) The Fashion dataset [41] is an upgraded version of the MNIST dataset. It contains ten categories of clothing images: a) T-shirt; b) trouser; c) pullover; d) dress; e) coat; f) sandal; g) shirt; h) sneaker; i) bag; and j) ankle boot. The training set contains 60 000 samples with 6000 samples per category, and the testing set contains 10 000 samples with 1000 samples per category.

In order to simulate the actual scenario, we consider the distribution of the training data under the following two situations.
1) **Quantity Imbalance**: The number of training samples held by each client is different. This situation is consistent with the actual scenario, because the amount of data held by different institutions (clients) is often different. In this experiment, we set the number of training samples of the two clients as six different ratios from 50%:50% to 5%:95%.

2) **Non-IID**: The label distribution of training data held by each client is not “independent and identically distributed.” That is, the proportion of various labels of data held by each client is different. This situation is to simulate the difference of data samples of different institutions (clients) in the actual scene. Moreover, this experiment considers a more extreme and difficult scenario, that is, sorting the training data in the increasing order of class sizes, and then assigning the first half of the data to client A and the second half of the data to client B. This ensures that the labels of the data held by the two clients are almost different, which significantly increases the difficulty of model training.

### B. Baselines

It should be noted that in MSBLS, the privacy of the testing data is also preserved. In addition, in order to verify the effectiveness of the algorithm, we design experiments from the following three perspectives.

1) By conducting a comparison with the classical BLS [4] without privacy protection, that is, feeding the direct fusion of the training data from the two clients into the classical BLS, denoted as Nonprivacy BLS, we will show that MSBLS does not lose the performance of the model on the premise of protecting data security.

2) By conducting a comparison with BLS in an absolute security environment, feeding the training data in each client into the classical BLS separately to train two independent BLS classifiers, denoted as Single-party BLS, we will show the performance difference between MSBLS and Single-party BLS, and hence draw a conclusion that MSBLS significantly outperforms Single-party BLS on the premise of protecting data privacy.

3) By conducting a comparison with the latest privacy protection machine learning method, namely, federated learning algorithm (FedProx) [13], we will show the performance difference between MSBLS and FedProx in terms of accuracy, training time, and testing time.

4) By conducting a comparison with FCL-BL [14], another BLS-based federated learning method, we will show the performance difference between MSBLS and FCL-BL. Because both of the FCL-BL method and the MSBLS method use the same broad neural network as the classifier, this comparison result can better demonstrate the model performance of the MSBLS method and the federated learning method from different perspectives.

### C. Nonprivacy Experiment Results

Table II reports the comparison results of MSBLS and Nonprivacy BLS on the three datasets. The classification accuracy on both of the training dataset and the testing dataset is, respectively, reported. The results show that the performance difference between MSBLS and Nonprivacy BLS is within 1% on the premise of protecting data privacy, indicating that MSBLS will not lose the performance of the model while protecting data privacy. In fact, the mathematical forms of the mapped features and the enhancement features generated by MSBLS are consistent with those by Nonprivacy BLS, so the final model performance will not be significantly different from that of Nonprivacy BLS.

### D. Comparison of Single-Party and Multiparty Experimental Results

Table III reports the comparison results of MSBLS and Single-party BLS on the three datasets. The classification accuracy on the testing dataset is reported. The results show that when the proportion of the training samples in two clients changes, MSBLS always maintains a very stable testing accuracy on each dataset. On the contrary, the performance of Single-party BLS fluctuates significantly. This shows that the machine learning model trained independently will significantly lose the performance of the model. That is, when the proportions of data samples held by the two clients are different, if the two servers train the model parameters separately (i.e., Single-party BLS), it will be difficult for the client with a small number of samples to train a classifier with high accuracy, which is also an important reason why small hospitals need the help of large hospitals (on data). The use of MSBLS will not lose the accuracy of the model, so it can achieve secure privacy computing.

### E. Comparison With Federal Learning

Tables IV–VI report the comparison results of MSBLS, FedProx, and FCL-BL on three datasets. Overall, compared with FedProx, MSBLS has certain advantages in training accuracy and testing accuracy and can save a lot of training time. This is because the performance of MSBLS is consistent with that of BLS, and the experimental effect of BLS has obvious advantages over the other machine learning algorithms.
such as deep neural network (see document [4] for detailed comparison). However, compared with FCL-BL, MSBLS can still maintain the relatively stable model performance despite the change in the ratio of training samples between the two clients, while FCL-BL suffers from a small loss of accuracy. On the other hand, FCL-BL consumes slightly more training time because it requires multiple updates of the model parameters.

F. Non-IID Scenario

Table VII reports the comparison results of MSBLS, Single-party BLS, FedProx, and FCL-BL in the Non-IID and IID scenarios. In the Non-IID scenario, the testing accuracy of Single-party BLS is only about 50%, because the Single-party BLS trained alone can only classify part of the label data. For example, if the training set of client A does not contain samples with label “car,” the samples with label car in the testing set can not be recognized at all. Compared with the IID scenario, the federal learning methods (FedProx and FCL-BL) lose about 6% of testing accuracy in the Non-IID scenario, which is due to the fact that the gradient parameters cannot fully replace the original data when each client holds different data labels. The MSBLS method does not lose model performance at all in this scenario, which is due to the fact that the interactive protocol1 greatly preserves the characteristics of the data during the encryption process. Based on the derivation of Protocol 1 and (9), it is clear that the model performance of MSBLS is theoretically consistent with the model performance of fusing data directly without considering data security, and this experiment confirms this conclusion.

G. Encryption Time of Data

Table VIII reports the data encryption times for the MSBLS, FedProx, and FCL-BL methods. It should be noted that we consider the gradient parameters sent by FedProx and FCL-BL as encrypted data, which is not encrypted data in the conventional sense, so we focus on the encryption time of the MSBLS method in this part of the experiment. Table VIII shows that the MSBLS method consumes very little computation time to encrypt the data, and the encrypted data can be used directly for training model parameters without decryption, which indicates that the data encryption cost of the MSBLS method is low.
TABLE VIII
COMPARISON OF DATA ENCRYPTION TIME (S)

| Dataset | Norb | MNIST | Fashion |
|---------|------|-------|---------|
| MSBLS   | 11.81| 17.54 | 21.73   |
| FedProx | 377  | 312   | 305     |
| FCL-BL  | 37.24| 70.09 | 81.95   |

TABLE IX
COMPARISON OF COMMUNICATION COST (MB)

| Dataset | Norb | MNIST | Fashion |
|---------|------|-------|---------|
| MSBLS   | 120.1| 205.8 | 205.8   |
| FedProx | 3.9  | 1.6   | 1.5     |
| FCL-BL  | 3.9  | 11.8  | 7.1     |

H. Communication Cost

Table IX reports the communication costs (in terms of communication traffic) for the MSBLS, FedProx, and FCL-BL methods. The MSBLS method consumes higher communication costs because MSBLS sends encrypted data, while FedProx and FCL-BL send gradient parameters. Because the communication costs required by directly sending the raw data are 47 MB (Norb), 45 MB (MNIST), and 45 MB (Fashion), respectively, the communication cost of the MSBLS method is relatively acceptable. According to the above experimental results, it can be concluded that the MSBLS method essentially improves the prediction accuracy and reduces the training time at the cost of an acceptable communication cost.

VII. DISCUSSION

A. Scenario of Multiple Clients

In this article, the proposed MSBLS method considers the information security problem of data cooperation between two clients. Similar to the idea of extending two-class support vector machine (SVM) to multiclass SVM, the MSBLS method can also be extended to the data cooperation problem of multiple clients. SVM is a classical linear classifier, and its basic idea is to search the maximum-margin hyperplane which can divide the data set correctly and has the largest geometric interval [42]. The earliest SVM can only be used to classify data sets containing two class labels. In 2000, Vapnik [43] popularized SVM and applied it to the multiclass classification problem. He regarded the multiclass problem as a classification problem of multiple one-versus-rest and then superimposed the classification results to obtain the classification results of the multiclass problem. In 2005, Milgram et al. [44] replaced the logistic function in SVM with the softmax function, so as to extend SVM to multiclass classification problems with low computational cost.

In fact, the MSBLS method proposed in this article can also be extended by similar methods. For the scenario of multiple clients, we can use the interactive protocol proposed in this article to encrypt the data of each two clients, and then the third-party server fuses the encrypted data and calculates the model parameters. Another method is to modify the interactive protocol, that is, client A sends the encrypted data to client B, and client B encrypts the obtained data again and sends it to client C, and so on to achieve data fusion of multiple clients.

However, these promotion methods may suffer from the relatively high computational cost or security problems, which need to be analyzed and solved in detail in future research.

B. Security of Output Label

The MSBLS method proposed in this article does not encrypt the output class labels for the following two reasons. The first reason is that since the original feature information of the data is encrypted, the third-party server cannot obtain the feature information of the data through the class labels, but only the number of samples of each class label. For example, a hospital encrypts the personal information and CT images of multiple patients who may have brain tumors, but not the disease type. The third-party server that obtains the above data only knows the number of patients with various diseases in the sample, but not whether a particular patient has a certain disease (because the personal information is encrypted). Another reason is that if the output class labels are encrypted in a similar way to Algorithm 1, it is essentially equivalent to replacing the class labels to another set of natural numbers (e.g., replacing [1, 2, 3] with [4, 5, 6]), which cannot really achieve information protection. For these reasons, the output class labels have not been encrypted in this article.

VIII. CONCLUSION

This article proposes a new PPML method, which is a pioneering research work different from other methods. The existing PPML methods generally cannot simultaneously take into account multiple requirements, such as security, application scope, efficiency, and model performance. Specifically, differential privacy fails to simultaneously consider security and efficiency. The application scope and efficiency of homomorphic encryption are largely limited. The security of federal learning is not guaranteed by theory. The application scope of the traditional SMC is relatively limited. The MSBLS method proposed in this article inherits the advantages of both SMC and neural network. It simultaneously takes into account the above four requirements and achieves very satisfactory results (both in theory and experiment).

As described above, this article has obtained a pioneering research achievement, which can provide an in-depth interactive perspective for the field of information security and machine learning. Researchers in these two fields can extend their research results to the field of PPML through the protocol provided in this article. In other words, this article opens up a new research path in the field of PPML, which combines the research results of the two fields more effectively. However, since this article only makes a preliminary exploration, there are still some problems to be further studied. From the perspective of information security, first, different interactive protocols need to be designed in the scenarios of the semi-honest model and the malicious model. Second, we need to expand the number of clients participating in privacy computing from two to multiple. In this case, we need to consider the balance between security and communication times when designing interactive protocols. Third, how to ensure the
security of data when some clients are attacked or colluded with each other? From the perspective of machine learning, first, MSBLS needs to adopt different feature extraction methods when applied to computer image, natural language, voice, and other data types. Different feature extraction methods need to design corresponding interactive protocols to protect data security. Second, MSBLS needs to consider various practical needs, such as the security of stream data, the possible impact of missing data, data privacy calculation methods with different feature dimensions, etc.

REFERENCES

[1] H. Greenspan, B. van Ginneken, and R. M. Summers, “Guest editorial: deep learning in medical imaging: Overview and future promise of an exciting new technique,” IEEE Trans. Med. Imag., vol. 35, no. 5, pp. 1153–1159, May 2016.
[2] W. Raghupathi and V. Raghupathi, “Big data analytics in healthcare: Promise and potential,” Health Inf. Sci. Syst., vol. 2, no. 1, p. 3, 2014.
[3] J. Le, X. Lei, N. Mu, H. Zhang, K. Zeng, and X. Liao, “Federated learning in heterogeneous networks,” in Proc. 26th ACM SIGKDD Conf. Knowl. Disc. Data Min. Virtual, 2020, pp. 2706–2714.
[4] J. Milgram, M. Cheriet, and R. Sabourin, “Estimating accurate multi-target localization in single-view,” IEEE Trans. Cybern., vol. 52, no. 4, pp. 1–19, 2022.
[5] J. Geiping, H. Bauermeister, H. Dröge, and M. Moeller, “Inverting gradients—How easy is it to break privacy in federated learning?” in Proc. Ann. Conf. Neural Inf. Process. Syst., 2020, pp. 1–11.
[6] J. Yi, F. Wu, C. Wu, R. Liu, G. Sun, and X. Xie, “Efficient-FedRec: Communication-efficient federated learning framework for privacy-preserving news recommendation,” 2021, arXiv:2109.05446.
[7] J. Geiping, H. Bauermeister, H. Dröge, and M. Moeller, “Inverting gradients—How easy is it to break privacy in federated learning?” in Proc. Ann. Conf. Neural Inf. Process. Syst., 2020, pp. 1–11.
[8] J. Geiping, H. Bauermeister, H. Dröge, and M. Moeller, “Inverting gradients—How easy is it to break privacy in federated learning?” in Proc. Ann. Conf. Neural Inf. Process. Syst., 2020, pp. 1–11.
[9] X. Jin, P.-Y. Chen, C.-Y. Hsu, C.-M. Yu, and T. Chen, “CAFE: Catastrophic data leakage in vertical federated learning,” 2021, arXiv:2110.15122.
[10] R. Bost, R. A. Popa, S. Tu, and S. Goldwasser, “Machine learning classification over encrypted data,” in Proc. 22nd Annu. Netw. Distrib. Syst. Security Symp., 2015, pp. 1–34.
[11] M. D. Cock et al., “Efficient and private scoring of decision trees, support vector machines and logistic regression models based on pre-computation,” IEEE Trans. Dependable Security Comput., vol. 16, no. 2, pp. 217–230, Mar./Apr. 2020.
[12] F. Pan, D. Meng, Y. Zhang, H. Li, and X. Li, “Secure federated feature selection for cross-feature federated learning,” in Proc. NeurIPS Workshop SpicyFL, 2020, pp. 1–12.
[13] Y. LeCun, F. J. Huang, and L. Bottou, “Learning methods for generic object recognition with invariance to pose and lighting,” in Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit. (CVPR), 2004, pp. 97–104.
[14] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, “Gradient-based learning applied to document recognition,” Proc. IEEE, vol. 86, no. 11, pp. 2278–2324, Nov. 1998.
[15] H. Xiao, K. Rasul, and S. Vollgraf, “Fashion-MNIST: A novel image dataset for benchmarking machine learning algorithms,” 2017, arXiv:1708.07747.
[16] C. Cortes and V. Vapnik, “Support-vector networks,” Mach. Learn., vol. 20, no. 3, pp. 273–297, 1995.
[17] V. N. Vapnik, The Nature of Statistical Learning Theory. New York, NY, USA: Springer, 2000.
[18] J. Milgram, M. Cheriet, and R. Sabourin, “Estimating accurate multi-class probabilities with support vector machines,” in Proc. IEEE Int. Joint Conf. Neural Netw., vol. 3, 2005, pp. 1906–1911.
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