A PRIVACY-PRESERVING OUTSOURCED DATA MODEL IN CLOUD ENVIRONMENT

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ABSTRACT

Nowadays, more and more machine learning applications, such as medical diagnosis, online fraud detection, email spam filtering, etc., services are provided by cloud computing. The cloud service provider collects the data from the various owners to train or classify the machine learning system in the cloud environment. However, multiple data owners may not entirely rely on the cloud platform that a third party engages. Therefore, data security and privacy problems are among the critical hindrances to using machine learning tools, particularly with multiple data owners. In addition, unauthorized entities can detect the statistical input data and infer the machine learning model's parameters. Therefore, a privacy-preserving model is proposed, which protects the privacy of the data without compromising machine learning efficiency. In order to protect the data of data owners, the ϵ -differential privacy is used, and fog nodes are used to address the problem of the lower bandwidth and latency in this proposed scheme. The noise is produced by the ϵ -differential mechanism, which is then added to the data. Moreover, the noise is injected at the data owner's site to protect the owners' data. Fog nodes collect the noise-added data from the data owners, then shift it to the cloud platform for storage, computation, and performing the classification tasks purposes.

Keywords Cloud Computing · Machine Learning · Fog Computing · Privacy Preservation · Differential Privacy

1 Introduction

Nowadays, Machine learning algorithm has become an essential tool in many applications, including product recommendations, fraud detection, speech recognition, etc. The cloud service providers such as Amazon Web Service (AWS), Google, Microsoft Azure, etc., offer 'ML-as-a-Service' (MLaaS) service as a black-box application programming interface (API) that accomplishes machine learning classification tasks [1, 2, 3]. Data owners can achieve classified results by uploading data sets and performing the tasks of classification [4, 5] by employing the machine learning classification model [6, 7, 8]. To train the classification model, it requires an ample amount of data from various sources, which can contain sensitive information, including intellectual properties, personal images, and health-related records [9, 10, 11]. These data are acquired from multiple owners [12, 13, 14]. Initially, data owners shift their data to the cloud service provider at the cloud server for storage, analysis, and classification tasks [15]. This data is passed through the fog nodes. The cloud service provider accesses all data from the fog nodes and stores it on its server [16, 17]. When the data from the owners' site is outsourced to the cloud server, owners lose ownership of their data at that time and are unaware of the outsourced data accessing it [18, 19, 20, 21, 22, 23]. Even outsourced data may be accessed by unauthorized entities, or any adversary [24, 25, 26]. The data owners may not believe on the fog nodes and cloud service provider, since third parties manage it [27, 28, 29, 30, 31, 32]. Although the owner's data play an essential role

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in classification tasks in the machine learning model, disclosing this data will lead to some significant privacy concerns [33, 34, 35]. Therefore, to protect the data, the owners initially encrypt their data for privacy reasons before transferring it to other entities [36, 37]. Nevertheless, the data is encrypted using some of the most well-known encryption techniques [38, 39, 40, 41, 42, 43, 44, 45, 46]. But, using this encrypted data with a machine-learning model is quite challenging [47]. Another problem is that an increase in the number of internet devices may lead to a rise in demand for low-latency real-time services that will be difficult for traditional cloud computing [48, 49, 50, 51, 52, 53, 54, 55, 56]. To tackle the aforementioned problems, we have proposed a model named Privacy-Preserving Outsourced Data (PPOD) model in cloud environment. Our proposed scheme is based on fog computing and differential privacy. Initially, each data owner transfers his data to each fog node under this scheme. Since they don't interact with one another, different privacy protection is taken into consideration at the owner's site. According to the various applications of the classification, each data owner injects different statistical noises into outsourced data. All the fog nodes collect the noisy data from each data owner and transfer all the noise-added data to the cloud service provider whenever the data owner sends the request for the classification tasks. The classification service is provided by the cloud service provider [57, 58, 59]. It gets noisy data from the data owner through the fog nodes. The classification task is carried out over the data collected from the data owners. The cloud service provider sends the result of the classification to the data owner. Therefore, our proposed scheme performs the machine learning classification task in a manner that preserves privacy.

2 Related Work

2.1 Privacy-Preserving Based on Cryptography

In order to perform classification tasks on the ciphertext under multiple keys, Ma et al. [60] devised a privacy-preserving deep learning model, referred to as PDLM, that enables the service provider (SP) to migrate majority computing to the cloud to train a deep learning model based on stochastic gradient descent (SGD). It also accomplishes the feed-forward and back-propagation procedure based on an effective privacy-preserving calculation toolkit in the cloud without releasing any confidentiality. By doing this, SP's storage and computational cost are reduced while ensuring the security of the training data. The experiments were conducted, and the result indicated that the PDLM model could effectively and efficiently train model while protecting data privacy. This model's classification accuracy result is very low and has a high computation cost. To tackle the issue of training deep neural network algorithms over encrypted data, Hesamifard et al. [61] presented a framework, namely CryptoDL, that preserves data privacy using homomorphic encryption. They provided the theoretical basis and demonstrated that it is feasible to identify the lowest degree polynomial approximation of a function within a given error bound. They developed entire neural networks over homomorphically encrypted data, with polynomial approximations used in place of the activation functions (Sigmoid and ReLU). The empirical results demonstrated that the proposed CryptoDL provided accurate privacy-preserving training and classification. While this secures personal information well, they did not take into account the need that several keys to protect confidential data from different data owners. A scheme for a classifier owner to delegate a remote server was introduced in [62], which offers the privacy-preserving classification service for users. The authors developed effective encryption methods for Naive Bayes and hyperplane decision-based classification, respectively. On the LAN server, the experiments were carried out. This system's disadvantage is that users' interactions are frequently involved when a classification query is launched. Aono et al. [63] devised a system called gradients encrypted asynchronous SGD (ASGD), which utilizes additively homomorphic encryption to secure the gradients across an honest-but-curious cloud server. The proposed method outperformed a similar deep learning system that had been trained on the shared dataset of all participants in accuracy terms. On the cloud server, all gradients are encrypted and kept safe. The computation across gradients is made possible by the additive homomorphic characteristic. The proposed scheme's drawback is that the proposed scheme's trade-off is the additional communication overhead between the cloud server and DL participants. A multiparty Back-Propagation neural (BPN) network learning scheme is presented in [64], which safeguards each participant's private data set and intermediate outcomes produced throughout the network learning process. With a data set that has been arbitrarily partitioned, the proposed method enables collaborative learning between two or more parties. The BGN homomorphic encryption technique was adopted and modified to provide flexible operations over ciphertexts. The proposed scheme has been demonstrated to be secure, effective, and accurate through numerical analysis and experiments on commodity clouds. However, the BGN cryptosystem only allows for a single multiplication operation and an infinite number of addition operations. Therefore, a fully homomorphic encryption strategy was utilized to safeguard the confidentiality of the encrypted data and allow an arbitrary amount of multiplication and addition operations. To maintain the multiplicative depth of the neural network, Chabanne et al. [65] designed and evaluated the privacy-preserving classification for neural networks with a depth greater than 2. The fundamental concept was to combine simplifications of the NN with Fully Homomorphic Encryptions (FHE) approaches to achieve both processing efficiency and data secrecy. They substituted low-degree polynomial approximations for the ReLU functions in the CNN utilized in the classification phase. The high degree is present in the ReLU function. Consequently, a batch normalization layer was added to the ReLU's polynomial approximation. Results of the experiments indicated that the

proposed framework obtained private classification accuracy on the private data is better than Cryptonets and near to non-private data accuracy. Moreover, devices with limited resources cannot handle homomorphic encryption's high computational requirements. A summary of the literature review of privacy-preserving based on Cryptography is shown in Table 1.

Methods/Schemes	Strategy	Datasets	Classifiers	Pros	Cons
A secure deep learn- ing model for train- ing the encrypted data [60]	DD-PKE	MNIST, CIFAR-10	SGD, Sigmoid Function	Trained the deep learning model efficiently and effec- tively	
preserving model	1	MNIST, CIFAR-10		Provided accurate privacy- preserving training and clas- sification	
preserving out-	momorphic encryption,	cer Original, SPECT Heart,		Preserved the privacy of the classification model	Communications among users con- tinually involved when establishing a classification query
A secure parameters protection scheme for deep learning [63]	momorphic en- cryption	,	dient Descent	Achieved high accuracy and retained the data privacy	The trade-off increases the communication overhead
A secure data pro- tection scheme for sharing cipher-text [64]	momorphic	Iris, kr-vs-kp, and diabetes	Propagation Neural Net-	The computation and trans- mission costs for each group are the least cost and are in- dependent of the number of participants	tains only one multi- plication but performs
A secure deep neu- ral network for clas- sification [65]		MNIST	ReLU, Sigmoid function	It provides better accuracy	The homomorphic en- cryption is too compu- tation

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2.2 Privacy-Preserving Based on Differential Privacy

To preserve the privacy of sensitive information of the data owners for classification, Li. et al. [66] devised a privacypreserving Naive Bayes learning scheme using multiple data sources. The proposed scheme enables a trainer to train a Naive Bayes classifier over the dataset that is jointly provided by various data owners without the assistance of a reliable curator. They designed the aggregation approach with the intention of hiding some statistical data (e.g., the number of total samples). The experiments which were conducted on a LAN server demonstrated the viability of the proposed approach for use in various applications. To accomplish privacy-preserving machine learning over cloud data from various data providers, Li et al. [67] proposed a scheme that protects the data sets of different providers and the cloud, respectively. The data sets of different providers have been encrypted by adopting the separate public keys by the public-key encryption with a double decryption algorithm (DD-PKE) cryptosystem. It allows the encrypted data to be transformed into a randomized data set without information leakage, while also protecting the cloud's data sets using ϵ -differential privacy. The experiments demonstrated that the proposed scheme enhanced data analysis precision and computational effectiveness. The Server-aided Network Topology (SNT) system and the Fully-connected Network Topology (FNT) system, depending on the connection with SNT or FNT among the trainers, were presented by Phong and Phuong [68] that protects the specific data of all trainers. The stochastic gradient descent (SGD) algorithm or its

Methods/Schemes	Strategy	Datasets	Classifiers	Pros	Cons
A secure classifier scheme for learning the process [66]	vacy	Breast Can- cer Original, SPECH Heart, Gene Se- quences		Designed Algorithm hides the statistics information and do not involve heavy cryptographic tools	sions are allowed, or ad- versaries have the abil- ity to alter the actual data
A secure data shar- ing scheme [67]		Cpu, Glass, and		Improved the efficiency of the computation	based on Laplace has less accuracy
vacy [68]	Network Topol- ogy, Fully- connected Network Topol- ogy	CIFAR-100, Pima (diabetes), Breast Cancer, Banknote Au- thentication, Adult Income, Skin/NonSkin	gradient de- scent (SGD) algorithm, ReLU, Sigmoid	Low computation and com- munication overhead and high accuracy	ing, the deep learning model is sequentially trained over the datasets
A secure and effi- cient data release scheme [69]		Original	Not available	Maintaind the data integrity	Less data utility
Secure outsourcing scheme for data publication [70]	vacy and Ad- ditively homo- morphic encryp- tion	tion, EEG Eye State, CPU, and Glass	Bayes		An efficient method does not exist in the proposed scheme
vacy model for sen- sitive data [71]	vacy	Arrhythmia, Hepatitis, Indian-liver- patient, Fram- ingham	Forest,KNN, Naïve Bayes, ANN	Achieved accuracy up to 93.75%	classification model
A data and classi- fication protection model [72]	vacy	disease, nursery, and balance scale	Naive Bayes	Acquired accuracy up to 94%	Performance degrada- tion
A machine learn- ing based model for medical data [73]		Parkinson, SpectF, Plan- ning Relax, and Wisconsin Breast Cancer	Deep neural net- work	Achieved accuracy up to 87.03%	It can be extended by devising more efficient privacy-preserving mechanism

Table 2: Pandect Summary of Privacy-Preserving driven on Differential privacy

derivatives can be used by multiple machine-learning trainers in the proposed systems to analyze the combined datasets of the trainers without exposing the local datasets of the individual trainers. Instead of using gradient parameters, these systems used weight parameters. They preserved privacy while achieving the same learning accuracy as SGD. The experiments were carried out, and the outcomes demonstrated that the proposed systems are practically effective in terms of computation, communication, and accuracy. However, the proposed scheme is not able to train the deep learning model parallel sequentially trained on private datasets. To address the issue of valuable data and responding thousands of queries under differential privacy (DP) is inappropriate and unprotected to attack, Ye et al. [69] proposed a secure and efficient outsourcing DP data release scheme with order-preserving encryption (OPE) rather than the general solution utilizing homomorphic encryption in the cyber-physical system. The proposed method allowed for the outsourcing of datasets by data providers to a cloud service provider with reduced connectivity costs. After uploading their encrypted data, data providers were not required to be online. Less accuracy is provided by the proposed scheme. To address the problems of effectiveness related to adding various types of noise to a dataset for differentially private publication, An efficient and secure outsourced differential privacy scheme was introduced in [70]. Additive homomorphic encryption was employed to encrypt the data, while noise was generated by using differential privacy. The proposed scheme allowed data providers to contract with cloud service providers with low communication costs to handle their dataset sanitization process. Furthermore, after uploading their datasets and noise parameters, data providers can go offline, which is another essential requirement for a practical system. Moreover, experiments were evaluated, confirming the proposed scheme's effectiveness. However, an efficient method only exists in the proposed system that permits data to be released once while maintaining the data's usefulness for numerous evaluation algorithms and applications is present in the proposed system. A summary of the literature review of privacy-preserving based on differential privacy is depicted in Table 2.

3 System Model

The system model consists of three entities, such as Data Owners (DO), Fog Nodes (FN), and Cloud Service Provider (CSP). The system model is split into three-tier, as shown in Fig. 1. All the tiers are described below:

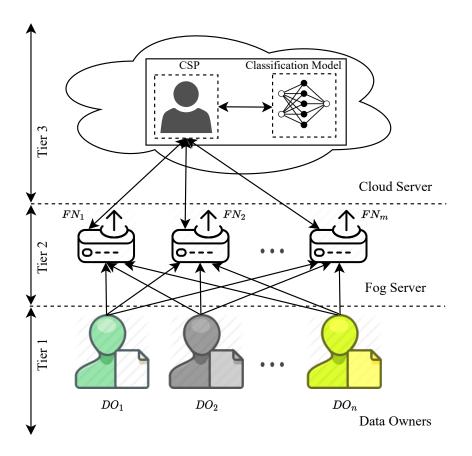


Figure 1: System model

- a) Tier1: The bottom-most layer of the proposed architecture is tier1. At tier1, multiple data owners $\{DO_1, DO_2, ..., DO_n\} \in \mathbb{D}\mathbb{O}$ exist . Each $DO_1, DO_2, ..., DO_n$ has its data $\{D_1, D_2, ..., D_n\} \in \mathbb{D}$, which is used for storage, computation, performing the classification task on the machine learning algorithm. $D_1, D_2, ..., D_n$ includes sensitive data. For example, DO_1 has D_1 data containing $\{X_{11}, X_{12}, ..., X_{1m}\}$ feature instance, DO_2 has D_2 data containing the feature instance $\{X_{21}, X_{22}, ..., X_{2m}\}, ..., DO_n$ has DO_n data containing $\{X_{n1}, X_{n2}, ..., X_{nm}\}$ feature instance. To preserve the privacy of data \mathbb{D} from the adversary, noise vector $\{N_1, N_2, ..., N_n\} \in \mathbb{N}$, is generated by the $DO_1, DO_2, ..., DO_n$. This generated noise $N_1, N_2, ..., N_n$ is injected into the data $D_1, D_2, ..., D_n$, respectively. After adding noise, $DO_1, DO_2, ..., DO_n$ have noised-added data $D_i^{N_i} = \{D_1^{N_1}, D_2^{N_2}, ..., D_n^{N_n}\}$. At tier1, this noise-added data is divided vertically, i.e. $\{X_{11}, X_{21}, ..., X_{n1}\}, \{X_{12}, X_{22}, ..., X_{n2}\},$ and $\{X_{1m}, X_{2m}, ..., X_{nm}\}$. The vertically partitioned data is transferred to tier2.
- b) *Tier*2: The middle layer of the system model is Tier2. This is known as the fog computing layer (including routers, access points, gateways, and switches). The main component of this layer is multiple fog nodes $\{FN_1, FN_2, \ldots, FN_s\} \in FN_j$, where $j \in [1, s]$. These fog nodes are smart intermediate devices with data storage, computation, routing, and packet forwarding capabilities. Each fog nodes access and store the vertically partitioned data of the multiple data owners from tier1. For example, the instance feature $\{X_{11}, X_{21}, \ldots, X_{n1}\}$ is stored on the FN_1 node, $\{X_{12}, X_{22}, \ldots, X_{n2}\}$ is stored on FN_2 node, and $\{X_{1m}, X_{2m}, \ldots, X_{nm}\}$ is stored on the FN_s node, respectively. The adversary cannot access the entire data when storing partitioned data on different fog nodes.
- c) *Tier3*: The cloud service provider is presented at the topmost tier in the system model. This tier contains many high-speed servers, data centers as well as the machine learning model. CSP offers ample storage space, computing capabilities, and classification services to cloud users as per their request at the topmost tier. CSP is a semi-honest entity. Besides, to perform the classification task, CSP obtains the noisy data set from different fog nodes. The achieved results from the classification model, CSP shares the outcomes to DO_1 , DO_2, \ldots, DO_n through FN_1, FN_2, \ldots, FN_s .

4 Conclusion

The work focuses on preserving the privacy of outsourced data of multiple data owners. Conventional cloud computing technology provides many benefits as storage, computation, and machine learning tasks to the cloud user. But the cloud storage creates several security conflicts. Whenever data owners store their data for storage on the cloud and perform machine learning tasks, the owners then lose their rights and are unable to handle and maintain the physical storage of their data. To tackle the problem of privacy protection in cloud storage and access the classification service from cloud computing, we propose a PPOD scheme. This proposed scheme is based on the fog computing model and differential privacy. Using differential privacy, noise is injected by the data owners, and data is divided vertically. The separated data is stored on the various fog nodes. Therefore, adversaries cannot access the actual and whole data from one place.

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