A Privacy-Preserving Model based on Differential Approach for Sensitive Data in Cloud Environment

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Abstract A large amount of data and applications need to be shared with various parties and stakeholders in the cloud environment for storage, computation, and data utilization. Since a third party operates the cloud platform, owners cannot fully trust this environment. However, it has become a challenge to ensure privacy preservation when sharing data effectively among different parties. This paper proposes a novel model that partitions data into sensitive and non-sensitive parts, injects the noise into sensitive data, and performs classification tasks using k-anonymization, differential privacy, and machine learning approaches. It allows multiple owners to share their data in the cloud environment for various purposes. The model specifies communication protocol among involved multiple untrusted parties to process owners' data. The proposed model preserves actual data by providing a robust mechanism. The experiments are performed over Heart Disease, Arrhythmia, Hepatitis, Indian-liver-patient, and Framingham datasets for Support Vector Machine, K-Nearest Neighbor, Random Forest, Naive Bayes, and Artificial Neural Network classifiers to compute the efficiency in terms of accuracy, precision, recall, and F1-score of the proposed model. The achieved results provide high accuracy, precision, recall, and F1-score up to 93.75%, 94.11%, 100%, and 87.99% and improvement up to 16%, 29%, 12%, and 11%, respectively, compared to previous works.

Keywords Machine learning \cdot Cloud computing \cdot Differential privacy \cdot Laplace distribution \cdot k-anonymity

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1 Introduction

Data storage, computation, utilization, analysis, and sharing are the vital required services for any organization to improve performance [1]. Numerous applications and data are shifting from the local to the cloud due to various benefits such as minimum cost, maximum efficiency, and high scalability [2]. Sensitive sample data also are shared with the cloud or other parties for distinguish services [3]. However, users hesitate to share data with the cloud for computation and storage since a third party manages it [4], and data may be misused as well as owners lose control of their data [5] [6]. The cloud may also provide outsourced data to other entities for different purposes [7]. Due to these reasons, data protection has become a critical challenge for any organization. Therefore, there is a need for a mechanism that can protect sensitive data. For this, the different kind of techniques, such as cryptography, differential privacy, k-anonymity, etc., are used to preserve the data for privacy reasons before transferring it to the cloud platforms [8] [9].

To address the aforementioned challenges, we propose a novel Privacy-Preserving Model based on Differential approach (PPMD) for sensitive data in the cloud environment. In the proposed model, owners partition their data into sensitive & non-sensitive [10]-[12], and different statistical noise is injected into sensitive data according to various applications and owner's queries [13]-[15]. Differential privacy protection is considered on the owner's side because they do not want to share actual data. The resulted data is uploaded to the cloud platform, and classification services are provided [16]. The machine learning algorithms are applied over resulted data for classification. The cloud platform obtains classified data from the classification model and sends it to the data owner rather than other parties. Fig. 1 presents a bird-eye view of the proposed work and highlights our consecutive contributions to preserve data privacy and perform classification tasks in the cloud environment. The summary of the main contributions of PPMD are as follows:

- PPMD allows various data owners to share outsourced data securely. To protect data against stealing or leakage, noise is injected, and noise-added data is shared.
- PPMD uses the cloud platform for storage, computation, and performing classification tasks over collected data from multiple owners. All entities are considered to be untrusted to protect data with enhanced privacy.
- PPMD maintains the degree of accuracy because of the data partition into sensitive & non-sensitive parts and statistical noise addition.
- A series of experiments are conducted using the distinct dataset to validate the practicality of the proposed model. Besides, the comparisons are performed among the various a) datasets, b) classifiers, and c) distinctly preprocessed data using differential privacy and with the state-of-the-art works to prove the superiority of PPMD.

Organization: The rest of this paper proceeds as follows. Section 2 describes the related work. In Section 3, we present the proposed model PPMD, and the



Fig. 1: Bird eye view of the proposed work

process of data partition is shown in Section 4. The data classification steps are defined in Section 5. Section 6 shows the implementation and evaluates the results of the experiment with statistical analysis. Finally, a conclusion and the direction of the future work are described in Section 7. The list of notations with their definitions is shown in Table 1 used in this paper.

Table 1: List of Terminologies with their Explanatory Terms

DO_{id} :	Data Owners	CSP:	Cloud Service Provider
P_{id} :	Patients	D_i :	Actual data
N_i :	Noise	CM:	Classification Model
D_i^S :	Sensitive data	CA:	Classification Accuracy
D_i^{NS} :	Non-sensitive data	<i>P</i> :	Precision
\bar{D}_i^S :	Noise-added data	\hat{D}_i :	Preprocessed data
R:	Recall	$\hat{D}_{t'}$:	Training data
$\hat{D}_{t''}$:	Testing data	FS:	F1-score
A_i :	Data attribute	s'	Scaling parameter
μ :	Mean	σ :	Standard deviation
ϵ :	Privacy budget	n^* :	Count of classes
n:	Number of data objects	L:	Label item
C:	Object category		

2 Related work

Yuan and Yu [17] proposed a secure, efficient, and accurate multiparty Back-Propagation Neural (BPN) network-based scheme that allowed two or more parties, each having an arbitrarily partitioned data set, to conduct the learning collaboratively. But, this scheme focused on facilitating data processing without considering the algorithm efficiency. Yonetani et al. [18] proposed a doubly permuted homomorphic encryption (DPHE) based privacy-preserving framework. It enabled multiparty protected scalar products with a reduction of the high computational cost. However, DPHE supports either addition or multiplications at a particular time. A system that utilizes additively homomorphic encryption to protect the gradients against the curious server is presented in [19]. This system achieved identical accuracy to a corresponding deep learning system, i.e., asynchronous stochastic gradient descent (ASGD) trained over the common dataset of all participants. All classifiers from multiple parties are trained over the single-source domain in this scheme, but the trade-off is a lower accuracy rate. To provide the privacy-preserving classification service for users, Li et al. [20] proposed a scheme for a classifier owner to delegate a remote server. But during the launch of a classification query, user interactions were often involved in this scheme. Li et al. [21] proposed a data protection scheme that enables a trainer to train a Naive Bayes classifier over the dataset provided jointly by the different data owners. To preserve the privacy of the data, ϵ -differential privacy is utilized. But, adversaries still have the ability to forge and manipulate the data in this scheme. Ma et al. [22] proposed a privacy-preserving deep learning model, namely PDLM, to train the model over the encrypted data under multiple keys. A privacy-preserving calculation toolkit was adopted to train the model based on stochastic gradient descent (SGD) in a privacy-preserving manner. The model reduced the storage overhead, but the classification accuracy is less, and the computation cost is high. Li et al. [23] proposed a privacy-preserving machine learning with multiple data provider (PMLM) scheme with improved computational efficiency and data analysis accuracy. The authors used public-key encryption with a double decryption algorithm (DD-PKE) and ϵ -differential privacy. But the scheme suffered from less accuracy as well as less data sharing. To protect the confidentiality of sensitive data without leakage, a privacy-conserving outsourced classification in cloud computing (POCC) framework was introduced [24] under various public keys using a fully homomorphic encryption proxy technique. However, data owners and storage servers are deemed to be in the same trustworthy domain that no longer exists in the cloud environment. Gao et al. [25] proposed a scheme to avoid information leakage under the substitution-thencomparison (STC) attack. A privacy-preserving classification mechanism was designed by adopting a double-blinding technique for Naive Bayes, and both the communication and computation overhead was reduced. But this scheme is unable to obtain the discovery of truth that protects privacy. To apply the deep neural network algorithms over the encrypted data, Hesamifard et al. [26] revert a neural networking-based framework named CryptoDL while considering the existing limitations of homomorphic encryption schemes. Although the approach works well to secure private data, but the data is protected using a key that is not feasible. Phong and Phuong [27] constructed a privacypreserving system, namely the server-aided network topology (SNT) system,

and the fully-connected network topology (FNT) system, depending on the connection with SNT and FNT server. In these systems, multiple machinelearning trainers can use the SGD or its variants over the combined dataset without sharing the local dataset of each trainer. The constructed systems used the weight parameters rather than the gradient parameters and achieved an accuracy similar to SGD. Wei et al. [28] proposed a framework, namely, noising before model aggregation federated learning (NbAFL), which prevents the information leakage effectively. The client's data is protected by using a differential privacy mechanism. However, this framework requires a large amount of noise to add and sacrificing mode utility. Gupta et al. [29] proposed a machine learning and probabilistic analysis-based model, namely MLPAM. It supports multiple participants to share their data safely for different purposes by using encryption, machine learning, and probabilistic approaches. The proposed model provided a mechanism that reduced the risk associated with the leakage for prevention coupled with detection. The experimental results showed that the proposed model ensured high accuracy and precision. A summary of the literature review is depicted in Table 2.

Table 2: Tabular sketch of the literature review

Model/Scheme /Framework	Workflow & Implementa- tion	Outcomes	Drawback
A secured scheme for processing ciphered text [17]	 The arbitrarily partitioned data is encrypted using a doubly homomorphic encryption scheme Experiments are performed on the Amazon EC2 cloud 	 Security analysis proves that this scheme is secure, scalable, and efficient Less error rates 	High com- putation and com- munication complexity
A privacy- preserving framework for visual learning [18]	 A homomorphic cryptosystem is used to update high-dimensional classifiers The experiments are performed on the CelebA and Life-logging datasets 	 Achieve 84% accuracy by performing facial recognition tasks Minimize the computational cost of homomorphic encryption 	Does not as- sist the mul- tiple opera- tions (addi- tion or mul- tiplication)
A secure deep learning sys- tem for pa- rameters pro- tection [19]	 The homomorphic encryption and asynchronous stochastic gradient are adopted to encrypt trained parameters The Adam optimizer is used for training with input learning rate 10⁻⁴ 	 More effective in pro- tecting sensitive in- formation from the curious server Achieve the same ac- curacy as that of the centralized DL algo- rithm 	The local data can still be sur- reptitiously extracted from two adjacent versions of parameters

A secure outsourcing scheme for the classifica- tion service [20]	 The additive homo- morphic encryption technique is used to protect the data The experiments are con- ducted on the LAN server 	• More practical and less communication cost	Only sup- port a single-party setting
A privacy- preserving scheme for learning al- gorithms [21]	 The differential privacy mechanism was used to protect the data The LAN server was used to conduct the experi- ments 	 Achieve data privacy will not break while the training data Less computational time requires for training 	Paillier cryp- tosystem can only work with integers
A privacy preserving deep learning model to train over the encrypted data [22]	 The model is trained based on stochastic gra- dient descent, the feed- forward, and a back- propagation procedure The experiments were conducted over MNIST, CIFAR-10 datasets 	 Minimize the storage overhead Errors are calculated to evaluate the performance of the model 	Low ef- ficiency utilizing the dis- tributed two trapdoors public-key cryptosys- tem
A privacy- preserving machine learning scheme for data protec- tion [23]	 A double encryption al- gorithm and differential privacy mechanism was used to preserve data pri- vacy MAGMA programming is used to perform the cryp- tosystem 	 Enhance the computational efficiency and data analysis accuracy The security analysis proves that the model is more secure 	High compu- tational cost due to the dependence on integer factorization
A privacy- preserving outsourced classification framework for confi- dentiality of sensitive data [24]	 A fully homomorphic encryption proxy technique is utilized to encrypt data The naive bayes classifier is performed over multi- ple datasets for experi- ment work 	 Reduce power con- sumption by cloud clusters Less computational overhead 	The data is encrypted with a single key, and it is not suitable for multi-user systems
A privacy- preserving Naive Bayes classifier scheme to prevent in- formation leakage [25]	 A double-blinding technique is used to avoid the attacks The GNU Multi-Precision library and the OpenSSL library are used for programming 	 Reduce the computa- tion cost because of not using fully homo- morphic encryptions More efficient due to offline phase of server 	Not suitable for the multi- label dataset

A CryptoDL framework for applying deep neural network algo- rithms over encrypted data [26]	 The polynomial approximation is used for continuous activation functions The experiments are conducted on MNIST and CIFAR-10 datasets 	 Perform proper privacy-preserving training and classifi- cation tasks The security model proves that the server cannot access the in- put data 	High com- putation cost and less accuracy
A privacy- preserving deep learning model for input privacy [27]	 The input data is protected through symmetric encryption A multilayer perceptron and a convolutional neural network are used for experiments 	 Achieve the same learning accuracy as SGD The security analysis proves that no train- ing information will be revealed using the weight parameters 	To up- date weight causes low efficiency and no con- sideration for output privacy
A privacy- preserving framework for data protection [28]	 To preserve privacy of data, the Gaussian noise is added to it The experiments are per- formed on the MNIST dataset using multi-layer perception 	 Maintain a privacy level with a low-performance loss Achieve high level privacy-preserving and secure capabilities 	Noise in- evitably reduces the accuracy
A machine learning and probabilistic analysis- based model for secure sharing data [29]	 The differential privacy, encryption, machine learning, and probabilis- tic approaches are used to encrypt, noise addi- tion, and share the data of multiple participants The SVM, Random For- est, KNN, and Naive Bayes classifiers train the model on Glass, Iris, Wine, and Balance Scale datasets 	 Minimize the risk affiliated with the leakage for prevention and detection Achieve high accuracy and precision up to 97% and 100% 	Does not provide ef- ficient data sharing and management in multiple environ- ments

The major limitations of the existing works are that the models injected the noise into entire data and/or protected it using various encryption approaches followed by machine learning-based classification, which reduced accuracy and/or increased computation cost. The earlier models considered a single owner and/or a single untrusted entity. Unlike the previous works, PPMD partitions the data using k-anonymization, injecting the noise into the sensitive part of data to make it private and applying various state-of-art classifiers. It also permits multiple owners to share outsourced data securely while treating all participating entities involved as untrustworthy.

3 Proposed model

The proposed model architecture, named PPMD (Fig. 2), comprises the involved entities and their communication with essential flows. This architecture



Fig. 2: Proposed PPMD architecture

contains two entities Data Owners (DO_{id}) and Cloud Service Provider (CSP) which are described as follow:

- 1) DO_{id} : An entity that generates data and requests to CSP for services. DO_{id} sends sensitive/non-sensitive data, but noise is added into sensitive data before transferring it to CSP. DO_{id} applies ϵ -differential privacy to protect sensitive data. Since it is assumed that DO_{id} can't leak its data but may leak other owners' data. Therefore, DO_{id} is considered an untrusted entity.
- 2) CSP: An entity that gathers all data from DO_{id} and provides facilities of storage and computation. It offers classification services to DO_{id} through the classification model (CM). It trains CM using machine learning algorithms over collected data and accesses classified data from CM. These

obtained results are shared among DO_{id} . In PPMD, CSP is treated as a semi-trusted entity, as it strictly follows the protocol but is curious to learn the information.

Let the data owners $DO_{id} = \{DO_1, DO_2, \dots, DO_n\}$ has data $D = \{D_1, D_2, \dots, DO_n\}$ \ldots, D_n , where the data object $D_i \in D$ is independent and can be of any type and size. DO_{id} needs to share D with the semi-trusted party like CSP for storage, computation, and performance enhancement. But, DO_{id} can't share D because it contains sensitive data also. Therefore, before sharing, DO_{id} partitions his data into sensitive data D^S and non-sensitive data D^{NS} using the k-anonymization mechanism. In order to make D^S private, $\{DO_1, DO_2, DO_2,$..., DO_n procure noisy data $\bar{D}^S = \{\bar{D}_1^S, \bar{D}_2^S, \dots, \bar{D}_n^S\}$ by adding noise $N = \{N_1, N_2, \dots, N_n\}$ into $D^S = \{D_1^S, D_2^S, \dots, D_n^S\}$ using the ϵ -differential privacy. DO_{id} has noise-added data \bar{D}^S & non-sensitive data D^{NS} that are combined, and sanitized data $\hat{D} = \{\hat{D}_{t,1}, \hat{D}_{t,2}, \dots, \hat{D}_{t,n}\}$ is obtained. DO_{id} sends \hat{D} to CSP that performs the classification tasks over it to make a fit CM. Any query can be made by DO_1, DO_2, \ldots, DO_n to CSP. The results of these queries are received by CSP from CM, and sent to the corresponding entity DO_1, DO_2, \ldots, DO_n . Algorithm 1 shows the operational summary of the proposed model. Initially, data D_i is divided into D_i^S and D_i^{NS} . Afterward, noise vector N_i is generated and performed the addition operation on D_i^S and N_i . The classification operation is carried out over noisy & non-sensitive data using the machine learning algorithms, and unknown class labels are obtained from CM. The accuracy, precision, recall, and F1-score are calculated using these class labels.

Algorithm 1: PPMD model operational summary

Input: Actual data D, Sensitive data D^S , Non-sensitive data D^{NS} , Noise vector N, input vector \hat{D} **Output:** CA, P, R, and FSInitialize data $D := \{D_1, D_2, \dots, D_n\}, \bar{D}^S := \{\bar{D}_1^S, \bar{D}_2^S, \dots, \bar{D}_n^S\}, N := \{N_1, N_2, \dots, D_n\}$ \ldots, N_n **2** for i = 1, 2, ..., n do **Data_Partition** (D_i) з $N_i = \operatorname{Lap}(0,1)$ 4 $\bar{D}_i^S = D_i^S + N_i$ $\hat{D}_i = (\bar{D}_i^S, D_i^{NS})$ 5 6 **Data_Classification** (\hat{D}_i) 7 8 end for $CA = (\#Correctly \ classified \ sample \ / \ \#test \ sample) * 100$ 9 10 P = (TP)/(TP + FP)11 R = (TP)/(TP + FN)12 FS = 2 * (P * R) / (P + R)

4 Data partition & noise addition

In PPMD, $DO_{id} = \{DO_1, DO_2, \ldots, DO_n\}$ has data $D = \{D_1, D_2, \ldots, D_n\}$ in the form of relation, D_1, D_2, \ldots, D_n has attributes $\{A_1, A_2, \ldots, A_{t_1}\}, \{A_1, A_2, \ldots, A_{t_2}\}, \ldots, \{A_1, A_2, \ldots, A_{t_n}\}$. These relations $\{D_1, D_2, \ldots, D_n\}$ are partitioned into two relations sensitive and non-sensitive based on row-level data sensitivity of using k-anonymization approach by applying Eq. (1) and (2). The Algorithm 2 presents the partition of data D_1 into $D_1^S = \{A_1, A_2, \ldots, A_{t_1-p}\}$ and $D_1^{NS} = \{A_{t_1-p+1}, A_{t_1-p+2}, \ldots, A_{t_1}\}, D_2$ is partitioned into $D_2^S = \{A_1, A_2, \ldots, A_{t_2-q}\}$ and $D_2^{NS} = \{A_{t_2-q+1}, A_{t_2-q+2}, \ldots, A_{t_2}\}, \ldots, D_n$ is partitioned into $D_n^S = \{A_1, A_2, \ldots, A_{t_n-r}\}$ and $D_n^{NS} = \{A_{t_n-r+1}, A_{t_n-r+2}, \ldots, A_{t_n}\}$ respectively, where $p, q, r, s \in Z$.

$$D_i^S = \prod_{(A_1, A_2, \dots, A_{t_i} - s)} (D_i) \tag{1}$$

$$D_i^{NS} = \prod_{(A_{t_i-s+1}, A_{t_i-s+2}, \dots, A_{t_i})} (D_i)$$
(2)

Algorithm 2: Data Partition

Input: Actual data D with \ddot{n} records, the value of \ddot{k} for k-anonymity **Output:** Sensitive data D^{S} , Non-sensitive data D^{NS} Initialize data $D := \{D_1, D_2, \dots, D_n\}, D^S := \{D_1^S, D_2^S, \dots, D_n^S\}, D^{NS} :=$ $\{D_1^{NS}, D_2^{NS}, \dots, D_n^{NS}\}$ **2** Set $\ddot{p} = \left\lfloor \frac{\ddot{n}}{\ddot{k}} \right\rfloor$ for i = 1, 2, ..., n do 3 for $\ddot{e} = 1, \ldots, \ddot{p}$ do 4 Randomly select distinct records $r_{\ddot{e}} \in D_i$ 5 while $(D_i \neq \phi)$ do 6 Add the records $r_{\ddot{e}}$ to D_i^S 7 $D_i^{NS} = D_i \setminus \{r_{\ddot{e}}\}$ 8 end while 9 10 end for return D_i^S, D_i^{NS} 11 12 end for

For instance, let the proposed PPMD model consist of fifty patients $P_{id} = \{P_1, P_2, \ldots, P_{50}\}$ having data $D = \{D_1, D_2, \ldots, D_{50}\}$ in the vector form $\{x_i, y_i\}$, shown in Table 3, which contains both sensitive and non-sensitive data. Therefore, we need to separate the Patients Report into two relations a) Patients Report1 with attributes Age & Gender, and b) Patient Report2 with attributes TB, DB, ALG, and Disease, correspondingly shown in Tables 4 and 5. In this way, diseases can't be recognized without knowing Age and Gender.

To preserve the privacy of sensitive data, noise is inserted into the tuples of Patients Report1 using differential privacy before transferring to the cloud

Age	Gender	TB	DB	ALG	Disease
65 62 68 58	Male Female Female Male	$0.7 \\ 10.9 \\ 7.3 \\ 3.9$	$0.1 \\ 5.5 \\ 4.1 \\ 2.0$	$3.3 \\ 0.2 \\ 3.3 \\ 0.4$	1 0 1 1
72 46 :	Female Male :	3.2 6.4	3.7 1.0 :	3.4 2.2 :	0 1 :
34	Female	4.6	2.4	3.1	1

Table 3: Patients Report

Table 4: Patients Report1	
(Sensitive)	

Table 5: Patients Report2 (Non-sensitive)

Age	Gender	ΤВ	DB	ALG	Disease
65	Male	0.7	0.1	3.3	1
62	Female	10.9	5.5	0.2	0
68	Female	7.3	4.1	3.3	1
58	Male	3.9	2.0	0.4	1
72	Female	3.2	3.7	3.4	0
46	Male	6.4	1.0	2.2	1
:	÷	÷	÷	÷	÷
34	Female	4.6	2.4	3.1	1

platform. But, Patients Report2 is outsourced to the same cloud platform without performing any operation. DO_{id} generates a noise vector $N = \{N_1, N_2, \ldots, N_n\}$ using the probability density function, and distribution function using Eq. (3).

$$N = \frac{1}{2s'} \cdot \left(exp(\frac{-|rn|}{s'})\right) \tag{3}$$

where rn is input, s' is the scale parameter, and N is a noise vector, which is drawn from the Laplacian distribution with scale s'. The generated noise vector N is added in the corresponding data $D^S = \{D_1^S, D_2^S, \ldots, D_n^S\}$ as $\bar{D}_i^S = D_i^S + N_i$ where $i \in [1, n]$. After adding noise, D^S data becomes noiseadded data $\bar{D}^S = \{\bar{D}_1^S, \bar{D}_2^S, \ldots, \bar{D}_n^S\}$ i.e. Patients Report3, shown in Table 6. \bar{D}^S and D^{NS} data are combined using the sanitization process, and sanitized data $\hat{D} = \{\hat{D}_{t,1}, \hat{D}_{t,2}, \ldots, \hat{D}_{t,n}\}$ is transferred to CSP.

5 Data classification

CSP obtains $\hat{D} = \{\hat{D}_{t,1}, \hat{D}_{t,2}, \dots, \hat{D}_{t,n}\}$ from DO_{id} and prepossess it by using the normalization function given in Eq. (4), where T_s is training sample, μ , and

(\mathbf{N})	Voise-ac	lded Data	,)
	Age	Gender	
	65.23	1.65	
	62.35	0.79	
	68.64	0.69	
	58.75	1.49	
	72.96	0.67	
	46.74	1.69	
	÷	÷	
	34.56	0.96	

Table 6: Patients Report3

 σ are the mean and the standard deviation of the training sample, respectively.

$$\hat{D} = \frac{(T_s - \mu)}{\sigma} \tag{4}$$

It is assumed that data $\hat{D} = \{\hat{D}_{t,1}, \hat{D}_{t,2}, \dots, \hat{D}_{t,n}\}$ belong to $n^* \leq n$ classes $C = \{C_1, C_2, \dots, C_{n^*}\}$ where n^* is count of classes, $\bigcup_{i=1}^{n^*} C_i = D$ and $C_i \cap C_j = \Phi, \forall_{i,j} = 1, 2, \dots, n^* \land i \neq j$. The steps for the classification of data are illustrated in Fig. 3. In which, data $\{\hat{D}_{t,1}, \hat{D}_{t,2}, \dots, \hat{D}_{t,n}\}$ is divided into training data $\hat{D}_{t'} = \{\hat{D}_{t,1}, \hat{D}_{t,2}, \dots, \hat{D}_{t,n-k}\}$, and testing data $\hat{D}_{t''} = \{\hat{D}_{t,n-k+1}, \hat{D}_{t,n-k+2}, \dots, \hat{D}_{t,n}\}$. The training data $\{\hat{D}_{t,1}, \hat{D}_{t,2}, \dots, \hat{D}_{t,n-k}\}$ is used to train CM, whereas accuracy of CM can be measured by testing data $\{\hat{D}_{t,n-k+1}, \hat{D}_{t,n-k+2}, \dots, \hat{D}_{t,n}\}$. During the testing process, the data object $\{\hat{D}_{t,n-k+1}, \hat{D}_{t,n-k+2}, \dots, \hat{D}_{t,n}\}$ is given to CM, which identifies their classes. CM analyzes $\{\hat{D}_{t,n-k+1}, \hat{D}_{t,n-k+2}, \dots, \hat{D}_{t,n}\}$ as an output, whereas $L_{i'} \in L$ specifies $C_i \in C$ to which $\hat{D}_{t'',i'} \in \hat{D}_{t''}$ pertains. The classification accuracy (CA) is calculated using Eq. (5), whereas CI indicates the number of items correctly classified and TI indicates the total number of test items.

$$CA = \frac{CI}{TI} \tag{5}$$

The precision (P), and recall (R) are calculated using Eq. (6) and (7) respectively, whereas TR indicates the total number of items returned by the classifier and RI indicates the total number of relevant items. The F1-score (FS) is measured using Eq. (8).

$$P = \frac{CI}{TR} \tag{6}$$

$$R = \frac{CI}{RI} \tag{7}$$



Fig. 3: Classification flow for shared data

$$FS = \frac{2PR}{P+R} \tag{8}$$

Sanitized data \hat{D} is the combination of both noisy data \bar{D}^S and nonsensitive data D^{NS} , which is given to the input layer with n nodes. A multilayer perceptron (Fig. 4) architecture consists of three layers: one input layer, one hidden layer, and one output layer. The input layer receives the data and prepares it for feeding the hidden layer H with n_2 nodes. The hidden layer H is responsible to process the acquired results from input layer. The results of H is $H_{n_2} = \{\varphi_1 \hat{D}_{t_1}, \varphi_2 \hat{D}_{t_2}, \ldots, \varphi_{n_2} \hat{D}_{t_n} + b_1\}$, where φ , b_1 are the weight and bias, respectively. The obtained results from the hidden layer is given to the output layer. The activation function is used to activate the neuron at the hidden layer as well as at the output layer. The results of the last layer with n_3 nodes as $y = \{\varphi_1 h_1, \varphi_2 h_2, \ldots, \varphi_{n_3} h_{n_2} + b_2\}$ is achieved, where b_2 is the bias. The final classification result $L = \{L_{t,n-k+1}, L_{t,n-k+2}, \ldots, L_{t,n}\}$ is obtained from CM. The steps for the data classification have been described by Algo-



Fig. 4: Learning Model for privacy preserving

rithm 3. Steps 3 to 5 in this algorithm display the Support Vector Machine (SVM) classifier's efficiency. In steps 6 to 8, the procedure for the K-Nearest Neighbor (KNN) classifier is provided. Using steps 9 to 11, the Random Forest (RF) classifier classifies the data. The Naive Bayes (NB) classifier is conducted

using step 12. Finally, the Artificial Neural Network (ANN) task is addressed in steps 13 to 18.

In algorithm 1, steps 2 to 8 perform the classification over noised data using a classification model, whose time complexity depends on the data partition, noise addition, and classifier usage. The data is separated using step 3, which takes the time $\mathcal{O}(n^2)$, and space $\mathcal{O}(n)$, where n be the total number of input records. To preserve the privacy of the data, noise is generated in step 3 and added using the Laplace mechanism in step 4, which requires $\mathcal{O}(n^2)$ time, and $\mathcal{O}(n)$ space. The classification model is performed using steps 7, which needs $\mathcal{O}(n^3)$ time, and $\mathcal{O}(n^2)$ space. Therefore, the total time complexity, and space complexity of PPMD is $\mathcal{O}(n^3) = (\mathcal{O}(n^2) + \mathcal{O}(n^2) + \mathcal{O}(n^3)), \mathcal{O}(n^2) = (\mathcal{O}(n) + \mathcal{O}(n) + \mathcal{O}(n^2))$, respectively. PPMD complexity analysis implies that the aid of endurable time and space protects the data, which establishes its potency.

Algorithm 3: Data Classification

Input: Input vector \hat{D} , weight w, bias b, activation function f(x)**Output:** unknown class label \bar{y} , tree numbers n_tree 1 Initialize input vector $\hat{D} = \{\hat{D}_1, \hat{D}_2, \dots, \hat{D}_n\}, \hat{D}_1 = \{(x_1, y_1), (x_2, y_2), \dots, \hat{D}_n\}$ $(x_{i}, y_{j})\}, w, b$ for i = 1, 2, ..., n do 2 $\begin{aligned} z_i &= \sum \hat{D}_i \cdot w^T + b \\ f(z_i) &> 0, \ \bar{y}_i := 1 \end{aligned}$ з 4 $f(z_i) < 0, \, \bar{y}_i := 0$ 5 for Compute Set I contains the minimum sets of k do 6 distance d (\hat{D}_i, \bar{y}_i) 7 8 end for for $\ddot{t} = 1, 2, \ldots, n$ -tree do 9 tree_classification(\hat{D}_i, \bar{y}_i) 10 end for 11 $\bar{y}_i = argmax_y P(y) \prod P(X_i \mid y)$ 12for $\ddot{k} = 1, 2$ do 13 for $\ddot{l} = 1, ..., n_{\ddot{k}+1}$ do 14 $z_{\vec{l}}^{(\vec{k}+1)} = \sum_{\hat{t}=1}^{n} x_{\hat{t}}^{(\vec{k})} \cdot w_{\hat{t}}^{(\vec{k})} + b_{\vec{l}}^{(\vec{k})}$ $\bar{y}_{i} = f(z_{\vec{l}}^{(\vec{k}+1)})$ 15 16 end for 17 end for 18 return \bar{u}_i 19 20 end for

6 Performance evaluation

6.1 Experimental setup

The experiments are performed on a machine equipped with Intel (R) Core (TM) i5-4210U CPU @ 1.70GHz clock speed. The computing machine runs Ubuntu 64-bit and has 8 GB of the main memory RAM. Python 2.7.15 programming language is used to complete the classification tasks. The five distinct classifiers: SVM, KNN, RF, NB, and ANN, have been used to train *CM* over training data.

6.2 Datasets and classification parameters

Heart Disease, Arrhythmia, Hepatitis, Indian-liver-patient, and Framingham datasets are taken from the UCI Machine Learning Repository [30] to train *CM*. There are 303, 452, 155, 583, 303 instances, 75, 280, 20, 11, 14 attributes, and 2, 13, 2, 2, 2 classes (binary and multi-class) in these datasets, correspondingly as shown in Table 7.

Table 7: Basic information of four datasets

Dataset	#Instances	#Features	#Classes	Samples in	Samples in
				training set	test set
Heart Disease	303	75	2	272	31
Arrhythmia	452	280	13	406	46
Hepatitis	155	20	2	139	16
Indian-liver-patient	583	11	2	524	59
Framingham	303	14	2	272	31

To train CM, 9/10 of data is used as training data from the entire dataset, while the rest is used as test data. For a particular case, there are 303 instances in the Heart Disease dataset. The 272 instances (i.e., 9/10 of 303 instances) are used as training samples and the remaining 31 instances for testing samples. The machine learning model is carried out over Clean, PPMD, PMLM [23], NbAFL [28], and MLPAM [29]. We have used the Laplace mechanism to generate the noise. However, PPMD, PMLM, NbAFL, and MLPAM schemes contain noise. The results of CM are measured using test data, and the CA, P, R, and FS are computed from these results.

6.3 Results

The CM obtains the classification results including CA, P, R, and FS over Clean, PPMD, PMLM [23], NbAFL [28], and MLPAM [29], as demonstrated in Figs. 5(a)-(e) to 8(a)-(e). In PPMD, the maximum value of CA is 93.75% on the Arrhythmia dataset using the ANN classifier. The minimum value of

CA is 62.50% on the Hepatitis dataset using the KNN classifier. The average value of CA is 72.20%, 73.40%, 73.61%, 70.03%, and 84.11% over Heart Disease, Arrhythmia, Hepatitis, Indian-liver-patient, and Framingham dataset, respectively. The highest value of P is 94.11% on the Indian-liver-patient dataset using the NB classifier. The lowest value of P is 43.33% on the Heart Disease dataset using the ANN classifier. The average value of P is 69.33%, 53.51%, 74.18%, 78.23%, and 76.15% over Heart Disease, Arrhythmia, Hepatitis, Indian-liver-patient, and Framingham dataset, respectively. The maximum value of R is 100% on the Indian-liver-patient dataset using the SVM classifier. The minimum value of R is 39.13% on the Arrhythmia dataset using the ANN classifier. The average value of R is 59.62%, 62.48%, 82.30%, 76.95%, and 84.06% over Heart Disease, Arrhythmia, Hepatitis, Indian-liver-patient, and Framingham dataset, respectively. The highest value of FS is 87.99% on the Hepatitis dataset using the RF classifier. The lowest value of FS is 41.37%on the Arrhythmia dataset using the ANN classifier. The average value of FS is 62.84%, 57.20%, 79.48%, 75.97%, and 78.77% over Heart Disease, Arrhythmia, Hepatitis, Indian-liver-patient, and Framingham dataset, respectively. The datasets' performance descends in order: Framingham, Hepatitis, Indian-liver-patient, Heart Disease, and Arrhythmia.

6.4 Comparison

The experimental results are compared with clean data, PMLM [23], NbAFL [28] as well as MLPAM [29], which is implemented on the same platform (Figs. 5(a)-(e) to 8(a)-(e)). The PPMD outperforms PMLM [23], NbAFL [28], and MLPAM [29] in all the cases because the proposed model reduces the impact of injecting noise by separating data into sensitive and non-sensitive parts. From Table 8, it is observed that the highest difference for CA among PPMD, PMLM, NbAFL, and MLPAM is 15.83% on the Hepatitis dataset using ANN classifier, and the lowest difference is found 0.0% on the Heart Disease dataset using SVM classifier, and the Hepatits dataset using KNN classifier. Likewise, the maximum gap for P is 28.39% on the Heart Disease dataset using the RF classifier, but the lowest difference is found 0.0% on the Arrhythmia dataset using the ANN classifier. The R of PPMD maximum improved by 11.33% from PMLM, NbAFL, and MLPAM on the Heart Disease dataset using the RF classifier, whereas the smallest improvement is 0.0% on the Hepatitis dataset using ANN classifier, and on the Indian-liver-patient dataset using the SVM, KNN, RF classifiers. The highest difference for FS is 10.56% on the Arrhythmia dataset using the KNN classifier, while the lowest difference for FS is 0.03% on the Framingham dataset using the KNN classifier.

Moreover, the results of PPMD are less than the results of Clean data in all the cases due to noise addition. Table 9 shows that the maximum gap for CA between PPMD and clean data is 6.25% on the Hepatitis dataset using the SVM, KNN, RF, and NB classifiers, but the smallest gap is found 0.12% on the Framingham dataset using the ANN classifier. Similarly, the highest



Fig. 5: Accuracy of CM in PPMD



Fig. 6: Precision of CM in PPMD



Fig. 7: Recall of CM in PPMD



Fig. 8: F1-score of CM in PPMD

Data	Class			Γ	ecrem	ents ir	the v	alue of	f parar	neters			
set	ifier -		CA			P			R			FS	
	-	[23]	[28]	[29]	[23]	[28]	[29]	[23]	[28]	[29]	[23]	[28]	[29]
	SVM	3.22	0.0	6.45	5.00	4.04	7.26	10.9	4.72	11.19	5.33	4.43	8.79
	KNN	3.23	3.23	3.23	1.92	2.17	5.81	4.16	2.15	5.37	2.19	1.47	2.69
Heart	\mathbf{RF}	1.01	1.01	1.01	24.45	22.94	28.39	11.33	1.5	1.72	5.25	3.63	7.64
Disease	NB	3.22	3.22	3.75	2.67	1.13	4.58	3.51	2.15	4.37	2.30	1.09	5.03
	ANN	0.61	3.06	3.80	0.48	0.48	0.48	3.23	3.23	3.23	1.95	0.20	1.95
	SVM	2.18	2.18	4.35	5.86	5.58	5.93	2.18	2.18	4.35	5.59	5.14	5.73
	KNN	6.52	2.17	6.52	9.30	8.45	10.77	6.52	2.17	6.52	9.98	4.01	10.56
Arrhy	\mathbf{RF}	4.35	2.17	8.70	3.94	0.93	5.00	4.35	4.35	8.70	6.32	4.92	7.91
thmia	NB	1.56	1.56	3.74	1.13	1.26	1.76	1.56	1.56	3.74	3.07	0.29	3.91
	ANN	0.25	0.25	1.08	0.0	0.53	1.05	1.75	0.67	2.18	2.24	0.56	4.06
	SVM	6.25	6.25	6.25	4.10	4.58	4.58	9.85	4.16	10.41	6.48	4.56	9.48
	KNN	6.25	0.0	0.0	4.76	2.19	2.19	1.52	1.52	2.08	4.92	1.92	4.93
Hepa	\mathbf{RF}	12.50	6.25	12.50	1.65	1.65	11.91	1.28	3.36	9.61	7.99	3.38	9.73
titis	NB	6.25	6.25	6.25	6.41	4.76	11.97	5.50	1.92	1.92	1.81	0.33	5.43
	ANN	15.11	8.0	15.83	4.28	2.48	5.95	0.0	0.0	8.34	2.57	1.67	2.09
	SVM	1.69	3.39	5.08	1.69	3.39	6.15	0.0	0.0	2.44	1.12	2.27	3.43
Indian	KNN	1.69	1.69	3.39	1.67	2.75	3.26	0.0	0.39	0.75	1.35	1.35	1.77
Liver	\mathbf{RF}	1.69	3.39	5.08	6.01	0.24	4.60	0.0	1.06	4.3	1.54	2.62	4.81
Patient	\mathbf{RF}	1.70	1.70	3.39	2.45	1.81	5.23	2.77	0.05	7.03	4.87	2.98	5.14
	ANN	3.05	1.46	3.24	9.49	3.77	9.49	4.48	1.70	2.56	3.82	1.67	5.24
	SVM	0.71	0.24	2.12	2.76	1.18	4.09	0.71	0.24	2.12	1.21	0.55	2.37
	KNN	0.71	0.24	1.18	0.90	0.74	2.29	0.71	0.24	1.18	0.03	0.04	0.98
Frami	\mathbf{RF}	1.18	0.71	2.13	2.04	1.77	3.24	1.18	0.71	2.13	0.35	0.38	1.32
ngham	NB	0.95	0.24	2.13	1.62	0.28	2.26	0.95	0.24	2.13	1.49	0.23	1.56
	ANN	0.24	1.13	9.23	0.09	1.08	1.29	1.69	1.22	1.69	0.11	0.90	0.90

Table 8: Improvement in the values of CA, P, R, and FS of PPMD in comparison with the values on PMLM [23], NbAFL [28], MLPAM [29]

difference for P is 8.09% on the Hepatitis dataset using the RF classifier, while the lowest difference is found 0.0% on the Hepatitis dataset using the KNN classifier. The R of PPMD the maximum decrement by 8.72% from clean data on the Hepatitis dataset using the RF classifier. The smallest decrement is 0.0% on the Arrhythmia dataset using the ANN, Hepatitis dataset using SVM, and Indian-liver-patient dataset using SVM and ANN classifiers. The highest difference for FS is 11.71% on the Heart Disease dataset using the RF classifier, but the lowest difference for FS is 0.03% on the Framingham dataset using the ANN classifier. But still, the results of PPMD are almost equal and also offer more protection compared to the clean data.

6.5 Statistical analysis

Statistical analysis is used to validate the CA, P, R, and FS of the proposed model. In this context, the non-parametric test is applied to the dataset that is not normally distributed. The null hypothesis states that the acquired results from different methods are statistically identical in the Wilcoxon signed-rank test. This test compares the performance of PPMD model to that of the existing PMLM [23], NbAFL [28], and MLPAM [29] models. The test is run on the dataset with a significance level [31] (p-value) of 0.05 to determine the importance of classifying parameters. Table 10 demonstrates the results of the test statistics.

While comparing PPMD and PMLM [23], it is observed that the null hypothesis for CA, P, R, and FS is rejected because their p-values are less than 0.05, indicating that PPMD for the Heart Disease dataset is valid. The null hypothesis is rejected for CA, R, and FS but accepted for P on the Arrhythmia dataset. The null hypothesis is rejected for CA, R, and FS but accepted for P, whereas accepted for R on the Hepatitis, and Indian-Liver-Patient datasets. The null hypothesis is rejected for CA, P, R, and FS on the Framingham dataset.

Similarly, comparing PPMD, and NbAFL [28], the null hypothesis is rejected for P, R, and FS but accepted for CA on the Heart Disease dataset. The null hypothesis is rejected for CA, P, R, and FS on the Arrhythmia dataset. The null hypothesis is rejected for P, and FS but accepted for CA, and R on the Hepatitis dataset. The null hypothesis is rejected for R on Indian-live-Patient dataset. The null hypothesis is rejected for CA, P, R, and FS.

Table 9: Reduction in the values of CA, P, R, and FS of PPMD in comparison to the values on clean data

Dataset	Classifier	% decrement in the value of parameters					
		CA	P	R	FS		
	SVM	3.23	1.92	2.19	2.05		
	KNN	3.22	3.08	4.76	2.65		
Heart Disease	\mathbf{RF}	2.21	4.61	7.78	11.71		
	NB	3.23	3.58	3.92	4.37		
	ANN	0.61	1.83	3.23	2.54		
	SVM	2.17	3.07	2.17	2.86		
	KNN	2.18	2.28	2.18	1.45		
Arrhythmia	\mathbf{RF}	2.17	3.80	2.17	1.86		
	NB	1.75	3.84	1.75	3.94		
	ANN	0.65	1.10	0.00	0.49		
	SVM	6.25	5.24	0.00	3.13		
	KNN	6.25	0.00	7.57	3.08		
Hepatitis	\mathbf{RF}	6.25	8.09	8.72	2.91		
	NB	6.25	6.67	4.89	3.90		
	ANN	2.63	7.94	6.25	7.24		
	SVM	1.70	1.70	0.00	1.10		
	KNN	1.70	2.99	0.37	0.42		
Indian Liver	\mathbf{RF}	1.70	0.97	1.67	0.96		
Patient	NB	1.69	0.33	1.28	1.06		
	ANN	3.05	1.23	0.00	0.63		
	SVM	0.71	0.37	0.71	1.43		
	KNN	0.71	0.95	0.71	1.37		
Framingham	\mathbf{RF}	0.41	0.21	0.41	0.35		
	NB	1.41	1.17	1.41	1.15		
	ANN	0.12	0.02	0.05	0.03		

Moreover, comparing PPMD and MLPAM [29], the null hypothesis is rejected for CA, P, R, and FS on the Heart Disease and Arrhythmia datasets. The null hypothesis is rejected for P, R, and FS but accepted for CA on the Hepatitis dataset. The null hypothesis is rejected for CA, P, R, and FS on the Indian-Liver-Patient and Framingham datasets.

Data	Classification	ı Compa	arison of	Comparison of		Comparison of	
set	Parameters	PPMD, F	PMLM [23]	PPMD, I	NbAFL [28]	PPMD, MLPAM [2]	
	-	p-value	Result	p-value	Result	p-value	Result
	CA	0.042	RE	0.68	AC	0.43	RE
Heart	P	0.043	RE	0.43	RE	0.43	RE
Disease	R	0.043	RE	0.42	RE	0.43	RE
	FS	0.043	RE	0.43	RE	0.43	RE
	CA	0.043	RE	0.42	RE	0.43	RE
Arrhy	P	0.068	AC	0.43	RE	0.43	RE
thmia	R	0.043	RE	0.43	RE	0.43	RE
	FS	0.043	\mathbf{RE}	0.43	RE	0.43	RE
	CA	0.039	RE	0.59	AC	0.66	AC
Hepa	P	0.043	RE	0.43	RE	0.43	RE
titis	R	0.068	\mathbf{AC}	0.68	\mathbf{AC}	0.43	RE
	FS	0.043	RE	0.43	RE	0.43	RE
	CA	0.042	RE	0.43	RE	0.41	RE
Indian	P	0.043	RE	0.43	RE	0.43	RE
Liver	R	0.180	AC	0.68	AC	0.43	RE
Patient	FS	0.043	\mathbf{RE}	0.43	RE	0.43	RE
	CA	0.043	RE	0.42	RE	0.42	RE
Frami	P	0.043	RE	0.43	RE	0.43	RE
ngham	R	0.043	RE	0.42	RE	0.42	RE
	FS	0.043	RE	0.43	RE	0.43	RE

Table 10: Wilcoxon test statistics (p-value is 0.05)

AC: The null hypothesis is accepted, RE: The null hypothesis is rejected

7 Conclusion and future work

This paper proposed a novel model named PPMD that preserves the privacy of outsourced sensitive data provided by various data owners in a real cloud environment. PPMD allows multiple data owners to outsource their data to the cloud for storing and computation. In this work, data owners added different statistical noise to sensitive data according to their queries for data protection. The cloud service provider has also provided the classification service. The experiments have been conducted, and results show that PPMD ensures high accuracy, precision, recall, and F1-score improvement up to 29% over the existing works. The model's performance over the well-known data sets and comparison with existing works showed that PPMD is more secure, efficient, and optimal. The future aim of this work would be to share collected data among requesting users and devise a more efficient privacy-preserving mechanism to protect the data for various owners. Acknowledgements This work is supported by University Grant Commission, New Delhi, India under the scheme of National Eligibility Test-Junior Research Fellowship (NET-JRF) with reference id-3515/(NET-NOV 2017).

Compliance with ethical standards

Conflict of interest The authors have no conflict of interest regarding the publication.

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Authors' contribution Both the authors have discussed and constructed the ideas, designed the privacy-preserving model, and wrote the paper together.

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