A Differential Approach for Data and Classification Service based Privacy-Preserving Machine Learning Model in Cloud Environment

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Abstract The massive upsurge in computational and storage has driven the local data and machine learning applications to the cloud environment. The owners may not fully trust the cloud environment as it is managed by third parties. However, maintaining privacy while sharing data and the classifier with several stakeholders is a critical challenge. This paper proposes a novel model based on differential privacy and machine learning approaches that enable multiple owners to share their data for utilization and the classifier to render classification services for users in the cloud environment. To process owners' data and classifier, the model specifies a communication protocol among various untrustworthy parties. The proposed model also provides a robust mechanism to preserve the privacy of data and the classifier. The experiments are conducted for a Naive Bayes classifier over numerous datasets to compute the proposed model's efficiency. The achieved results demonstrate that the proposed model has high accuracy, precision, recall, and F1-score up to 94%, 95%, 94%, and 94%, and improvement up to 16.95%, 20.16%, 16.95%, and 23.33%, respectively, compared with state-of-the-art works.

Keywords Cloud computing · Machine learning · Differential privacy · Classification · Privacy-preserving

1 INTRODUCTION

Cloud computing has the capability to provide an ample amount of data storage, computation, analysis, and sharing services to organizations without revealing its

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implementation and platform details [1]. Due to these illimitable services, any organization outsources its data and model from the local to the cloud platform [2], [3]. Nowadays, machine learning has gained a lot of attention in a wide range of real-world applications, including image recognition, spam detection, financial market analysis, and recommendation systems [4], [5]. The machine learning classifier is extensively utilized in these applications. Thereafter, the emerging challenges include handling the privacy of the model and sensitive data [6]. The cloud stores and computes massive amounts of collected data and the classification model that are outsourced from various owners without interaction with each other. The owners hesitate to share their data and model with the cloud for computation and storage since a third party runs it [7]. The owners lose control of their outsourced data, model and are unaware of its extraction from the cloud platform [8]. According to a Cisco survey, 76% of owners have no clue about their data utilization by other parties [9]. The cloud may misuse and provide both data and the model to other parties for different purposes [10], [11]. Due to these reasons, the privacy-preserving of data and the model has become a challenge for any organization. Therefore, it is essential to protect the data and classification model by applying some privacy strengthening process before transferring them to an untrusted cloud server.

To address the challenges mentioned above, we propose a Differential Approach for data and classification service-based Privacy-preserving Machine Learning Model (DA-PMLM) in the cloud environment. In the proposed model, ε -differential privacy protection is considered on the owner's side because they do not aspire to disclose actual data, and the model [12–15]. Fig. 1 outlines a bird-eye view of the proposed work and emphasizes our consistent contributions to protect the data as well as the classification model from unauthorized parties. The owners inject different statistical noise into data and the model according to various applications and queries. The achieved data and model are uploaded to the cloud platform, and classification services are provided. The obtained machine learning model is applied over collected data for classification. The cloud platform receives the classified data from the classification model and distributes it to the data owners or users rather than other parties. It classifies tasks and allows data sharing in the cloud environment. The main contributions of the proposed work have been described as follows:

- DA-PMLM permits several data owners and the classifier owner to share their data and machine learning model without hindrance. The Laplace mechanism has been used to keep the data and model private before sharing.
- DA-PMLM uses two clouds: cloud1 and cloud2. Cloud1 handles the data storage and sharing process, whereas cloud2 carries out the classification tasks over accumulated data from various owners. To secure data and model with improving privacy, all entities are deemed untrustworthy.
- DA-PMLM ensures the level of security because the value of the privacy budget is assigned according to the requirement of protection.
- Implementation and evaluation are performed using various datasets, which shows that DA-PMLM outperforms the state-of-art works in terms of privacy, accuracy, precision, recall, and f1-score.

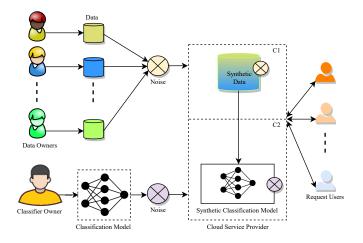


Fig. 1: Bird eye view of DA-PMLM

Organization: Section 2 describes the related work followed by the proposed model and the process of preserving data in Sections 3 and 4, respectively. The privacy-preserving of the model and the data classification steps are presented in Section 5 and Section 6, respectively. The illustration of the proposed model is defined in Section 7. The operational design and computational complexity are discussed in Section 8. The experimental results with statistical analysis are shown in Section 9, followed by the conclusion and future work in Section 10. Table 1 demonstrates the list of symbols with their descriptive terms that have been used throughout this manuscript.

Table 1: List of Terminologies with their Explanatory Terms

<i>CO</i> :	Classifier Owner	<i>n</i> **:	Training objects	<i>P</i> :	Precision
UE:	Untrusted Entity	D_i :	Actual data	N_i :	Noise
<i>CM</i> :	Classification Model	RU _{id} :	Request Users	D_i^N :	Synthetic Data
CA:	Classification Accuracy	$\check{D}^N_{L'}$:	Training Data	<i>R</i> :	Recall
\hat{D}_i^N :	Preprocessed Data	\mathbb{C}^{L} :	Label Vector	$\check{D}^N_{t''}$:	Testing Data
Δf :	Absolute distance	<i>n</i> :	No. of data object	F'P:	False Positive
DP:	Differential Privacy	CS:	Cloud Storage	Pr:	Probability
ϑ:	Scaling parameter	<i>n</i> ***:	Testing objects	ε:	Privacy budget
\hat{R} :	Random function	f:	Query function	<i>n</i> *:	count of classes
CM^N :	Synthetic Model	CF:	Classifier	FS:	F1-Score
CSP:	Cloud Service Provider	<i>C</i> 1:	Cloud1	<i>C</i> 2:	Cloud2
σ :	Standard deviation	μ:	Mean	Λ:	Data attribute

2 Related Work

To protect the data, and machine learning model using the differential privacy mechanism has been categorized at the two levels: (a) At the data level, (b) At the model level.

2.1 At Data Level

To protect data privacy, Li et al. [16] proposed a differentially private scheme called Privacy-preserving Machine Learning with Multiple data providers (PMLM) with improved computational efficiency and data analysis accuracy. The PMLM scheme uses public-key encryption with a double decryption algorithm (DD-PKE) to transform the encrypted data into a randomized dataset and ε -differential privacy to make the data private. But the PMLM scheme suffered from less accuracy as well as limited data sharing. Wang et al. [17] proposed a distributed agent-based privacypreserving framework, namely DADP, for real-time spatial statistics data collection and publication with an untrusted server. A distributed budget allocation mechanism and an agent-based dynamic grouping mechanism were developed to achieve global w-event ε -differential privacy in a distributed manner. In DADP, crowd-sourced data is aggregated, and then the noise is added to it using the Laplace mechanism. However, it was considered a semi-centralized setting and resulted in a more complex system because it initiated a batch of trusted proxies (Agents) and anonymous connection technology to protect the privacy of users under an untrusted server. A privacypreserving deep learning model, namely PDLM, is presented in [18] that protects training data by encrypting it with multiple keys using a public-key distributed two trapdoors (DT-PKC) cryptosystem. The proposed scheme minimized the storage cost. However, it necessitates more calculations on the ciphertext, resulting in decreased efficiency. Hassan et al. [19] proposed an efficient privacy-preserving scheme based on machine learning to protect data privacy. The partially homomorphic encryption technique was utilized to re-encrypt data, and a differential privacy mechanism was used to add noise to the data. It permits all participants to publicly verify the validity of the ciphertext using a unidirectional proxy re-encryption (UPRE) scheme that reduces computational costs. But the proposed scheme has limited data sharing. A local differential privacy (LDP)-based classification algorithm for data centers is introduced [20] with high efficiency and feasible accuracy. Sensitive information is protected by adding the noise using the Laplace mechanism in the pattern mining process. They devised a method for determining the level of privacy protection. However, the proposed method does not allow for data sharing. To prevent information leakage, a framework, namely, noising before model aggregation federated learning (NbAFL), was proposed by Wei et al. [21]. Before the model aggregation, a differential privacy mechanism was utilized to add the noise to clients' local parameters. Nevertheless, this framework requires a significant amount of noise to add and sacrifices model utility. An adaptive privacy-preserving federated learning framework is introduced in [22], which protects gradients by inserting the noise with varying privacy budgets. They devised a randomized privacy-preserving adjustment technology (RPAT) to

enhance the accuracy, but the proposed framework makes the classification process computationally costly. A machine learning and probabilistic analysis-based model, namely MLPAM, is presented in [23]. It supports various participants to share their data safely for different purposes using encryption, machine learning, and probabilistic approaches. This scheme reduced the risk associated with the leakage for prevention coupled with detection, but it does not provide privacy for the classifier. To protect the Spatio-temporal aggregated data in real-time, Xiong et al. [24] proposed a privacypreserving framework based on the local differential approach. The authors also devised a generalized randomized response (GRR) framework for obtaining reliable aggregated statistics continuously while maintaining user's privacy. The proposed framework improves data usage but exposes the user's privacy by adding independent identically distributed noise to the associated data. Liu et al. [25] proposed a differential privacy for local uncertain social network (DP-LUSN) model that protects the social network's community structured data. DP-LUSN increased the data utilization by minimizing the noise effect on a single edge. However, DP-LUSN only operates on static social networks. Sharma et al. [26] proposed a Differential Privacy Fuzzy Convolution Neural Network framework, namely DP-FCNN, which protects the data and query processing by adding the noise using the Laplace mechanism. The authors used the lightweight Piccolo algorithm to encrypt the data and the BLAKE2s algorithm to extract the key attributes from the data. However, DP-FCNN increases the computational overhead.

2.2 At Model Level

A privacy-preserving Naive Bayes learning scheme with various data sources using ε -differential privacy and homomorphic encryption is presented in [27]. This scheme enables the trainer to train the Naive Bayes classier over the dataset provided jointly by the different data owners. But still, adversaries can forge and manipulate the data in this scheme. Gao et al. [28] proposed a privacy-preserving Naive Bayes classifier scheme to avoid information leakage under the substitution-then-comparison (STC) attack. They adopted a double-blinding technique to preserve the privacy of Naive Bayes. The proposed scheme reduced both the communication and computation overhead. But this scheme is unable to obtain the discovery of truth that protects privacy. A privacypreserving outsourced classification in the cloud computing (POCC) framework was introduced in [29]. It protects the privacy of sensitive data under various public keys using a fully homomorphic encryption proxy technique without leakage. However, encryption for outsourced data can protect privacy against unauthorized behaviors. It also makes effective data utilization, such as search over encrypted data, a complicated issue. Liu et al. [30] proposed a private decision tree algorithm based on the noisy maximal vote. An effective privacy budget allocation strategy was adopted to make the balance between the true counts and noise. It was constructed as an ensemble model with differential privacy to boost the accuracy and improve the stableness. In the proposed algorithm, the privacy analysis was performed only on each separate tree and not on the ensemble as a whole. A differentially private gaussian processes classification (GPC) model was presented in [31], which adds noise to the classifier to

provide privacy. The authors used the Laplacian approximation method to determine GPC's sensitivity and scaled noise to outputs generated from other dataset sections. In this manner, the total noise can be decreased. However, the proposed model is not sparse. Wang and Zhang [32] proposed a differential privacy version of convex and nonconvex sparse classification approach based on alternating direction method of multiplier (ADMM) algorithm with mild conditions on the regularizers. By adding exponential noise to stable stages, they were able to turn the sparse problem into a multistep iteration process and accomplish privacy protection. However, estimating the noise introduced to stochastic algorithms in the proposed approach is problematic. A differentially private ensemble learning method for classification, referred to as DPEL, was presented in [33] which provides privacy protection while ensuring prediction accuracy. The authors applied the Bag of Little Bootstrap and the Jaccard similarity coefficient techniques to enhance the ensemble's diversity. A privacy budget allocation strategy was designed to make the differentially private base classifiers by adding noise. But the DPEL method is affected by limited data sharing. Table 2 provides an overview of the literature review.

Model/Scheme /Framework	Workflow & Implementation	Outcomes	Drawback
A machine learning- based privacy- preserving model for data protection [16]	 To prevent data leakage, additively homomorphic encryption and differential privacy techniques were employed Abalone, Wine, Cpu, Glass, and Krkopt data sets were used for experiments 	 Improve the accuracy of data analysis and the effi- ciency of computations The model seems to be more protected as per the security analysis 	For the classi- fier, it does not provide privacy
A distributed privacy- preserving task allocation framework [17]	 w event and <i>ɛ</i>-Differential Privacy mechanisms were used to protect data Python language and taxi trajectory, nice rider datasets were used for experiments 	 Less Mean Absolute Error (MAE) and Mean Relative Error (MRE) Enhance the overall throughput of the whole vehicular network 	A trade-off be- tween accuracy and the overall payment of crowd-sensing server
A cloud-based Deep Learning model for data privacy [18]	 A homomorphic encryption mechanism was adopted to en- crypt the data To assess PDLM perfor- mance, a LeNet deep learning model was utilized 	 Achieve high accuracy up to 94% Perform the tasks of privacy-preserving train- ing and classification ap- propriately 	The use of multiple keys for big data reduced the efficiency of the machine learners
A privacy- preserving with public verifia- bility scheme [19]	 Data is protected by applying differential privacy and partially homomorphic encryption techniques Java pairing based cryptography (JPBC) library was used for experiments 	 Lower computational as well as communication costs The security analysis ver- ifies that the scheme is more secure under the random oracle model 	With ho- momorphic encryption, the issue of ciphertext expansion arise

Table 2: Tabular sketch of the literature review

A classification algorithm satis- fies local dif- ferential privacy [20]	 Internet of Multimedia Things (IoMT) produces the sensitive information Laplace noise is injected into the data during pattern mining 	 High efficiency, reliabil- ity, and precision Less MAE, mean squared error (MSE) metrics 	IoMT devices need higher la- tency and band- width
A framework protects training data based on differential privacy [21]	 Inject the noise into the parameters of the local learning model This framework was assessed by utilizing multi-layer perception and MNIST datasets 	 A trade-off between fed- erated learning perfor- mance and privacy Acquire high privacy us- ing random mini-batches 	Less accuracy due to injected noise in the pa- rameters
A secure multi- party compu- tation strategy by adaptive privacy- preserving [22]	 The Laplace mechanism was adopted to add noise with dif- ferent privacy budget TensorFlow library and MNIST dataset were used for experiments 	 Achieve high accuracy up to 88.46% Less computation and transmission overhead 	Data perturba- tion may de- grade the data utility
A secure data sharing model for determining guilty entities against data leakage [23]	 The attribute based encryption and differential privacy were used to preserve the privacy of multiple participants' data The pyhton language and Glass, Iris, Wine, and Balance Scale datasets were utilized for experiments 	 Perform secure data distribution among users by an effective allocation mechanism Achieve high accuracy up to 97% 	High compu- tational and communi- cation costs while trans- ferring the data
A real-time spatio-temporal data aggrega- tion method [24]	 LDP was employed for data protection MATLAB R2018a program- ming language and Geolife, Taxi Service datasets were used to conduct the experi- mentations 	 Less MAE, Mean MAE (MMAE), Mean KL divergence (MKLD), and Mean RelativeError (MRE) Acquire adequate trade- off of privacy and utility 	High com- putation and communica- tion costs due to generalized randomized response
A local differ- ential privacy scheme for social network publishing [25]	 The perturbed local method was applied to yield a syn- thetic network The experiments are per- formed using Python lan- guage, and WebKB, Citation, and Cora datasets 	 Decrease network structure information's loss This model provides a substantial degree of privacy 	It does not support dy- namic social networks
A fuzzy con- volution neural network frame- work based on Differential Pri- vacy for data se- curity [26]	 Data is encrypted with the help of a 128-bit block cipher Java Development toolkit (JDK) 1.8, Weka tools, and Adult and Heart dis- ease dataset were used for experimentations 	 The comparative analysis shows that it takes less run-time up to 14 ms More effective in terms of scalability and accu- racy 	Not suitable for hybrid ma- chine learning algorithms

A privacy- preserving learning algo- rithm based on differential privacy[27]	 The differential privacy and homomorphic encryption mechanisms were used for data preservation A GMP library was adopted to execute cryptographic oper- ations 	 Achieve secure data shar- ing without breaking pri- vacy Require less computa- tional time for training model 	Less efficiency because of en- cryption
A privacy- preserving scheme for protecting the trained model [28]	 Additively homomorphic encryption was used to encrypt the data The experiments were conducted over Breast Cancer Wisconsin (Original), Statlog Heart datasets 	 Less the computation overhead because of the offline stage of the server Accomplish suitable privacy-preserving training tasks 	It does not pro- vide efficient information sharing
A framework for protecting the outsourced classification model [29]	 Data was encrypted by using the multikey homomorphic encryption proxy The experiments were carried out using a naive bayes classifier 	 More effective for data utilization Achieve high-level data protection 	Less effi- ciency due to additions, multiplica- tions, and the nonlinear computations over encrypted data
A method for learning a differ- entially private decision tree [30]	 The differentially-private decision tree was trained by leveraging the noisy maximal vote The experiments were carried out over Mushroom and Adult datasets 	 Improve the learned classifier's utility Provide high accuracy up to 81.19% 	The ensemble model's perfor- mance can not be maximized
A privacy- preserving model for data classification [31]	 A variant-noise mechanism was used to perturb the clas- sifier with the different scaled noise The experiments are con- ducted over an actual oil dataset provided by NCRG of Aston University 	 Achieve elevated accuracy up to 75.00% Retain the classifier's accuracy 	Noise in- evitably decreases the accuracy
A privacy- preserving for convex and non- convex sparse classification [32]	 The sparse problem was transformed into a multistep iteration process through ADMM algorithm The logistic regression and KDDCup99 dataset were used for experiments 	 More effective and efficient for performing sensitive data analysis Accomplish appropriate privacy-preserving training and classification tasks 	It does not share the data effectively in several environments

A privacy- preserving method for pre- venting leakage in the process of classification [33]	 Laplace noise is injected into the classifier's objective func- tion The experiments were run over Wisconsin, User knowl- edge, Mushroom, Adult, and Bank Market datasets 	 Perform a trade-off be- tween privacy and accu- racy Acquire high accuracy up to 94.66% 	It does not pro- vide the data protection
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In the light of the aforementioned discussion, it can be concluded that earlier works limited data sharing and injected the noise into either data or classification model and/or protected them by employing diverse encryption techniques followed by the machine learning-based classification, resulting in decreased privacy, accuracy, and higher computing cost. In addition, the prior models only supported a single owner or untrustworthy entity. Unlike the previous works, DA-PMLM ensures that both data and the classification model are protected before being shared. The proposed model enables numerous data and classifier owners to securely share outsourced data and classification model while assuming all entities to be untrustworthy.

3 PROPOSED MODEL

The proposed model (Fig. 2) consists of four entities: Data Owners (DO_{id}) , Classifier Owner (*CO*), Cloud Service Provider (*CSP*), and Request Users (RU_{id}), which are described as follows in terms of intercommunication and vital information flow:

- 1) DO_{id} : An entity that yields the data and appeals to *CSP* for storing, computing, and sharing services. To protect the data, DO_{id} injects the noise into data using the ε -differential privacy mechanism prior send it to *CSP*. DO_{id} permits *CSP* to share the data with RU_{id} . Since it is assumed that DO_{id} can not misuse its data, it may disclose the data of other owners. Therefore, DO_{id} is not considered a trusted entity.
- 2) *CO*: An entity that has a classification model (*CM*) and offers the services to perform the classification tasks through *CSP*. Before passing *CM* to *CSP*, *CO* injects the noise utilizing the ε -differential privacy mechanism to retain the privacy and stores it. *CO* is viewed as an untrustworthy entity in the proposed model.
- 3) *CSP*: An entity that collects all the data from DO_{id} and *CM* from *CO*. It provides storage, computation, and data sharing services to DO_{id} , *CO*, and RU_{id} . It also offers the classification services using *CM* to DO_{id} , and RU_{id} . *CSP* trains *CM* using the machine learning algorithm over collected data and obtains classified data from *CM*. These accessed results are shared between DO_{id} , or RU_{id} . *CSP* is introduced as a semi-trusted entity in the proposed model, as it strictly follows the protocol but is curious to learn the information. In our model, the Cloud Platform (*CP*) consists of two clouds: Cloud1 (*C1*) and Cloud2 (*C2*). The data is stored in Cloud Storage (*CS*) at *C1* while the classification model is kept in Classifier (*CF*) at *C2*. *CSP* is the only entity that acts as a bridge among DO_{id} , *CO*, and RU_{id} . It stores the data and model to perform the data sharing and classification tasks.

 RU_{id}: An entity that requests CSP to obtain the owner's data, and classification service. RU_{id} receives the data from C1 and accesses the CM from C2 through the CSP. RU_{id} is treated as an untrusted entity in our model.

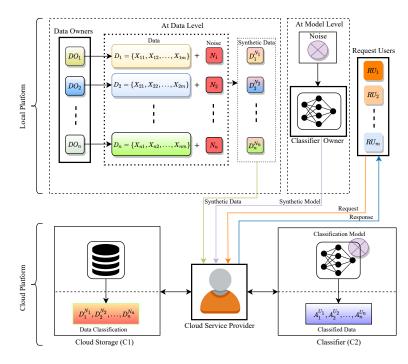


Fig. 2: Proposed DA-PMLM architecture

Consider the data owners $\mathbb{DO} = \{DO_1, DO_2, ..., DO_n\}$ having data \mathbb{D} , such as $\mathbb{D} \in \{D_1, D_2, ..., D_n\}$. It is essential that \mathbb{DO} must share \mathbb{D} among the other parties, such as *CSP*, and several request users $\mathbb{RU} = \{RU_1, RU_2, ..., RU_m\}$ for storage, computation, and data usage purposes. Due to the sensitive data, \mathbb{DO} do not aspire to disclose \mathbb{D} to unauthorized parties. As a result, each \mathbb{DO} procures synthetic data $\mathbb{D}^{\mathbb{N}} = \{D_1^{N_1}, D_2^{N_2}, ..., D_n^{N_n}\}$ by injecting noise $\mathbb{N} = \{N_1, N_2, ..., N_n\}$ into sensitive data $\{D_1, D_2, ..., D_n\}$ using ε -differential privacy to make the data private before sharing (details discussion in Section 4). DA-PMLM makes the use of Differential Privacy (*DP*) mechanism to inject $N_1, N_2, ..., N_n$ into $D_1, D_2, ..., D_n$, respectively, because *DP* is the most appropriate mechanism for generating $N_1, N_2, ..., N_n$ and sharing data $D_1^{N_1}, D_2^{N_2}, ..., D_n^{N_n}$ without sacrificing or revealing sensitive and personal information about individual owners [34]. Each $DO_1, DO_2, ..., DO_n$ delivers $D_1^{N_1}, D_2^{N_2}, ..., D_n^{N_n}$ to *CSP* that store it on *CS* at *C1* for computation, and sharing purposes. Due to the lack of storage space and the need to handle multiple requests, *CO* aspires to store *CM* on the cloud. Nevertheless, *CO* injects noise $\hat{\mathbb{N}}$ into *CM* to protect privacy before transferring it (as described in Section 5). *CO* sends the synthetic model (*CM*^N) to

CSP that keeps it on *CF* at *C2*. *CSP* utilizes the stored data $D_1^{N_1}$, $D_2^{N_2}$, ..., $D_n^{N_n}$ to accomplish the classification tasks to make a fit CM^N , and also share it with RU_1 , RU_2 , ..., RU_m . *CSP* also uses the stored model CM^N to handle the query of DO_{id} , and RU_{id} . DO_1 , DO_2 , ..., DO_n and RU_1 , RU_2 , ..., RU_m can make any query and send it to *CSP*. Afterward, *CSP* interacts with *CF* and achieves the results of these queries from CM^N . The obtained results are sent to the corresponding entity DO_1 , DO_2 , ..., DO_n , and RU_1 , RU_2 , ..., RU_m by *CSP*.

4 Privacy-Preserving of Data

Data owners $(DO_1, DO_2, ..., DO_n)$ injects the noise $(N_1, N_2, ..., N_n)$ into data $(D_1, D_2, ..., D_n)$, respectively, using ε -differential privacy. A random function \hat{R} is referred to as ε -differential privacy [35] if for any combination of dataset D and its neighbor D', and for all $\vartheta \subseteq \text{Range}(\hat{R})$ are defined using Eq. (1):

$$Pr[\hat{R}(D) = \vartheta] \le exp(\varepsilon) \times Pr[\hat{R}(D') = \vartheta]$$
(1)

where Pr[.] is the probability function that has been applied to the function \hat{R} and demonstrates the privacy disclosure risk. The privacy budget (ε) is defined by the results of statistical computation, analysis, and the individual's information that has to be kept private. To achieve a higher level of privacy protection, the value of ε should be reduced. A numeric query function (f) that is utilized to map the data set D into real space with d-dimensional, assigned as $f: D \to R^d$. The sensitivity of f for all the combinations of dataset D and D' is defined using Eq. (2):

$$\Delta f = \max_{D,D'} \| f(D) - f(D') \|_{P_1}$$
(2)

where $\| \cdot \|_{P_1}$ is norm. The sensitivity Δf is only depend on the query function f and finds the maximum gap of query results on neighboring datasets. For any function f: $D \to R^d$, the Laplace mechanism F is defined using Eq. (3). The mechanism F takes input χ , and $\varepsilon > 0$, a numeric query function f, and computes the output. It is based on the sensitivity of f and receives the statistical noise from a Laplace distribution. Afterward, the obtained noise is injected into the datasets.

$$F(\boldsymbol{\chi}) = f(\boldsymbol{\chi}) + (Lap_1(\boldsymbol{\varpi}), Lap_2(\boldsymbol{\varpi}), \dots, Lap_d(\boldsymbol{\varpi}))$$
(3)

where the noise $Lap_j(\varpi)$ $(j \in [1, d])$, and ϖ belongs to R^+ comes from a Laplace distribution, whose the probability density function is calculated using Eq. (4).

$$N = \frac{1}{2\varpi} \cdot \left(exp(\frac{-|\chi|}{\varpi}) \right) \tag{4}$$

where *N* is a noise vector. The noise $N_1, N_2, ..., N_n$ is generated taking the sample from the Laplace distribution with scaling parameter $\overline{\boldsymbol{\omega}} = \Delta f/\varepsilon$. The parameter $\overline{\boldsymbol{\omega}}$ is under the control of ε . The generated noise vector $N_1, N_2, ..., N_n$ is injected into the corresponding $D_1, D_2, ..., D_n$ as $D_i^{N_i} = D_i + N_i$, where $i \in [1, n]$. After adding N_1 , $N_2, ..., N_n, DO_1, DO_2, ..., DO_n$ obtains the Synthetic Data $D_1^{N_1}, D_2^{N_2}, ..., D_n^{N_n}$. DO_1 , $DO_2, ..., DO_n$ sends data $D_1^{N_1}, D_2^{N_2}, ..., D_n^{N_n}$ to *CSP* that stores it on *CS* at *C1*, shares it among $RU_1, RU_2, ..., RU_m$ and performs the classification task over it.

5 Privacy-Preserving of Classification Model

To protect the privacy of *CM*, *CO* injects the noise $\hat{\mathbb{N}}$ into *CM* before sharing it on the cloud. In DA-PMLM, *CO* has a Naive Bayes (*NB*) classifier, which is used to perform the classification tasks. The *NB* classifier takes the input vector $\mathbb{D}^{\mathbb{N}} = \{x_1, x_2, \dots, x_d\}$, which belongs to \mathbb{R}^d , and classify *d* into a class in the form of discrete set $\mathbb{C} = \{C_1, C_2, \dots, C_n\}$. The functionality of the *NB* classifier based on the Bayes decision rule [36] is to select the class \mathbb{C} with the highest posterior probability of $\mathbb{D}^{\mathbb{N}}$ and measures it by using Eq. (5).

$$\mathbb{C}^{\mathbb{L}} = \underset{i \in n}{\operatorname{argmax}} p(\mathbb{C} = C_i | \mathbb{D}^{\mathbb{N}} = x)$$
(5)

The highest posterior probability's value $(p(\mathbb{C} = C_i, \mathbb{D}^{\mathbb{N}} = x))$ is equal to the factorization of $p(\mathbb{C} = C_i) \prod_{j=1}^d P(\mathbb{D}^N = x_j | \mathbb{C} = C_i)$. Each component of x is conditionally independent based on the attribute conditional assumption. It can also be expressed as $(log \ p(\mathbb{C} = C_i) = \sum_{j=1}^d log \ p(\mathbb{D}^N = x_j))$ in a logarithm form. The conditional probabilities $P(\mathbb{D}^N = x_j | \mathbb{C} = C_i)$ is computed using the mean $(\mu_{i,j})$, and variance $(\sigma_{i,j}^2)$, which are calculated for class j using the values of attribute X from the training set. As a result, the sensitivity of both μ_i , and standard deviation $(\sigma_{i,j})$ are computed. It is assumed that the feature value of \mathbb{D}_j^N is bounded in range $[g_i, h_i]$. The sensitivity of $\mu_{i,j}$ is calculated using $(h_i - g_i)/(n+1)$, and the sensitivity of $\sigma_{i,j}$ is computed using $n * (h_i - g_i) / (n+1)$. After calculating the $\mu_{i,j}$ and $\sigma_{i,j}$, CO generates the noise using the Eqs.1 to 4. The obtained noise \hat{N}_i and \hat{N}_i are injected into μ_i and σ_i , respectively, using Eqs. 6 and 7.

$$\mu_i' = \mu_i + \hat{N}_i \tag{6}$$

$$\sigma_i' = \sigma_i + \hat{N}_i \tag{7}$$

CO uses μ'_i , and σ'_i to calculate $p(\mathbb{C} = C_i, \mathbb{D}^{\mathbb{N}} = x)$. Afterword, synthetic model CM^N is sent to *CSP* to handle the queries of DO_1, DO_2, \ldots, DO_n , and RU_1, RU_2, \ldots, RU_m . Therefore, unauthorized users or any attacker are unable to acquire the sensitive classification model from *CSP*; the proof is provided in the following theorem:

Theorem 1 In the proposed model, the privacy-preserving mechanism of the classification model satisfies the parallel composition of ε -differential privacy.

Proof. Let $\hat{R}_1, \hat{R}_2, ..., \hat{R}_n$ be *n* mechanisms, where each mechanism \hat{R}_i ($i \in [1, n]$) provides ε -differential privacy. Let $\mu_1, \mu_2, ..., \mu_n$ and $\sigma_1, \sigma_2, ..., \sigma_n$ are *n* arbitrary mean and standard deviation to calculate the conditional probability attributes. For a new mechanism \hat{R} , the sequence of $\hat{R}(\hat{R}_1(\mu_1), \hat{R}_2(\mu_2), ..., \hat{R}_n(\mu_n))$ and $\hat{R}(\hat{R}_1(\sigma_1), \hat{R}_2(\sigma_2), ..., \hat{R}_n(\sigma_n))$ provide $max_{1 \le i \le n} \varepsilon$ - differential privacy. *CO* generates the Laplace noise \hat{N}_i and \hat{N}_i according to sensitivity (Δf), privacy budget (ε) to inject the produced noise into $\mu_1, \mu_2, ..., \mu_n$ and $\sigma_1, \sigma_2, ..., \sigma_n$, respectively, which satisfy $Pr[\hat{R}(\mu) = \vartheta] \le exp(\varepsilon) \times Pr[\hat{R}(\mu') = \vartheta]$, and $Pr[\hat{R}(\sigma) = \vartheta] \le exp(\varepsilon) \times Pr[\hat{R}(\sigma') = \vartheta]$. It can be observed that the mechanism \hat{R} provides privacy to the classification model. Hence this privacy-preserving mechanism of the classification model satisfies the parallel composition of ε -differential privacy.

6 Data Classification

CSP receives the synthetic data $D_1^{N_1}, D_2^{N_2}, \ldots, D_n^{N_n}$ from DO_1, DO_2, \ldots, DO_n and prepossesses it by applying the normalization function shown in Eq. (8), where $D_i^{N_i}$ is training sample, μ , and σ are the mean and the standard deviation of the training sample, respectively.

$$\check{D}_i^{N_i} = \frac{(D_i^{N_i} - \mu)}{\sigma} \tag{8}$$

CSP achieves the prepossessed data $\check{\mathbb{D}}_{i}^{N_{i}} = \{\check{D}_{1}^{N_{1}}, \check{D}_{2}^{N_{2}}, \dots, \check{D}_{n}^{N_{n}}\}$, which belongs to n^{*} is less than equal to n classes $\mathbb{C} = \{C_{1}, C_{2}, \dots, C_{n^{*}}\}$, for all $\mathbb{C}_{i} = \mathbb{D}, i \in [1, n^{*}]$ and $\mathbb{C}_{i} \cap \mathbb{C}_{k} = \phi$, where $k \in [1, n^{*}] \land i \neq k$. Fig. 3 depicts the stepwise process for data classification in which the prepossessed data $\check{\mathbb{D}}_{i}^{N_{i}} = \{\check{D}_{1}^{N_{1}}, \check{D}_{2}^{N_{2}}, \dots, \check{D}_{n}^{N_{n}}\}$ is split into training data $\check{\mathbb{D}}_{i}^{N} = \{\check{D}_{i,1}^{N_{1}}, \check{D}_{i,2}^{N_{2}}, \dots, \check{D}_{i,n^{**}}^{N_{n^{**}}}\}$, and testing data $\check{\mathbb{D}}_{i}^{N} = \{\check{D}_{i,1}^{N_{1}}, \check{D}_{i,2}^{N_{2}}, \dots, \check{D}_{i,n^{**}}^{N_{n^{**}}}\}$ fulfill the following conditions a) $\check{\mathbb{D}}_{i}^{N} \cup \check{\mathbb{D}}_{i}^{N} = \check{\mathbb{D}}^{N}$; b) $\check{\mathbb{D}}_{i}^{N} \cap \check{\mathbb{D}}_{i}^{N} = \phi$; c) n^{**} , $n^{***} \leq n$; and d) $n^{**} = n \times z$, and $n^{***} = n \times (1-z)$, where z belongs to \mathbb{Z} or the value of z can lie between 0 and 1 for CM^{N} . The utilization of training data $\check{D}_{i,1}^{N_{1}}, \check{D}_{i,2}^{N_{2}}, \dots$,

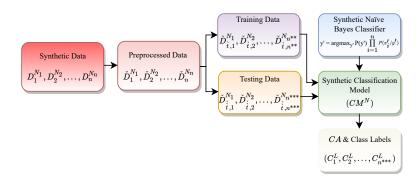


Fig. 3: Classification flow for shared data and model

 $\check{D}_{i,n^{***}}^{N_{n^{***}}}$ is to train CM^N , whereas the accuracy of CM^N is assessed by the testing data $\check{D}_{i,1}^{N_1}, \check{D}_{i,2}^{N_2}, \dots, \check{D}_{i,n^{***}}^{N_{n^{***}}}$. Data objects $\check{D}_{i,1}^{N_1}, \check{D}_{i,2}^{N_2}, \dots, \check{D}_{i,n^{***}}^{N_{n^{***}}}$ are provided to CM^N in the testing process to determine the classes. CM^N examines $\check{D}_{i,1}^{N_1}, \check{D}_{i,2}^{N_2}, \dots, \check{D}_{i,n^{***}}^{N_{n^{***}}}$, and generates the output as the class label vector $\mathbb{C}^L = \{C_1^L, C_2^L, \dots, C_{n^{***}}^L\}$. Using $C_1^L, C_2^L, \dots, C_{n^{***}}^L$, the Classification Accuracy (*CA*) of CM^N is measured by applying the Eq. (9). In this Eq., $C_1^L, C_2^L, \dots, C_{n^{***}}^L$ is the total number of sample in test data, where $n''' \in [1, n^{***}]$.

$$CA = \frac{C_1^L, C_2^L, \dots, C_{n'''}^L}{C_1^L, C_2^L, \dots, C_{n^{***}}^L}$$
(9)

The precision (P), and recall (R) are computed using Eq. (10) and (11), respectively.

$$P = \frac{(C_1^L, C_2^L, \dots, C_{n'''}^L) \cap (C_1^L, C_2^L, \dots, C_{n^{***}}^L)}{C_1^L, C_2^L, \dots, C_{n'''}^L}$$
(10)

$$R = \frac{(C_1^L, C_2^L, \dots, C_{n''}^L) \cap (C_1^L, C_2^L, \dots, C_{n^{***}}^L)}{C_1^L, C_2^L, \dots, C_{n^{***}}^L}$$
(11)

The F1-Score (FS) is measured using Eq. (12).

$$FS = 2 \times \frac{(P \times R)}{(P+R)} \tag{12}$$

7 Illustration

Let's assume that the proposed model consists of twenty owners: $DO_{id} = \{DO_1, DO_2, \dots, DO_{20}\}$ possess data $D = \{D_1, D_2, \dots, D_{20}\}$. Data D_1 contains the information (4.2575, 7.1754, -1.7685, -2.6898, 0), D_2 contains the information (0.7536, 0.9137, 6.1110, -4.0517, 0), ..., D_{20} contains the information (6.2122, 7.6552, -2.4515, -1.4451, 0). Before sending it to *CSP*, DO_1 , DO_2 , ..., DO_{20} generate the noise N_1 , N_2 , ..., N_{20} by applying the Eqs. (1) to (4). The obtained noise N_1 incorporates 0.6569, N_2 incorporates 0.8015, ..., N_{20} incorporates 0.6959. Table 3 shows the synthetic data (*SD*) that are produced after injecting N_1 , N_2 , ..., N_{20} into actual data (*AD*). To

Table 3: Synthetic data v/s Actual data

Data Owners	Λ	1	Λ	2	Λ_3		Λ	4	Λ_5
Data Owners	SD_1	AD_1	SD_2	AD_2	SD ₃	AD ₃	SD_4	AD_4	1 15
DO_1	4.9144	4.2575	7.8223	7.1754	-1.1116	-1.7685	-2.0329	-2.6898	0
DO_2	1.5551	0.7536	1.7152	0.9137	6.9125	6.1110	-3.2502	-4.0517	0
DO ₃	1.3112	1.0978	-2.6567	-2.8701	2.8156	2.6022	-1.8123	-2.0257	0
DO_4	2.9124	2.1312	-2.3231	-3.1043	3.4122	2.631	-2.9158	-3.6970	1
DO_5	5.1451	4.9639	3.4256	3.2444	-1.6823	-1.8635	1.2151	1.0339	1
DO_6	1.0132	0.7983	5.7588	5.5439	0.4724	0.2575	-0.6125	-0.8274	0
DO ₇	2.5156	1.9033	9.1772	8.5649	-0.7336	-1.3459	-0.7353	-1.3476	0
DO_8	4.4157	4.2046	8.7779	8.5668	-4.4035	-4.6146	-0.8064	-1.0175	0
DO_9	1.9877	1.6659	1.1038	0.7820	2.3946	2.0728	0.8629	0.5411	1
DO ₁₀	2.9935	2.5039	7.6625	7.1729	0.1539	-0.3357	-1.0175	-1.5071	1
DO ₁₁	-2.6128	-2.9317	10.8430	10.5241	2.5462	2.2273	-2.7926	-3.1115	0
DO ₁₂	2.4121	2.012	8.7261	8.3260	-3.0030	-3.4031	-0.5724	-0.9725	0
DO ₁₃	3.6651	2.7939	-3.3924	-4.2636	3.4896	2.6184	1.4771	0.6059	0
DO14	1.7219	1.5800	3.0646	2.927	0.8747	0.7328	0.5861	0.4442	1
DO15	1.4512	1.2401	2.8473	2.6362	4.3439	4.1328	1.6524	1.4413	1
DO16	2.7159	2.5497	-4.0257	-4.1919	8.3428	8.1766	-2.1086	-2.2748	0
DO ₁₇	3.2153	2.7866	11.0272	10.5985	-2.3564	-2.7851	-2.1113	-2.5400	0
DO ₁₈	1.7121	1.5903	7.8902	7.7684	-1.3663	-1.4881	-1.5650	-1.6868	0
DO ₁₉	1.2192	0.9812	-1.1117	-1.3496	2.7118	2.4739	-1.4445	-1.6824	1
DO_{20}	6.9081	6.2122	8.3511	7.6552	-1.7556	-2.4515	-0.7492	-1.4451	1

preserve the privacy of CM, CO also generates the noise \hat{N}_1 , \hat{N}_2 using Eqs. (1) to (4). It

is supposed that the value of \hat{N}_1 is 0.5654, and \hat{N}_2 is 0.3651. Initially, *CO* measures the sensitivity of mean (μ), and standard deviation (σ) by adopting Eq. (5). It is observed that the value of μ is 16.3258, and the value of σ is 9.6894. Afterward, \hat{N}_1 , and \hat{N}_2 are injected into μ and σ , respectively, by applying Eqs. (6) and (7). The synthetic model CM^N , and *SD* are uploaded to cloud platform. *CSP* preprocesses *SD* using Eq. (8) and acquires the preprocessed data as \check{D}^N as (1.2456, 2.4523, -0.4452, 1.3425), (-2.5434, -0.8145, 1.9315, 1.3155), ..., (-1.3141, 2.5145, -1.3145, -1.0485). The CM^N accepts 30 input data, and provides 30 output labels. The *CA* of CM^N is calculated by using Eq. (9). If CM^N identifies 18 correct labels then CM^N 's *CA* is 60% ((18/30) * 100), where 30 is the total number of test items. The *P* of CM^N is measured by applying Eq. (10). If $C_1^L, C_2^L, \ldots, C_{1}^{L'''}$ is 10, $C_1^L, C_2^L, \ldots, C_{n^{***}}^L$ is 30, and common labels among them is 6 then CM^N 's *P* is 60% ((6/10) * 100). The *R* of CM^N is estimated by using Eq. (11). The CM^N 's *R* is 20% ((6/30) * 100). The *FS* of CM^N is estimated by using Eq. (12). The CM^N 's *FS* is 30% (2 * (*P* * *R*) / (*P* + *R*)), where *P* is 60%, and *R* is 20%.

8 Operational Design and Computational Complexity

The operational summary of the proposed model is described by Algorithm 1, which protects the data as well as the model and performs the classification task. Initially, the list of data (*D*), noise (*N*), and preprocessed data \check{D}^N are initialized. To preserve the privacy of the owner's data *D*, *N* is generated. The obtained *N* is used to construct the synthetic data after injecting it into *D*. To protect the classification model, the sensitivity of μ is calculated. Based on this sensitivity, the scale factor is measured for μ . Using the scale factor, the noise is generated and adds it into μ . Similarly, the sensitivity of σ is also computed, and the scale factor is determined using this sensitivity. Based on this scale factor, noise is produced and added into σ . The synthetic μ , and σ are used to compute $P(\mathbb{D}^N = x_j | \mathbb{C} = C_i)$. The test data is given and received class labels from the classification model. Using these class labels, the classification parameter values are measured in a privacy-preserving manner.

In algorithm 1, steps 2 to 19 perform the classification over synthetic data using a synthetic model, whose time complexity depends on the noise generation, noise addition, and classifier use. To preserve the privacy of the data, noise is generated in step 3 and added using the Laplace mechanism in step 4, which takes $\mathcal{O}(n^2)$ time, where *n* is the total rows in the dataset. The classification model is protected using steps 5 to 18. The *NB* classifier takes $\mathcal{O}(ni)$ time. The computation time for the sensitivity of μ and σ is $\mathcal{O}(n^2)$ time. Steps 20 to 23 require $\mathcal{O}(1)$ time. Therefore, the total time complexity of DA-PMLM is $\mathcal{O}(n^2)$.

9 Performance Evaluation

9.1 Experimental Setup

The experiments are conducted on a system equipped with Intel (R) Core (TM) i5-4210U CPU and 3.60 GHz clock speed. The computation machine is deployed

Algorithm 1: DA-PMLM operational summary

Input: Actual data D, Noise vector N, Privacy parameter ε **Output:** unknown class label C_i^L , CA, P, R, and FS 1 Initialize data $D := \{D_1, D_2, \dots, D_n\}, N := \{N_1, N_2, \dots, N_n\}, \check{D}_1^N = \{(x_1, y_1), (x_2, y_2), \dots, N_n\}$ $(x_{\tilde{i}}, y_{\tilde{j}})$ for i = 1, 2, ..., n do 2 $N_i = \operatorname{Lap}(0,1)$ 3 $D_i^N = D_i + N_i$ 4 for each attribute X_i do 5 Compute the sensitivity S^{μ} with mean μ with bound $[g_i, h_i]$ 6 Scale factor for μ (*Sf*^{μ}) \leftarrow *S*^{μ} / ε 7 $\mu_i' = \mu_i + \operatorname{Lap}(0, Sf^{\mu})$ 8 Compute the sensitivity S^{σ} with standard deviation σ with bound $[g_i, h_i]$ Scale factor for σ (*Sf*^{σ}) \leftarrow *S*^{σ} / ε 10 $\sigma'_i = \sigma_i + \operatorname{Lap}(0, Sf^{\sigma})$ 11 Use μ_i' , and σ_i' to compute $P(\mathbb{D}^N = x_j | \mathbb{C} = C_i)$ 12 end for 13 for each class c_i do 14 Count $nc_i' \leftarrow nc_i + \text{Lap}(0,1)$ 15 Use nc'_i to compute the prior $P(c_i)$ 16 end for 17 $C_i^L = argmax_c P(C) \prod P(X_j \mid c)$ 18 19 end for 20 CA = (#Correctly classified sample / #test sample) * 100 21 $P = \{ \text{relevant data labels} \cap \text{retrieved data labels} \} / \{ \text{retrieved data labels} \}$ 22 $R = \{\text{relevant data labels} \cap \text{retrieved data labels} \} / \{\text{relevant data labels} \}$ 23 FS = 2 * (P * R) / (P + R)

with 64-bit Ubuntu along with 8 GB of main memory. The classification tasks are accomplished using Python 2.7.15 programming language. The *NB* classifier has been used over testing data.

9.2 Datasets and Classification Parameters

Heart Disease, Iris, Balance Scale, and Nursery datasets, all of which were obtained from the UCI Machine Learning Repository [37] to train *CM*. These datasets have 75, 5, 5, 9 attributes and 303, 150, 625, 12960 instances. The description of the datasets is shown in Table 4.

The 9/10 of the data from the complete dataset is utilized as training data, while the remaining is used as test data for the purpose of training the *CM*. The machine learning tasks are accomplished over the clean data, DA-PMLM, PMLM [16], MLPAM [23], DPEL [33], and PDLM [18]. We have used the Laplace mechanism to generate the noise. However, DA-PMLM, PMLM [16], MLPAM [23], as well as DPEL [33] schemes contain noise, and PDLM [18] scheme is based on a homomorphic encryption technique. The results of *CM* are evaluated using test data, and *CA*, *P*, *R*, and *FS* are computed from these results.

Dataset	#Instances	#Features #Classes		Samples in	Samples in
				training set	test set
Heart Disease	303	75	2	272	31
Iris	150	5	3	135	15
Balance Scale	625	5	3	562	63
Nursery	12960	9	5	11664	1296

Table 4: Basic information of four datasets

9.3 Results

The CM acquires the classification results including CA, P, R, and FS over the clean data, DA-PMLM, PMLM [16], MLPAM [23], DPEL [33], and PDLM [18] as shown in Figs. 4(a)-(d) to 7(a)-(d). In DA-PMLM, the maximal value of CA is 93.33% on the Iris dataset with 2.0 privacy budget. The minimal value of CA is 33.87% on the Nursery dataset with 0.01 privacy budget. The average value of CA is 70.04%, 74.97%, 61.44%, and 46.28% over Heart Disease, Iris, Balance Scale, and Nursery datasets, respectively. The greatest value of P is 94.44% on the Iris dataset with 2.0 privacy budget. The lowest value of P is 31.57% on the Nursery dataset with 0.01 privacy budget. The average value of P is 70.53%, 72.67%, 59.66%, and 44.89% over Heart Disease, Iris, Balance Scale, and Nursery datasets, respectively. The maximum value of R is 93.33% on the Iris dataset with 2.0 privacy budget. The minimum value of R is 33.87% on the Nursery dataset with 0.01 privacy budget. The average value of R is 70.04%, 74.97%, 61.44%, and 46.28% over Heart Disease, Iris, Balance Scale, and Nursery datasets, respectively. The highest value of FS is 93.33% on the Iris dataset with 2.0 privacy budget. The lowest value of FS is 28.66% on the Nursery dataset with 0.01 privacy budget. The average value of FS is 69.30%, 73.13%, 58.43%, and 43.64% over Heart Disease, Iris, Balance Scale, and Nursery datasets, respectively. The performance of the datasets decreases in order: Iris > Heart Disease > Balance Scale > Nursery datasets.

9.4 Comparison

The results of the experiments are compared to clean data, PMLM [16], MLPAM [23], DPEL [33], and PDLM [18], which are also deployed on the same platform (Figs. 4(a)-(d) to 7(a)-(d)). The parameters (*CA*, *P*, *R*, and *FS*) results for DA-PMLM are less than the results of Clean, PMLM [16], MLPAM [23], and DPEL [33] in all the cases because of the noise addition in the data and classification model. From Table 5, it is observed that the highest difference for *CA* between DA-PMLM and DPEL is 13.35% on the Nursey dataset with 0.5 privacy budget. The lowest difference is found 0.0% on the Heart Disease dataset with 0.1, 0.5, 1.0, 1.5, and 2.0 privacy budget, and on the Iris dataset with 0.5 privacy budget, but the lowest differences are found 0.11% on the Heart Disease dataset with 2.0 privacy budget. The maximum decrement for *R* of DA-PMLM is 13.35% from DPEL on the Nursey dataset with 0.5 privacy budget. In contrast, the smallest decrement is 0.0% on the Heart Disease dataset with 0.1, 0.5, 0.0% on the Heart Disease dataset with 0.1, 0.5, 0.0% on the Heart Disease dataset with 0.1, 0.5, 0.0% on the Nursey dataset with 0.1, 0.5, 0.0% on the Heart Disease dataset with 0.1, 0.5, 0.0% on the Heart Disease dataset with 0.1, 0.5, 0.0% on the Heart Disease dataset with 0.1, 0.5, 0.0% on the Heart Disease dataset with 0.1, 0.5, 0.0% on the Heart Disease dataset with 0.1, 0.5, 0.0% on the Heart Disease dataset with 0.1, 0.5, 0.0% on the Heart Disease dataset with 0.1, 0.5, 0.0% on the Heart Disease dataset with 0.1, 0.5, 0.0% on the Heart Disease dataset with 0.1, 0.5, 0.0% on the Heart Disease dataset with 0.1, 0.5, 0.0% on the Heart Disease dataset with 0.1, 0.5, 0.5% on the Heart Disease dataset with 0.1, 0.5, 0.5% on the Heart Disease dataset with 0.1, 0.

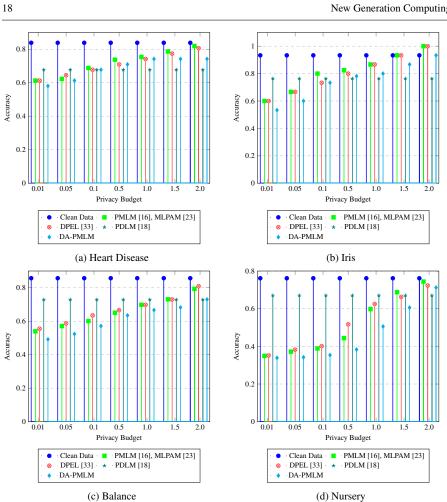


Fig. 4: Accuracy of CM in DA-PMLM

1.0, 1.5, and 2.0 privacy budget, and on the Iris dataset with 0.1 privacy budget. The highest difference for FS is 14.05% on the Iris dataset with 0.01 privacy budget, while the lowest difference for FS is 0.1% on the Heart Disease dataset with 1.0 privacy budget.

Additionally, the parameters (CA, P, R, and FS) results for DA-PMLM are less than the results of PMLM and MLPAM in all the cases due to noise addition in the model. The maximum gap for CA is 9.25% on the Nursey dataset with 1.0 privacy budget, but the smallest gap is found 1.0% on the Heart Disease with 0.05 privacy budget. Similarly, the highest difference for P is 19.33% on the Iris with 0.01 privacy budget, while the lowest difference is found 0.16% on the Heart Disease dataset with 0.05 privacy budget. The R of DA-PMLM the maximum decrement by 8.72% from PMLM, MLPAM on the Nursery dataset with 1.0 privacy budget, whereas the smallest decrement is 1.0% on the Heart Disease dataset with 0.05 privacy budget. The highest

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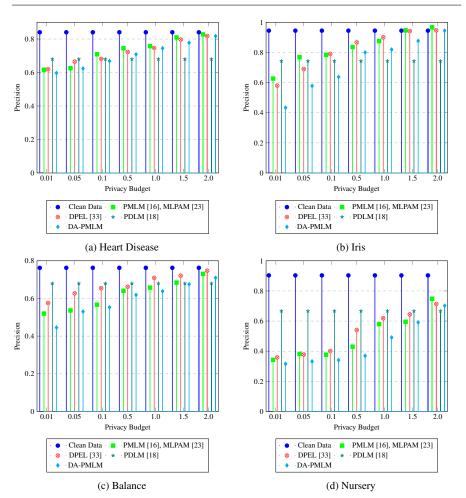


Fig. 5: Precision of CM in DA-PMLM

difference for FS is 13.29% on the Iris dataset with 0.05 privacy budget, but the lowest difference for FS is 0.18% on the Balance dataset with 0.5 privacy budget.

Likewise, DA-PMLM outperforms PDLM [18] because the proposed model's efficiency is increased by performing fewer calculations on synthetic data instead of ciphertext. Table 6 shows that the improvement ranges for *CA*, *P*, *R*, and *FS* are 0.08% to 16.95%, 2.87% to 20.16%, 0.08% to 16.95%, and 2.62% to 23.33% over all datasets.

Moreover, the parameters (*CA*, *P*, *R*, and *FS*) results for DA-PMLM are less than the results of clean data in all the cases due to noise addition. The maximum gap for *CA* is 42.28% on the Nursey dataset with 0.01 privacy budget, but the lowest gap is found 0.0% on the Iris dataset with 2.0 privacy budget. Similarly, the highest difference for *P* is 58.75% on the Nursey dataset with 0.01 privacy budget, while

Dataset	Epsilon												
			Accuracy			Precision			Recall			F1-Score	
		Clean data	[16], [23]	[33]									
	0.01	25.81	3.23	3.23	24.37	1.97	2.29	25.81	3.23	3.23	25.44	2.88	3.05
	0.05	22.58	1	3.22	21.62	0.16	4.11	22.58	1	3.22	22.96	1.62	4.46
Heart	0.1	16.13	1.11	0	17.21	4.08	1.34	16.13	1.11	0	17.71	2.91	1.62
Disease	0.5	12.91	2.81	0	13.17	3.59	1.43	12.91	2.81	0	13.57	3.6	0.65
	1.0	9.68	1.21	0	9.55	1.29	0.21	9.68	1.21	0	9.73	1.04	0.1
	1.5	6.46	1.27	0	6.27	3.16	1.94	6.46	1.27	0	7.66	2.66	1.41
	2.0	3.23	1.32	0	2.32	1.07	0.11	3.23	1.32	0	4.13	2.55	1.22
	0.01	40	6.67	6.67	51.11	19.33	14.64	40	6.67	6.67	46.71	13.29	14.05
	0.05	33.33	6.66	6.66	36.67	19.08	11.23	33.33	6.66	6.66	34.04	5.74	8.2
	0.1	20	6.67	0	30.74	14.63	15.34	20	6.67	0	25.21	6.42	5.72
Iris	0.5	15.18	4.32	1.85	14.45	3.56	6.67	15.18	4.32	1.85	15.01	1.58	1.12
	1.0	13.33	6.66	6.66	12.53	5.59	8.09	13.33	6.66	6.66	13.08	6.22	5.1
	1.5	6.67	6.67	6.67	6.83	7.05	6.55	6.67	6.67	6.67	7.56	7.63	7.07
	2.0	0	6.67	6.67	0	2.22	0.22	0	6.67	6.67	0.04	0.81	0.11
	0.01	36.51	4.76	6.35	31.72	7.42	13.05	38.51	4.76	6.35	35.61	7.94	7.5
	0.05	33.33	4.76	6.35	22.65	0.57	9.09	35.33	4.76	6.35	29.26	4.71	10.11
	0.1	28.57	3.17	6.35	20.95	1.39	10.13	30.57	2.99	6.35	28.76	7.77	11.38
Balance	0.5	22.22	1.58	3.17	14.42	2.21	4.39	24.22	1.58	3.17	16.98	0.18	2.33
	1.0	19.05	3.18	3.18	12.41	1.92	7.08	21.05	3.18	3.18	15.15	2.54	5.46
	1.5	17.46	4.76	4.76	8.74	0.89	4.57	19.46	4.86	4.76	12.63	2.88	4.31
	2.0	12.7	6.35	7.94	5.33	2.11	3.83	14.7	6.35	7.94	8.23	4.92	5.78
	0.01	42.28	1.08	1.31	58.75	2.68	4.3	42.28	1.08	1.31	51.45	4.63	3.28
	0.05	41.97	3.01	4.09	57.11	4.96	4.59	41.97	3.01	4.09	50.95	6.09	8.16
	0.1	40.89	3.62	4.86	56.22	3.57	6.03	40.89	3.62	4.86	49.2	6.58	8.13
Nursery	0.5	37.81	6.02	13.35	53.37	6.07	17.16	37.81	6.02	13.35	42.51	6.03	8.65
	1.0	25.61	9.25	11.96	41.22	8.91	12.78	25.61	9.25	11.96	31.2	9.64	13.11
	1.5	15.58	8.18	5.71	31.21	10.42	5.33	15.58	8.18	5.71	20.29	7.92	4.97
	2.0	4.94	3.17	1.08	20.12	4.59	1.17	4.94	3.17	1.08	9.66	3.03	1.19

Table 5: Accuracy, precision, recall, and f1-score; DA-PMLM v/s state-of-the-art works [16], [23], [33] and the baseline schemes

Table 6: Improvement in the values of CA, P, R, and FS of DA-PMLM vs PDLM [18]

Dataset	Epsilon	Increments in the value of parameters							
		CA	Р	R	FS				
	0.01	-9.71	-8.33	-9.71	-8.34				
	0.05	-6.48	-5.58	-6.48	-5.86				
Heart	0.1	-0.03	-1.17	-0.03	-0.61				
Disease	0.5	3.19	2.87	3.19	3.53				
	1.0	6.42	6.49	6.42	7.37				
	1.5	9.64	9.77	9.64	9.44				
	2.0	12.87	13.72	12.87	12.97				
	0.01	-23.05	-30.95	-23.05	-23.34				
	0.05	-16.38	-16.51	-16.38	-10.67				
	0.1	-3.05	-10.58	-3.05	-1.84				
Iris	0.5	1.77	5.71	1.77	8.36				
	1.0	3.62	7.63	3.62	10.29				
	1.5	10.28	13.33	10.28	15.81				
	2.0	16.95	20.16	16.95	23.33				
	0.01	-23.73	-23.45	-23.73	-24.76				
	0.05	-20.55	-14.95	-20.55	-18.41				
	0.1	-15.79	-12.68	-15.79	-17.91				
Balance	0.5	-9.44	-6.15	-9.44	-6.13				
	1.0	-6.27	-4.14	-6.27	-4.3				
	1.5	-4.68	-0.47	-4.68	-1.78				
	2.0	0.08	2.94	0.08	2.62				
	0.01	-33.16	-35.09	-33.16	-34.79				
	0.05	-32.85	-33.45	-32.85	-34.29				
	0.1	-31.77	-32.56	-31.77	-32.54				
Nursery	0.5	-28.69	-29.71	-28.69	-25.85				
-	1.0	-16.49	-17.56	-16.49	-14.54				
	1.5	-6.46	-7.55	-6.46	-3.63				
	2.0	4.18	3.54	4.18	7.00				

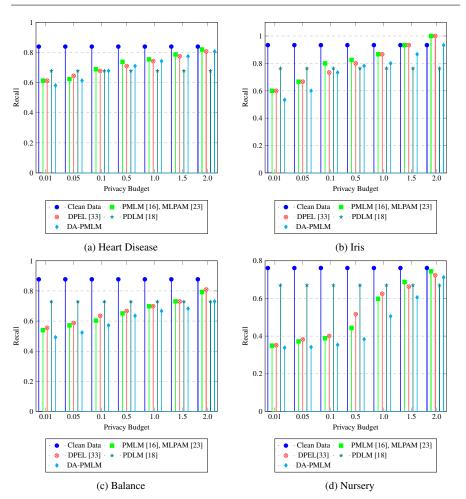


Fig. 6: Recall of CM in DA-PMLM

the lowest difference is found 0.0% on the Iris Disease with 2.0 privacy budget. The maximum decrement for R of DA-PMLM is 42.28% from clean data on the Nursey dataset with 0.01 privacy budget, whereas the smallest decrement is 0.0% on the Iris dataset with 2.0 privacy budget. The highest difference for FS is 51.45% on the Nursey dataset with 0.01 privacy budget, but the lowest difference for FS is 0.04% on the Iris dataset with 2.0 privacy budget. However, The parameters (CA, P, R, and FS) results for DA-PMLM are less or equal and provide more protection than the clean data, PMLM, MLPAM, DPEL, and PDLM. The proposed model acquires a trade-off between accuracy loss and privacy improvement when the noise is added using individual privacy constraints.

Furthermore, a comprehensive feature analysis along with a comparison of DA-PMLM against the state-of-the-art works [16], [23], [33], [18] is performed. From

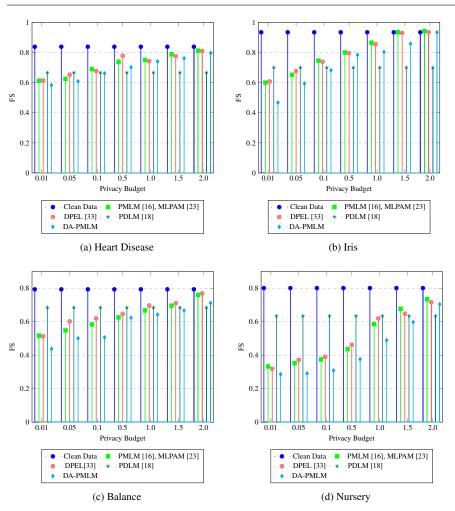


Fig. 7: F1-Score of CM in DA-PMLM

Table 7, it is observed that DA-PMLM is the only model that preserves the privacy of data and classification model. It also permits several untrusted entities, data owners, request users, and classifier owners to participate. DA-PMLM works on the dynamic privacy budget. In DA-PMLM, the use of the privacy budget is according to the level of protection required. Therefore, the performance of DA-PMLM outperforms than the existing schemes [16], [23], [33], [18].

9.5 Statistical Analysis

Statistical analysis is used to validate the *CA*, *P*, *R*, and *FS* of the model. In this context, the non-parametric test is applied to the dataset that is not normally distributed. The

Schemes	UE	DO	RU	СО	Privacy Budget	Data Privacy	Model Privacy
PMLM [16]	multiple	multiple	no	×	static	\checkmark	×
MLPAM [23]	multiple	multiple	multiple	×	static	\checkmark	×
DPEL [33]	single	single	no	×	dynamic	×	\checkmark
PDLM [18]	single	multiple	no	×	no	\checkmark	×
DA-PMLM	multiple	multiple	multiple	\checkmark	dynamic	\checkmark	\checkmark

Table 7: Comparative analysis of relevant schemes

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 DA-PMLM to that of the existing DPEL [33], PMLM [16], MLPAM [23], and PDLM [18] models. The test is run on the dataset with a significance level [38] (p-value) of 0.05 to determine the importance of classifying parameters. Table 8 demonstrates the results of the test statistics.

Table 8: Wilcoxon test statistics (p-value is 0.05)

Dataset	Classification	Comparison of		Compari	son of DA-PMLM,	Comparison of		
	Parameters	DA-PML	M & DPEL [33]	PMLM [16] & MLPAM [23]	DA-PMLM & PDLM [1		
		p-value	Result	p-value	Result	p-value	Result	
	Accuracy	0.180	Accepted	0.018	Rejected	0.612	Accepted	
Heart	Precision	0.018	Rejected	0.018	Rejected	0.398	Accepted	
Disease	Recall	0.180	Accepted	0.018	Rejected	0.612	Accepted	
	F1-score	0.018	Rejected	0.018	Rejected	0.398	Accepted	
	Accuracy	0.026	Rejected	0.016	Rejected	1.000	Accepted	
Iris	Precision	0.018	Rejected	0.018	Rejected	0.866	Accepted	
	Recall	0.026	Rejected	0.016	Rejected	1.000	Accepted	
	F1-score	0.018	Rejected	0.018	Rejected	0.735	Accepted	
-	Accuracy	0.017	Rejected	0.018	Rejected	0.028	Rejected	
Balance	Precision	0.018	Rejected	0.018	Rejected	0.043	Rejected	
Scale	Recall	0.017	Rejected	0.017	Rejected	0.028	Rejected	
	F1-score	0.018	Rejected	0.018	Rejected	0.043	Rejected	
	Accuracy	0.018	Rejected	0.018	Rejected	0.028	Rejected	
Nursery	Precision	0.018	Rejected	0.018	Rejected	0.028	Rejected	
	Recall	0.018	Rejected	0.018	Rejected	0.028	Rejected	
	F1-score	0.018	Rejected	0.018	Rejected	0.043	Rejected	

While comparing DA-PMLM and DPEL, it is observed that the null hypothesis for *P*, and *FS* is rejected but accepted for *CA*, and *R* on the Heart Disease dataset. The null hypothesis is rejected for *CA*, *P*, *R*, and *FS* on the Iris, Balance Scale, and Nursery dataset, because their p-values are less than 0.05. Similarly, comparing DA-PMLM, PMLM, and MLPAM, the null hypothesis is rejected for *CA*, *P*, *R*, and *FS* on the Heart Disease, Iris, Balance Scale, and Nursery datasets. Moreover, comparing DA-PMLM and PDLM, the null hypothesis is accepted for *CA*, *P*, *R*, and *FS* on the Heart Disease, Iris datasets, but rejected for Balance Scale, and Nursery datasets. Based on the achieved statistics results, DA-PMLM improves *CA*, *P*, *R*, *FS*, which demonstrates the superiority of the proposed model.

10 Conclusion

This paper proposed a novel model named DA-PMLM that protects the sensitive data and classification model outsourced by multiple owners in a real cloud environment. DA-PMLM permits the various data owners to store and analyze their data and the classifier owner to share the model to handle the multiple requests in the cloud. In this work, data owners inject varying statistical noise to sensitive data according to their queries as well as classifier owner adds the statistical noise into the model to preserve privacy. The experiments have been performed, and the results demonstrate that the parameter's values of classification of DA-PMLM (accuracy, precision, recall, and f1-score) are degraded by increased privacy (i.e., lower ε). However, the results also illustrate that more elevated ε can enhance the parameter's classification values of DA-PMLM. The performance of DA-PMLM on the prominent data sets is more secure, efficient, and optimal than existing works in this regard. As part of our future work, we will devise a more efficient privacy-preserving mechanism that reduces performance degradation.

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