

Differentially Private Machine Learning for Breast Cancer Classification

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1. Problem

- Breast cancer among women is one of the most common and deadliest cancers worldwide.
- Recent advancement in ML is helping to develop efficient and effective intelligent systems for the early detection of breast cancers.
- Privacy vulnerability: From model training to model deployment, privacy leakage can occur at any step in the lifecycle of machine learning.
- Therefore, protecting users' privacy is highly important in breast cancer classification, and very little works have been done to meet this requirement.
- Differential privacy (DP)-based approaches attempt to add statistical noise drawn from a probability distribution (e.g. Laplace distribution) to classifiers.

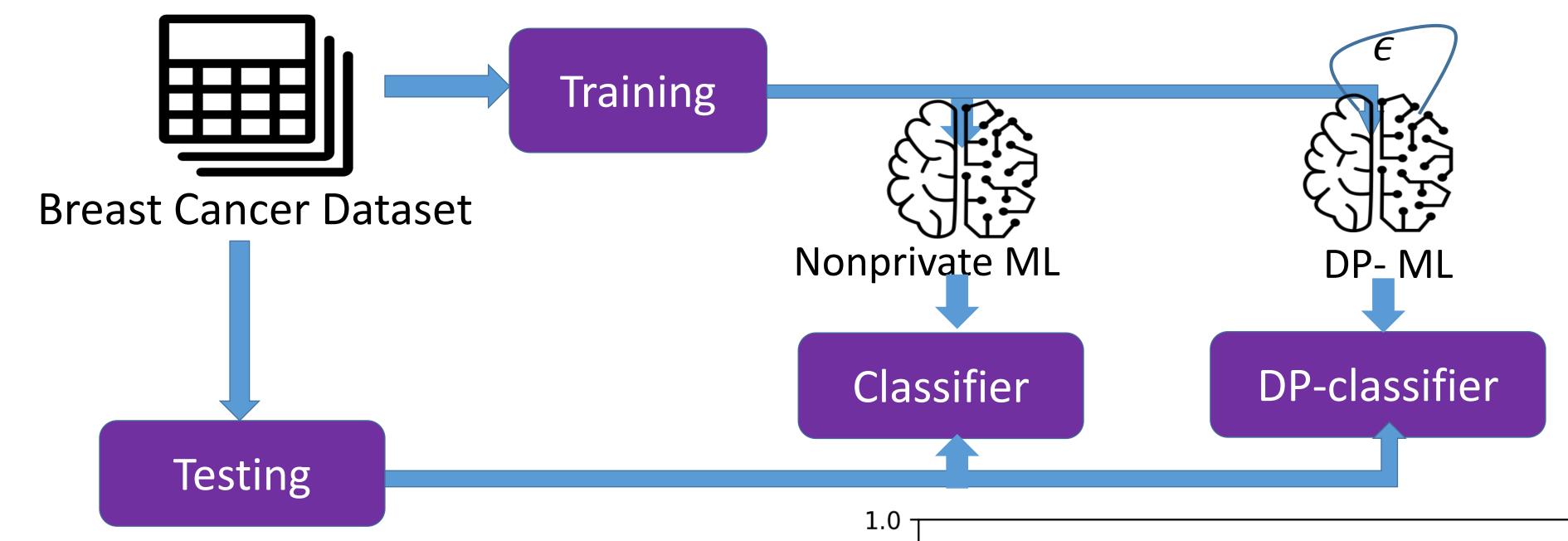
2. Contribution

- We present the results of our research on developing differentially-private machine learning models for breast cancer classification.
- We implemented privacy-preserving Logistic Regression and Naïve Bayes in breast cancer classification and compare them with non-private Logistic Regression and Naïve Bayes algorithms.

3. ML and DP-ML Models

- Logistic Regression (LR) is a model mainly used for binary classification which computes the weighted sum of the input features and output the logistic of the results.
- The Naïve Bayes (NB) is a probabilistic classifier based on Bayes' theorem with the assumption of independence between the features.
- **Differentially Private Logistic Regression (DP-LR)**: Chaudhuri et al. [1] designed a privacy preserving logistic regression approach by introducing differential privacy to perturb the objective function.
- **Differentially Private Naive Bayes (DP-NB)**: Vaidya et al. [2] proposed a differentially-private Naïve Bayes model where noises drawn from Laplace distribution are added to the mean and standard deviation of each attribute.

4. Methodology



5. Experimental Result

- In the experiment, we used the popular Wisconsin Breast Cancer Dataset [3].
- We implemented four different models: Logistic Regression, Naive Bayes, differentially-private Logistic Regression, and differentially-private Naive Bayes.
- We used the scikit-learn and IBM diffPrivLib libraries.

0.8 O.6 Non-private Naive Bayes Non-private Logistic Regression Differentially private Naive Bayes Differentially private Logistic Regression 0.0 0.25 0.50 0.75 1.00 1.25 1.50 1.75 2.00 epsilon

 The results show that it is possible to achieve high accuracy with both privacypreserving models.

6. Lesson Learned,Conclusion, andFuture Work

- Privacy concerns can be a big hurdle in developing intelligent systems to perform sensitive tasks.
- We have developed a differentially private Naive Bayes and Logistic Regression classifiers for breast cancer classification.
- We have tested both classifiers on a real world dataset and results show that it is possible to achieve high accuracy with both models, compared to baseline models.
- In the future, we plan to look at how different feature engineering methods, such as data augmentation, can improve the accuracy of the models.

7. References

- 1. Farzad Zafarani and Chris Clifton.

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- 2. Kamalika Chaudhuri, Claire Monteleoni, and Anand D Sarwate. Differentially private empirical risk minimization. Journal of Machine Learning Research, 12(3), 2011.
- 3. Dua, D. and Graff, C. (2019). UCI Machine Learning Repository [http://archive.ics.uci.edu/ml]. Irvine, CA: University of California, School of Information and Computer Science.