Paper Review-"A Transfer Learning Approach to Breast Cancer Classification in a Federated Learning Framework"

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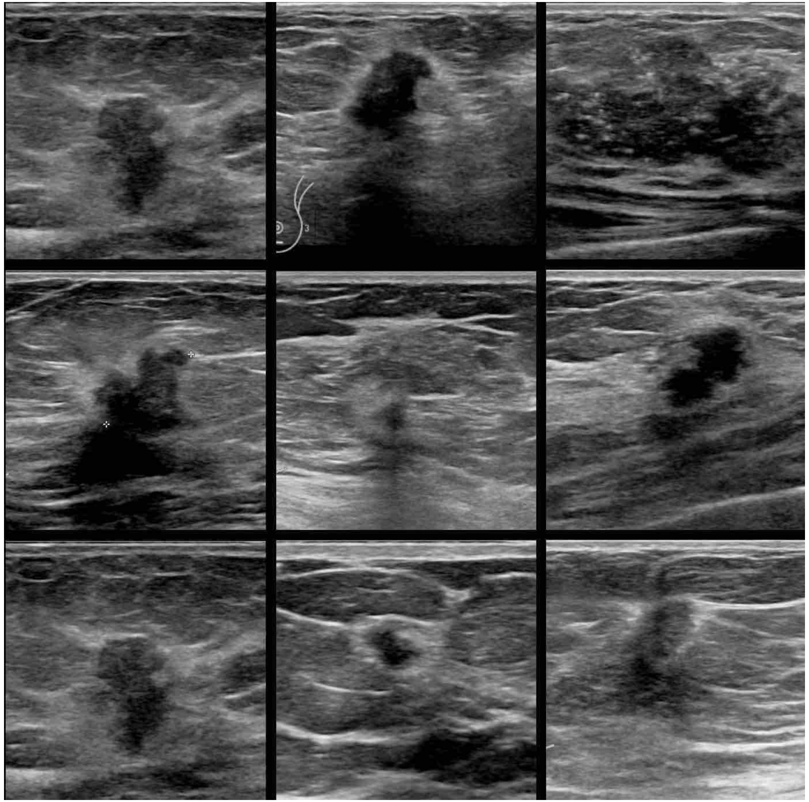
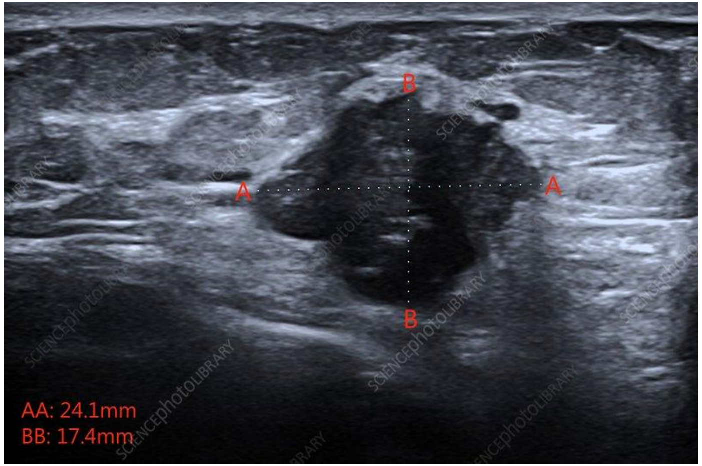


Motivation

- Challenges in breast cancer classification in medical imaging.
- Emphasis on dynamic nature of DDSM dataset and importance of accurate evaluations.
- Goal to enhance diagnostic processes, especially in imbalanced data scenarios.



Contribution

- Introduction of Transfer Learning using pre-trained models (MobileNet, DenseNet121, Xception, ResNet50).
- Leveraging SMOTE for handling imbalanced datasets.
- Efficient data splitting through scikit-learn.
- Practical application of Federated Learning in medical image classification.
- Balance between accuracy and preserving data privacy.

Summary

Methodology

- Transfer Learning approach with pre-trained models.
- FL framework with Python 3.8, TensorFlow 2.9, NVIDIA TESLA P100 GPU.
- Three edge servers, four clients, and 60 communication rounds.
- Data splitting using scikit-learn, FedAvg algorithm implementation.
- Model assessment with K-fold cross-validation, focusing on accuracy, precision, recall, F1-score, and AUC.

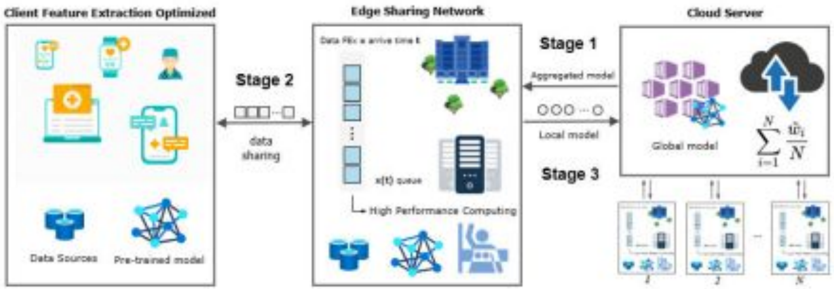


FIGURE 1. Architecture of the proposed approach federated learning settings.

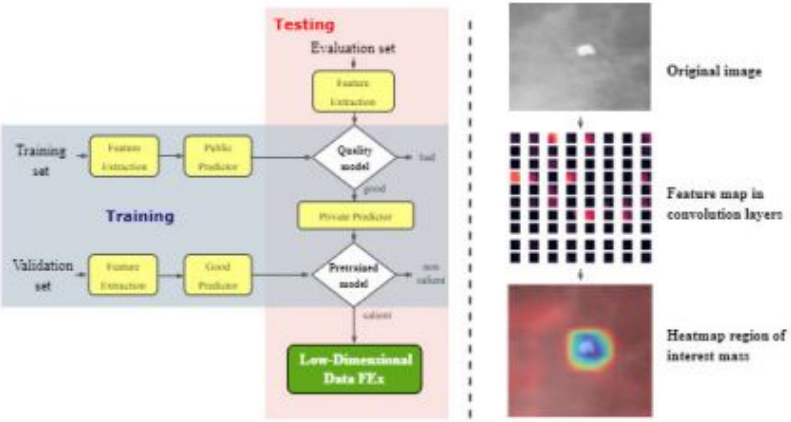


FIGURE 2. Flowchart of data processing for training and evaluation.

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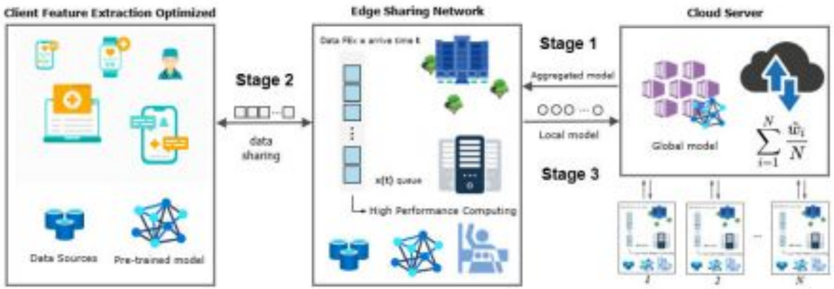

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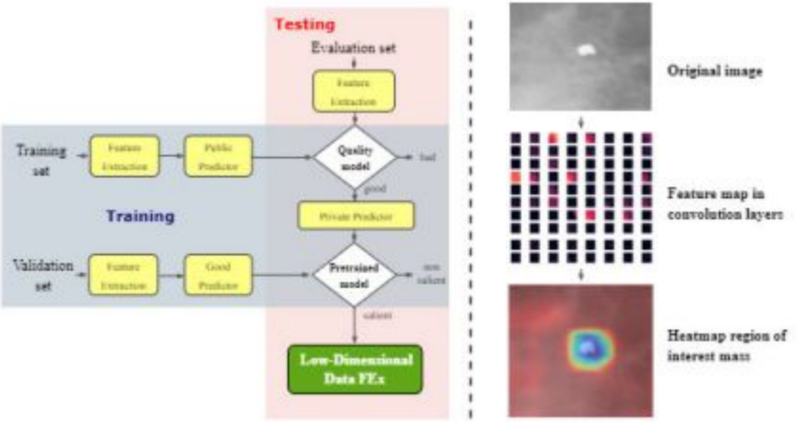

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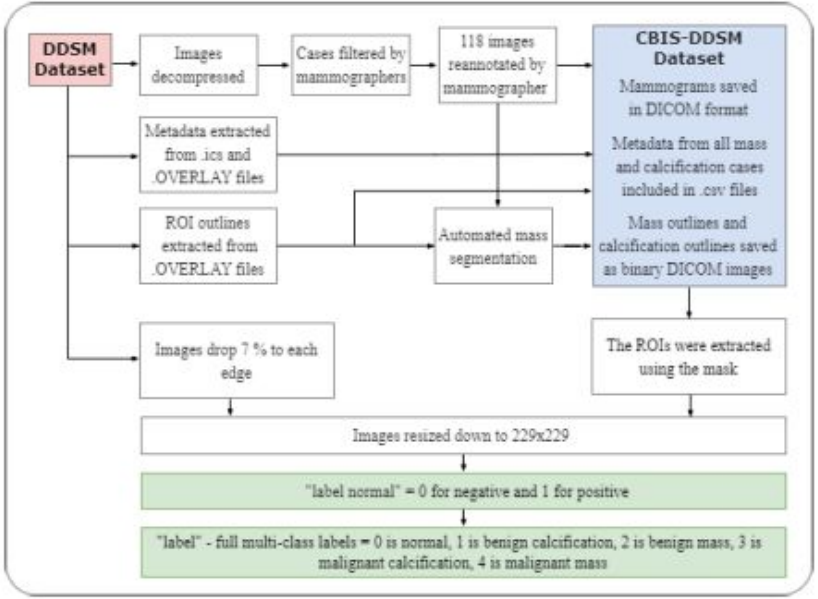

FIGURE 3. Diagram of DDSM data processing and conversion to images by ROI extraction.

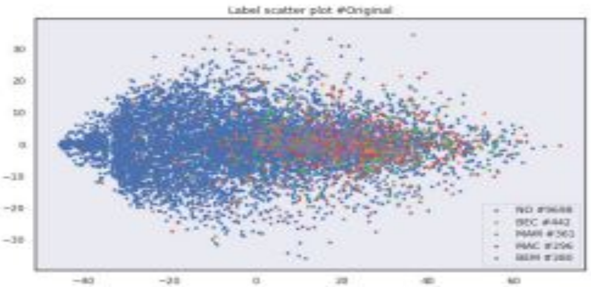

FIGURE 6. Class distribution predictive breast cancer data before SMOTE use.

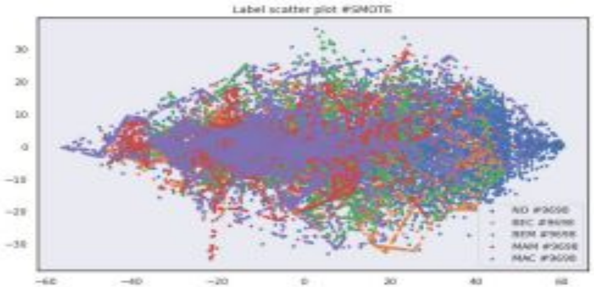

FIGURE 7. Class distribution predictive breast cancer data after SMOTE use.

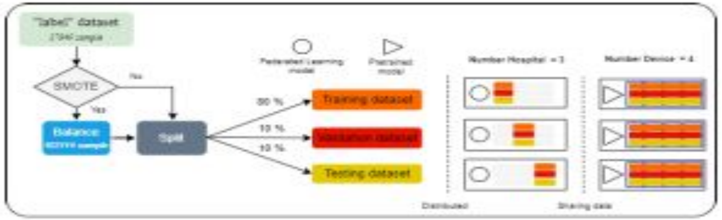

FIGURE 8. Data division process with the DDSM dataset.

Conclusion

- Key findings emphasizing comparable accuracy to centralized learning.
- Preservation of data privacy across multiple participating units.

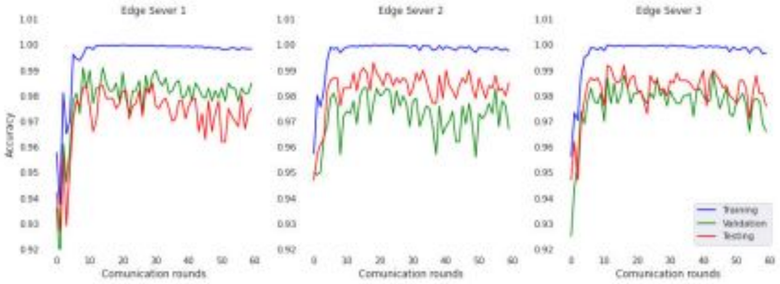

FIGURE 9. **Comparison of training, testing, and validation accuracy per communication round for three edge servers with the same settings.**

Limitations

First Limitation

- Prolonged training times associated with federated learning.
- Transparent discussion of challenges adds credibility.

Second Limitation

- Performance decline in real-world scenarios, especially with an increasing number of participants.
- Candid admission provides insights into practical constraints.

Synthesis

- Pioneering exploration of federated learning and MobileNet for breast cancer classification.
- Potential to transform collaborative learning in healthcare.
- Findings indicate improved diagnostics and personalized patient care.
- Extended training times pose a challenge, requiring careful consideration.
- Broader applications in collaborative learning across diverse industries suggested, emphasizing privacy-centric approaches.

Reference

Tan, Y. N., Tinh, V. P., Lam, P. D., Nam, N. H., & Khoa, T. A. (2023). A Transfer Learning Approach to Breast Cancer Classification in a Federated Learning Framework. IEEE Access, 10.1109/ACCESS.2023.3257562.

Thank you