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Federated Learning in Melanoma Detection with Lightweight Transfer Learning Models and Averaging Techniques

Abstract: - Melanoma, a severe form of skin cancer, poses a significant challenge to healthcare systems worldwide due to its high malignancy and the need for early detection to improve patient outcomes. Recent advancements in artificial intelligence (AI) and deep learning have shown promise in enhancing melanoma detection accuracy. However, traditional centralized training approaches often face limitations related to data privacy, security, and the heterogeneity of data sources. Federated learning (FL) emerges as a solution, enabling decentralized training of models across multiple institutions while preserving data privacy. This study investigates the efficacy of federated learning in melanoma detection, leveraging lightweight transfer learning models and averaging techniques. We explore the performance of three transfer learning models—Inception, ResNet, and MobileNet—within two federated learning frameworks: Federated Averaging (FedAvg) and Federated Proximal (FedProx). Our experimental results demonstrate that FedProx generally outperforms FedAvg across all models. Specifically, Inception achieved accuracies of 71.67% and 74% under FedAvg and FedProx, respectively. ResNet showed a notable improvement with accuracies of 73% under FedAvg and 82.67% under FedProx. MobileNet, known for its efficiency in mobile and embedded applications, achieved the highest accuracies of 78.33% with FedAvg and 81.33% with FedProx. The findings suggest that leveraging lightweight models within federated learning frameworks can maintain high detection accuracy while addressing privacy concerns. The superior performance of FedProx indicates its robustness in handling data heterogeneity and providing stable convergence. This study highlights the potential of federated learning to enhance melanoma detection, promoting collaborative efforts across institutions without compromising patient data privacy. Future research should focus on further optimizing federated learning algorithms and exploring their application in other medical imaging domains to ensure wide-scale clinical adoption.

Keywords: Melanoma Detection, Federated Learning, Transfer Learning, FedAvg, FedProx, Inception, ResNet, MobileNet, Data Privacy, Medical Imaging.

1. Introduction

Melanoma, an aggressive form of skin cancer originating in melanocytes, poses significant challenges to healthcare systems worldwide due to its high malignancy and potential for rapid progression. Early detection is paramount for improving patient outcomes, as early-stage melanoma is often curable, while advanced stages require more complex treatments and have lower survival rates as shown in figure-1 melanoma and its various stages. The importance of early detection cannot be overstated, as it leads to better prognoses, reduces treatment costs, and enhances the quality of life for patients. However, achieving early detection is fraught with challenges, including the need for specialized diagnostic tools and the expertise required to differentiate melanoma from benign skin lesions[1], [2].

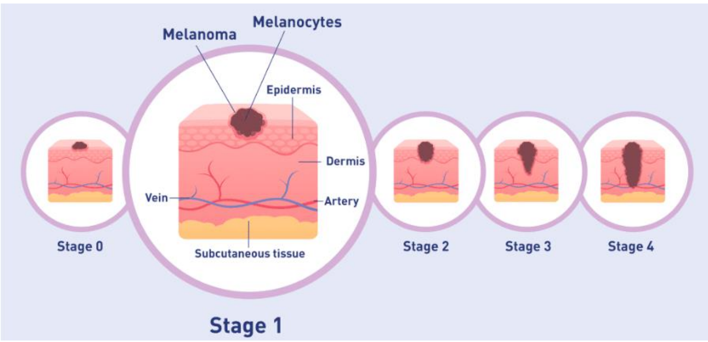

Figure 1 Melanoma and its various stages

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Advancements in artificial intelligence (AI) and deep learning have revolutionized medical imaging, providing powerful tools for enhancing diagnostic accuracy. AI models, particularly convolutional neural networks (CNN), have demonstrated remarkable success in various medical applications, including melanoma detection. These models excel at learning complex patterns in imaging data, enabling automated and accurate classification of skin lesions. The integration of AI in dermatology promises to alleviate some of the burdens on healthcare professionals by providing decision support systems that can operate with high accuracy and efficiency[3], [4].

Despite the successes of AI in enhancing diagnostic accuracy, traditional centralized training approaches face significant limitations. Centralized training requires aggregating data from multiple sources into a single location, which raises concerns about data privacy and security. In the healthcare sector, patient data is highly sensitive, and its centralized storage and processing pose risks of data breaches and unauthorized access. Furthermore, centralized approaches struggle with data heterogeneity, as medical imaging data collected from different institutions can vary in terms of equipment, protocols, and patient demographics.

Federated Learning (FL) emerges as a compelling solution to the challenges associated with centralized training. FL is a decentralized machine learning approach that enables the training of models across multiple devices or institutions without requiring the transfer of raw data. Instead, each participant trains a local model on their dataset and periodically shares only the model updates (such as gradients) with a central server. The central server aggregates these updates to form a global model, which is then distributed back to the participants. This iterative process continues until the model converges[5], [6].

The advantages of FL are manifold, particularly in the context of healthcare. First and foremost, FL enhances data privacy and security by keeping patient data localized. Since raw data never leaves the premises of the contributing institutions, the risk of data breaches is significantly reduced. FL also facilitates collaborative efforts among institutions, enabling them to leverage larger and more diverse datasets without compromising patient privacy. Moreover, FL addresses the issue of data heterogeneity by allowing each institution to retain its unique data characteristics, thereby enhancing the generalizability of the trained models[7].

Federated Learning has been increasingly applied in medical applications, offering a promising avenue to address these challenges. Studies employing FL in healthcare have shown its potential to facilitate collaborative research while preserving data privacy. However, gaps remain in optimizing FL techniques for specific medical imaging tasks, such as melanoma detection. The need for lightweight and efficient models within FL frameworks is crucial to ensure the practical deployment of these technologies in resource-constrained environments.

There is a pressing need for improved methods for melanoma detection that can effectively address the challenges of data privacy, security, and heterogeneity in medical imaging. Existing approaches, while demonstrating high accuracy in controlled settings, often fail to translate seamlessly into clinical practice due to the constraints of centralized data processing. Moreover, the heterogeneity of medical imaging data from different sources poses significant challenges for model generalizability. Addressing these issues requires innovative approaches that can leverage the strengths of decentralized training while ensuring high diagnostic accuracy and robustness[8].

This study aims to investigate the efficacy of federated learning in melanoma detection, focusing on the integration of lightweight transfer learning models within federated frameworks. The specific objectives are as follows:

- To explore the performance of lightweight transfer learning models, namely Inception, ResNet, and MobileNet, within federated learning frameworks.
- To compare the effectiveness of Federated Averaging (FedAvg) and Federated Proximal (FedProx) techniques in enhancing the performance of these models.
- To evaluate the potential of federated learning to maintain high detection accuracy while preserving data privacy and addressing data heterogeneity.

The federated learning framework employed in this study involves two primary techniques: Federated Averaging (FedAvg) and Federated Proximal (FedProx). FedAvg is a widely used approach that aggregates model updates from all participants to form a global model. FedProx extends FedAvg by incorporating a proximal term in the optimization objective to address issues related to data heterogeneity and convergence stability.

Three transfer learning models—Inception, ResNet, and MobileNet—were selected for this study due to their demonstrated success in image classification tasks. These models were fine-tuned within the federated learning framework, and their performance was evaluated based on accuracy and other relevant metrics. The experimental setup involved training the models on decentralized datasets, simulating the real-world scenario where data resides across multiple institutions.

This study introduces a federated learning framework tailored for melanoma detection, which addresses critical issues of data privacy and heterogeneity. We implemented and compared the performance of three lightweight transfer learning models—Inception, ResNet, and MobileNet—within two federated learning techniques, Federated Averaging (FedAvg) and Federated Proximal (FedProx). Our findings demonstrate that MobileNet achieves the highest accuracy, particularly under the FedProx framework, followed by ResNet and Inception. This research underscores the potential of federated learning to maintain high diagnostic accuracy while preserving patient data privacy, paving the way for broader application of AI in healthcare.

The study of federated learning for melanoma detection is crucial in addressing the pressing challenges of data privacy, security, and heterogeneity in medical imaging. By leveraging lightweight transfer learning models and federated learning techniques, this research aims to enhance the diagnostic accuracy of melanoma detection while preserving patient data privacy. The findings from this study are expected to pave the way for the practical deployment of AI-driven diagnostic tools in clinical settings, fostering collaborative efforts across healthcare institutions and ultimately improving patient outcomes. The promising results obtained from this study highlight the potential of federated learning to revolutionize the field of medical imaging, encouraging further research and development in this domain.

2. Literature review

The detection of melanoma, a highly aggressive form of skin cancer, has witnessed significant advancements with the advent of deep learning and artificial intelligence (AI) techniques. These methods have shown promise in enhancing diagnostic accuracy and early detection, crucial for effective treatment and improved survival rates. This literature review aims to provide an overview of recent research on deep learning approaches for melanoma detection, highlighting key methodologies, findings, and identified research gaps that inform the proposed approach in this study.

Shaaban et al.[9] explored the application of deep learning methods for skin cancer detection. Demonstrated the efficacy of CNN in distinguishing melanoma from other skin lesions with notable accuracy. Shorfuzzaman[10] proposed an explainable stacked ensemble of deep learning models aimed at improving the detection of melanoma. This study emphasized the need for interpretability in AI models to ensure clinical acceptance and highlighted the superior performance of ensemble methods over single models. Lafraxo et al.[11] introduced MelaNet, a deep learning framework specifically designed for melanoma detection using dermoscopic images. Their approach leveraged advanced image processing techniques to enhance feature extraction, leading to improved detection accuracy .

Drugge et al.[12] investigated the diagnostic accuracy of a total body photography system integrated with an AI dermoscopy application. Their findings underscored the potential of combining AI with dermoscopic imaging to enhance diagnostic precision and reduce the need for invasive procedures. Thapar et al.[13] developed a hybrid Grasshopper optimization algorithm for skin lesion segmentation and melanoma classification. This innovative approach integrated optimization algorithms with deep learning, resulting in enhanced segmentation accuracy and classification performance. Aljohani et al.[14] explored the use of DCNN for the automatic classification of melanoma. Their study highlighted the robustness of DCNN in handling complex image data and achieving high classification accuracy.

Liu et al.[15] proposed an optimal method for melanoma detection using reinforcement learning and SVM, optimized by an enhanced fish migration optimization algorithm. This hybrid approach demonstrated significant improvements in detection accuracy and computational efficiency. Priyadharshini et al.[16] introduced a novel hybrid method combining "Extreme Learning Machine" (ELM) and "Teaching-Learning-Based Optimization" (TLBO) for skin cancer detection. Their results indicated that the hybrid approach outperformed traditional methods in terms of accuracy and computational speed. Ghosh et al.[17] conducted a comprehensive study on the application of machine learning and deep learning techniques for skin cancer detection. Their review provided insights into various methodologies and identified challenges such as data heterogeneity and model interpretability.

Yousefi et al.[18] developed a method for automatic melanoma detection using discrete cosine transform features and metadata from dermoscopic images. This approach showcased the effectiveness of integrating feature extraction techniques with deep learning models for accurate melanoma detection. Melarkode et al.[19] reviewed AI-powered diagnostic approaches for skin cancer, identifying open challenges and future research directions. Their work emphasized the need for robust and explainable AI models to ensure clinical applicability and trust. Patel et al.[20] systematically reviewed AI-based approaches applied to non-invasive imaging for early melanoma detection. Their analysis highlighted the progress made in this field and pointed out the necessity for further research in enhancing model accuracy and reducing false positives.

The reviewed literature indicates significant progress in the use of deep learning for melanoma detection, with various methodologies demonstrating improved diagnostic accuracy and efficiency. However, several research gaps remain. There is a need for more robust and interpretable models that can be seamlessly integrated into clinical workflows. Additionally, addressing data heterogeneity and ensuring the generalizability of AI models across diverse populations remain critical challenges. The proposed research aims to address these gaps by exploring lightweight transfer learning models and novel averaging techniques within a federated learning framework, enhancing both the accuracy and applicability of melanoma detection systems.

3. Methodology

3.1. Dataset

The SIIM-ISIC Melanoma Classification competition on Kaggle involves predicting the presence of melanoma in dermoscopic images. The dataset includes images and metadata from the "International Skin Imaging Collaboration" (ISIC) and the "Society for Imaging Informatics in Medicine" (SIIM). This dataset is used to classify images as benign or malignant, aiming to enhance early detection and improve patient outcomes as shown in figure-2.

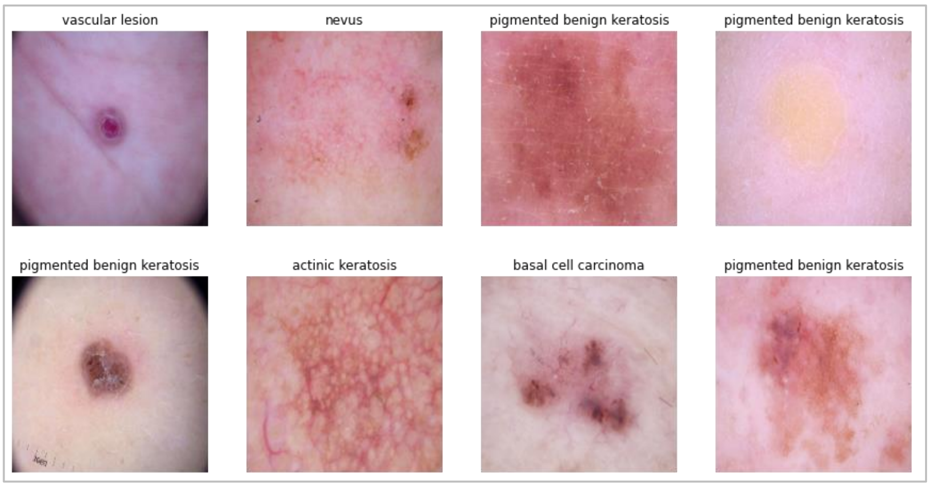

Figure 2 Dataset Sample

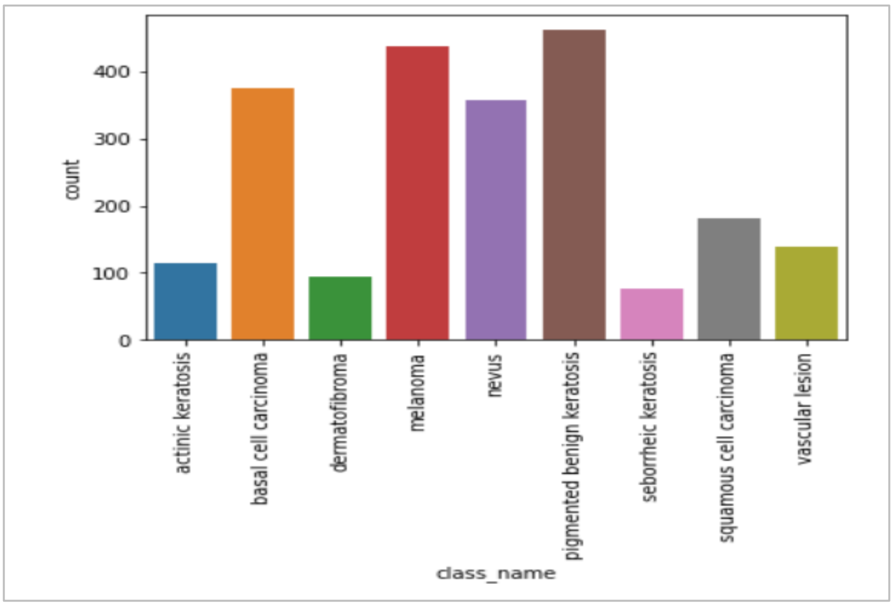

Figure 3 Dataset class distribution

3.2. Dataset Preprocessing

3.2.1. Resize Image (224*224)

In the preprocessing phase, all images are resized to a uniform dimension of 224x224 pixels. This ensures consistency in input size for the neural network. Mathematically, if an image I has dimensions $H \times W$, resizing transforms it to I' with dimensions 224×224. ,expressed as:

$$I'(x, y) = I(\frac{H}{224}x, \frac{W}{224}y)$$

3.2.2. RGB to Gray Image Conversion

The RGB images are converted to grayscale to reduce computational complexity and focus on intensity variations. The conversion uses the formula:

$$I_{gray} = 0.2989 \times R + 0.5870 \times G + 0.1140 \times B$$

3.2.3. Shuffle Dataset

Shuffling the dataset ensures that the model does not learn any order-related patterns, which promotes better generalization. The shuffling process rearranges the dataset indices using a permutation function, denoted as:

$$Shuffle(D) = D[\pi]$$

Where, π is a random permutation of the dataset indices D.

3.3. Data Augmentation

3.3.1. Constant Fill Augmentation

Constant fill augmentation involves extending the image by adding a border filled with a constant value, typically zero (black) or the average pixel value of the image. This technique is useful for increasing the size of an image without altering its core content, ensuring that the added pixels do not introduce new features or distort existing ones as shown in figure-4.

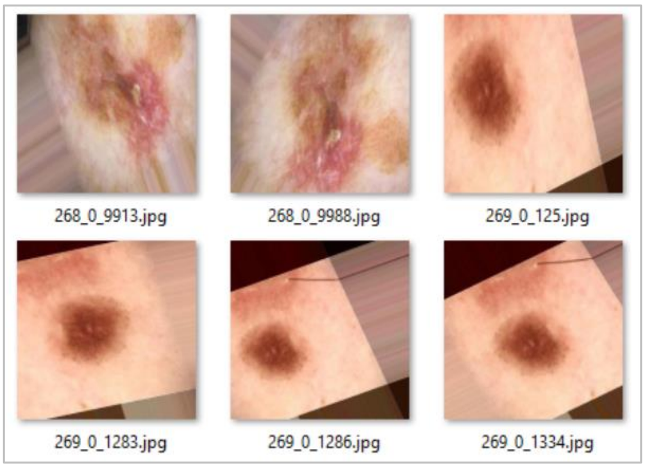

Figure 4 Constant fill augmentation

3.3.2. Nearest Fill Augmentation

Nearest fill augmentation extends the image by replicating the edge pixels outward to create a border. This method preserves the image's original characteristics by using the nearest pixel values for padding. It ensures that the contextual information at the edges is maintained, which can be beneficial for training neural networks as shown in figure-5.

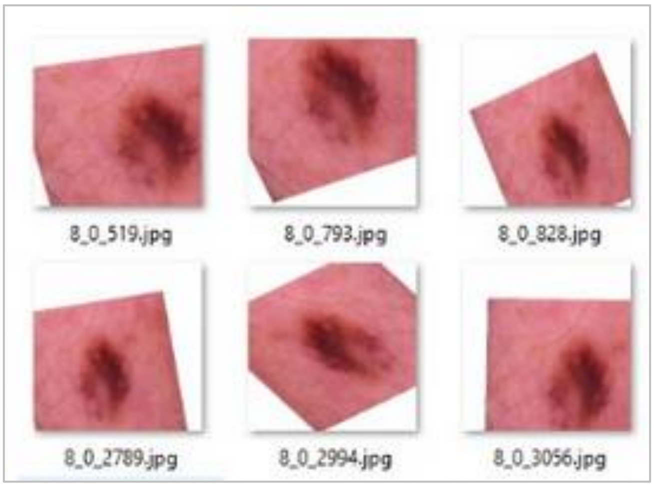

Figure 5 Nearest fill augmentation

3.4. Create Clients

3.4.1. Provide Name to Clients: In this step, each client in the federated learning system is assigned a unique identifier to facilitate data management and model training coordination.

3.4.2. Divide input data into number of clients: The entire dataset is divided into segments corresponding to the number of clients, ensuring each client receives a portion of the data for localized training.

3.4.3. Size : The size of each client's dataset is determined by the formula:

$$size = \frac{len\_data}{nim(clients)}$$

3.4.4. Distribute data to each client: Data is distributed among clients based on the calculated size, ensuring each client has a balanced subset of the total data.

3.4.5. Separate shard data into data and labels lists: Each client's dataset is further divided into input data and corresponding labels, preparing it for the training phase in the federated learning process.

3.5. Apply Federated Averaging Technique

3.5.1. FedAvg

Federated Averaging (FedAvg) is a technique where model updates from multiple clients are averaged to form a global model. Each client i trains a local model using its dataset $D_i$and computes the model update w_i. These updates are then aggregated by the central server to update the global model w using:

$$w = \frac{1}{N}\sum_{i=1}^{N} w_i$$

Where, N is the no. of clients, the client weights can be averaged based on the no. of data samples n_i, each clients holds:

$$w = \frac{n_i}{\sum_{j=1}^{N} n_j} w_i$$

3.5.2. FedProx

Federated Proximal (FedProx) extends FedAvg by introducing a proximal term to address data heterogeneity and improve convergence stability. Each client *I* minimizes a local objective function with an added regularization term $\mu||w - w^t||^2$ where $w'$is the global model from the previous iteration:

$$min_w f_i(w) + \frac{\mu}{2}||w - w'||^2$$

The updates w_i from each client are then aggregated in similar to FedAvg; this approach helps in balancing the influence of local updates, making the global model more robust to discrepancies in local data distributions.

3.6. Calculate Weight Scaling Factor

To calculate the weight scaling factor, determine the proportion of each client's data to the total dataset. If n_i represents the number of samples for client *i* and *N* is the total number of samples across all clients, the scaling factor s_i for client *i* is given by:

$$s_i = \frac{n_i}{N}$$

3.7. Calculate Scale Model Weights

Scaling a model's weights involves multiplying each weight by the calculated scaling factor. For a weight matrix *W* of client iii and scaling factor s_i , the scaled weights $W_i'$are:

$$W_i' = s_i . W_i$$

3.8. Calculate Sum Scaled Weights

The sum of the scaled weights from all clients provides an aggregated model. If *Wi'* are the scaled weights of client *i* and *N* is the number of clients, the aggregated weight matrix *W* is:

$$W = \sum_{i=1}^{N} W_i'$$

3.9. Use Transfer Learning Model

3.9.1. Lightweight Federated MobileNet

MobileNet is a lightweight convolutional neural network designed for mobile and embedded vision applications. In the context of federated learning, each client trains a local MobileNet model on its dataset, and the updates are aggregated to form a global model. The transfer learning aspect involves using pre-trained MobileNet weights and fine-tuning them for the specific task. If *W* represents the pre-trained weights and ΔWi the updates from client *i,* the global model weights *W'* are:

$$W' = W + \frac{1}{N}\sum_{i=1}^{N} \Delta W_i$$

This ensures efficient training and high performance while maintaining a lightweight model structure.

3.9.2. Lightweight Federated Inception

Inception networks are deep learning models designed to capture multi-scale features through parallel convolutional layers. For federated learning, each client trains an Inception model on its data and shares the updates. Using transfer learning, pre-trained Inception weights are adapted for the task. The weight update for client i, ΔWi, is aggregated as:

$$W' = W + \sum_{i=1}^{N} s_i \Delta W_i$$

where $s_i$is the scaling factor for client i. This approach leverages the powerful feature extraction capabilities of Inception networks while distributing the computational load across clients.

3.9.3. Lightweight Federated ResNet50

ResNet50, a deep residual network, addresses the vanishing gradient problem with skip connections, making it suitable for deep learning tasks. In federated learning, clients fine-tune a pre-trained ResNet50 model and share their updates. The global model is updated by aggregating these local changes. If W represents the pre-trained weights and ΔWi the update from client iii, the aggregated update W' is computed as:

$$W' = W + \frac{\sum_{i=1}^{N} n_i \Delta W_i}{\sum_{i=1}^{N} n_i}$$

This method ensures robust training while maintaining the lightweight nature of ResNet50.

3.10. Performance Evaluation

Performance evaluation of the federated learning models involves several key metrics. The global accuracy curve tracks the overall accuracy of the model across all clients over training epochs, providing insight into the learning progress. The global loss curve measures the loss function's value across epochs, indicating how well the model is minimizing errors. Additionally, metrics such as accuracy, precision, recall, and F1-score are used to evaluate the model's performance comprehensively. Accuracy indicates the proportion of correctly predicted cases, precision measures the correctness of positive predictions, recall assesses the model's ability to identify all relevant instances, and F1-score provides a harmonic mean of precision and recall, offering a balanced evaluation metric.

4. Results and Discussion

4.1. Global Model Accuracy and Loss Curve Comparison Using FEDAVG

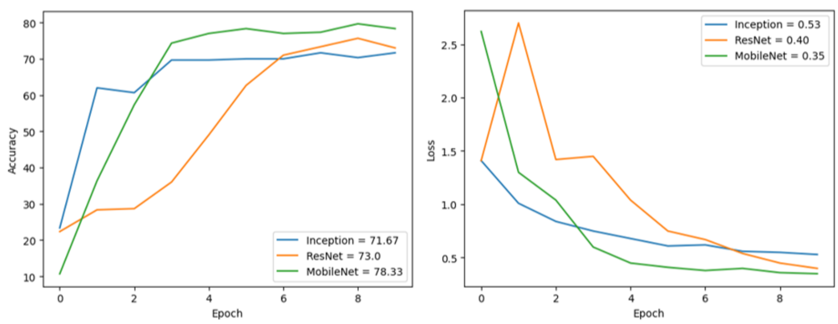

Figure 6 Global Model Accuracy and Loss Curve Comparison Using FEDAVG graph

4.2. Global Model Accuracy and Loss Curve Comparison Using FEDPROX

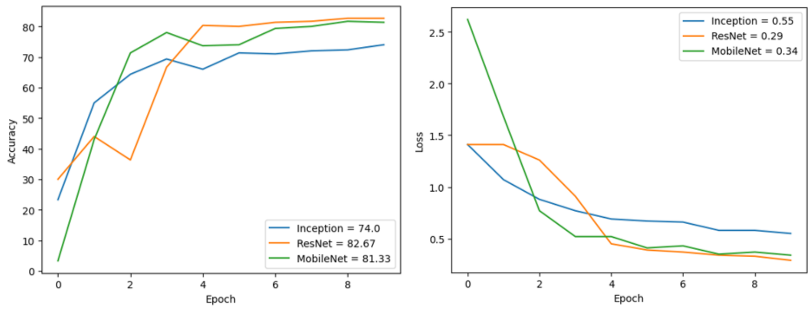

Figure 7. Global Model Accuracy and Loss Curve Comparison Using FEDPROX graph

4.3. COMPARATIVE ANALYSIS

4.3.1. Global Model Accuracy Performance Parameters Comparison

The performance evaluation of the federated learning models using FedAvg and FedProx techniques reveals notable insights. In terms of global accuracy as shown in figure-8, MobileNet achieves the highest accuracy with 78.33% using FedAvg and 81.33% with FedProx. ResNet shows significant improvement with FedProx, reaching 82.67% compared to 73% with FedAvg. Inception demonstrates a modest gain, increasing from 71.67% to 74%.

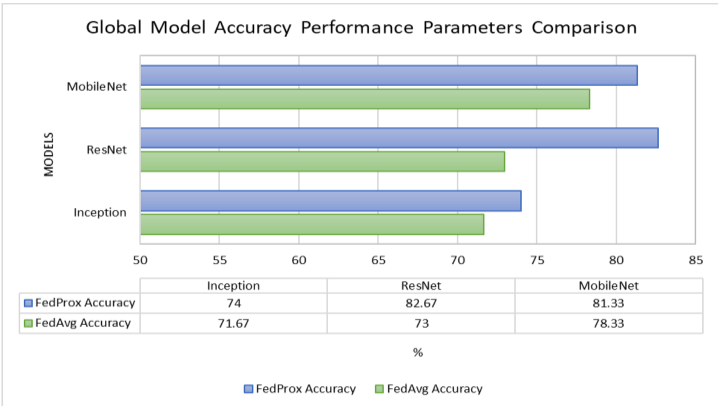

Figure 8 Global model accuracy graph

4.3.2. Global Model Loss Performance Parameters Comparison

For global loss, ResNet benefits greatly from FedProx, reducing loss from 0.4 to 0.29. MobileNet also shows a slight decrease in loss from 0.35 to 0.34, while Inception experiences a slight increase from 0.53 to 0.55 as shown in figure-9. These results highlight the effectiveness of FedProx in improving accuracy and reducing loss, particularly for deeper models like ResNet.

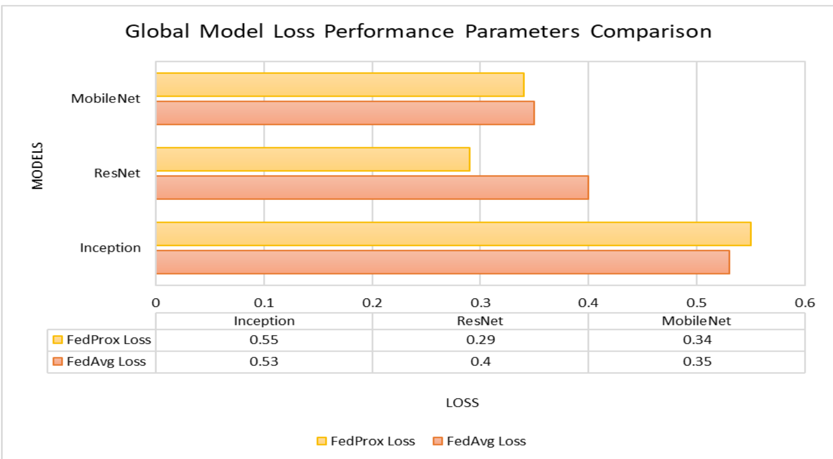

Figure 9 Global model loss

5. Conclusion and future scope

The study demonstrated the potential of federated learning (FL) to enhance melanoma detection while maintaining data privacy. By leveraging lightweight models such as Inception, ResNet, and MobileNet within FL frameworks, particularly FedProx, we achieved notable improvements in accuracy and loss reduction. MobileNet showed the highest performance, followed by ResNet, with both benefiting significantly from the FedProx technique. This research underscores the viability of FL in healthcare, enabling collaborative efforts without compromising patient privacy.

Future Scope

1. Enhancing Model Robustness: Further research could explore more sophisticated FL algorithms and advanced regularization techniques to improve model robustness against diverse data distributions.
2. Extending to Other Medical Conditions: Applying the developed FL framework to other medical imaging tasks, such as detecting different types of skin cancers or other diseases, can validate its broader applicability.
3. Real-World Implementation: Implementing the FL models in real-world clinical settings, assessing their integration with existing medical systems, and evaluating their impact on clinical workflows and outcomes.

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