Skin Cancer Classification and Detection Using Federated Learning

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Abstract: Detecting skin cancer involves challenges like ensuring the secure and private handling of sensitive medical data. Traditionally, centralized models have been used for classification and diagnosis, but these can risk data leaks and compromise patient privacy. To address this, a distributed learning system is proposed, allowing data to remain private while maintaining model accuracy. In this paper, we introduce a federated learning model for skin cancer classification. This system uses four independent clients: two trained on the ISIC 2018 dataset (with 7 skin disease types) and two trained on the ISIC 2019 dataset (with 8 disease types). The weights from the clients are combined and updated using the FedAvg algorithm to create a global model without sharing raw data between clients. The clients use CNN and MobileNetV2 for building the classifiers. This federated learning approach not only ensures data privacy but also achieves better performance, surpassing the current state-of-the-art accuracy for skin cancer classification across different datasets

1 INTRODUCTION

Early and accurate diagnosis of skin cancer in the dermatology field is the most critical factor in improving survival rates. Conventionally, dermatologists have always relied on medical history and physical examination that depends on direct visual diagnoses of cutaneous lesions to determine the presence of skin cancers. However, this form of diagnosis is prone to inherent human mistakes in the process, as well as subjective judgment when time is of the essence. The integration of machine learning and artificial intelligence has led to the emergence of automated systems that aid in the diagnosis of skin diseases. However, centralization of sensitive medical data towards training the machine learning model does pose a privacy concern regarding sensitive information in health care where security for data is concerned.

Federated learning(FL) addresses privacy concerns by enabling multiple institutions or devices to collaboratively train a model without sharing raw patient data, ensuring data privacy and security while leveraging distributed data sources. In this approach, each institution, or client, trains a model locally on its own dataset and shares just the learned model updates (the changes in the weight) with the central server. This has allowed learning while keeping sensitive patient data private and compliant with regulations like HIPAA and GDPR.

The proposed work introduces a federated learning- based system that utilizes the architecture of Convolutional Neural Networks and MobileNetV2 to classify skin diseases and cancer. In this work, four local clients are used for training. The ISIC 2018 dataset is utilized by two of the clients that covers seven kinds of diseases, while the remaining two clients utilize the ISIC 2019 dataset which comprises nine varieties of diseases. By using transfer learning, wherein pre-trained models are fine-tuned on local datasets, the system can achieve high classification accuracy without requesting large amounts of labelled data. Once trained, each client submits its model updates to a central server, which aggregates them using the FedAvg algorithm to create a global model.

The rest of the article is structured as follows: In section 2, we review the research attempts related to the skin disease classification. Section 3 explains the proposed methodology and the set of experiments conducted. The results of the experiments are presented in Section 4 along with a discussion and finally, we provide the conclusion of our work in Section 5.

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2 LITERATURE REVIEW

Below we present an overview of the recent attempts to classify the skin cancer using deep learning models.

(Sandler, Howard et al. 2018) used MobileNetV2, a highly iterative version of the original MobileNet to combat some major issues with deep learning on resource-constrained devices such as smartphones and embedded systems. A balance between being computationally efficient and giving an enhanced feature extraction performance has made the model useful in image classification, object detection, or even medical diagnosis applications.

(Guan, Yap et al. 2024) reviews the FL methods- those methods that allow the collaborative training of machine learning models without sharing the sensitive medical data. The authors classify the FL approaches into three major categories: client-side learning, server-side aggregation, and communication optimization. In addition to presenting empirical experiments on the FL performance for medical imaging, the authors highlight challenges, benchmark datasets, and software platforms.

The work by (Hossen, Panneerselvam et al., 2022) titled "Decentralized Training of a Model for Skin Disease Classification based on FL, while ensuring Data Privacy and Security issues related to Internet of Medical Things" describes skin disease classification with the help of FL in the decentralized model and CNN. It aims at dealing with data privacy and security issues associated with the Internet of Medical Things.

(Ali, Shaikh et al. 2022) investigates automated classification of several skin cancer types by EfficientNet architectures. The main goal is to enhance early diagnosis and prevention by improving reliable, deep learning-based diagnostic tools. This study can be said to take a step towards advanced dermatology by implementing efficient AI models in practice.

(Gautam et al., 2024) explores the implementation of deep learning techniques, particularly convolutional neural networks (CNNs), for the detection of skin cancer. The main focus of this research is to analyze dermoscopic images for improving diagnostic accuracy, in addition to the early detection of skin cancer, to develop automated tools for dermatological diagnosis.

(Lilhore et al. 2024) presented an accurate skin cancer diagnosis model based on the combination of a hybrid U-Net and an enhanced MobileNet-V3 architecture using techniques that perform hyperparameter optimization. The results were an enhanced performance in segmentation and classification of skin lesions.

(Agbley et al. 2021) investigated multimodal melanoma detection using federated learning in enhancing privacy and collaboration between different datasets. The methodology fused various data modalities, such as images and patient metadata, in a way that enhances diagnostic precision. Their study underscored the potential of federated learning to support safe and efficient training without the need to centralize sensitive data.

From the review of the recent attempts, we understand that despite the challenges related to non-IID data are discussed, yet tailored solutions for diverse dermatological datasets across demographics remain underexplored. Scalability and deployment in real-world, resource-constrained healthcare facilities, along with the impact of communication costs in FL, are insufficiently addressed.

3 IMPLEMENTATION

3.1 Federated Learning

Federated learning enables secure, collaborative model training across decentralized datasets from various hospitals, clinics, and personal devices. In conventional machine learning, all data are centralized at one server; however, with federated learning the patient data stay on local devices, detailing only trained model parameters or weights with a central server. Hence, this provides privacy and compliance with the regulations regarding medical applications, such as HIPAA and GDPR.

Local models are trained using pretrained CNN and MobileNet-V2, which are excellent at extracting features and making classifications. After training on their own dermatoscopic datasets, the updated model weights are sent to a central server. The server combines these weights from different models using a method called Federated Averaging (FedAvg), creating a global model that works well across multiple datasets. This global model is then sent back to local devices for further improvement in the next training rounds.

This approach makes the models more reliable and reduces errors caused by relying on a single dataset. FL allows for accurate and robust skin cancer detection while keeping data private, making it adaptable for use in hospitals or personal devices

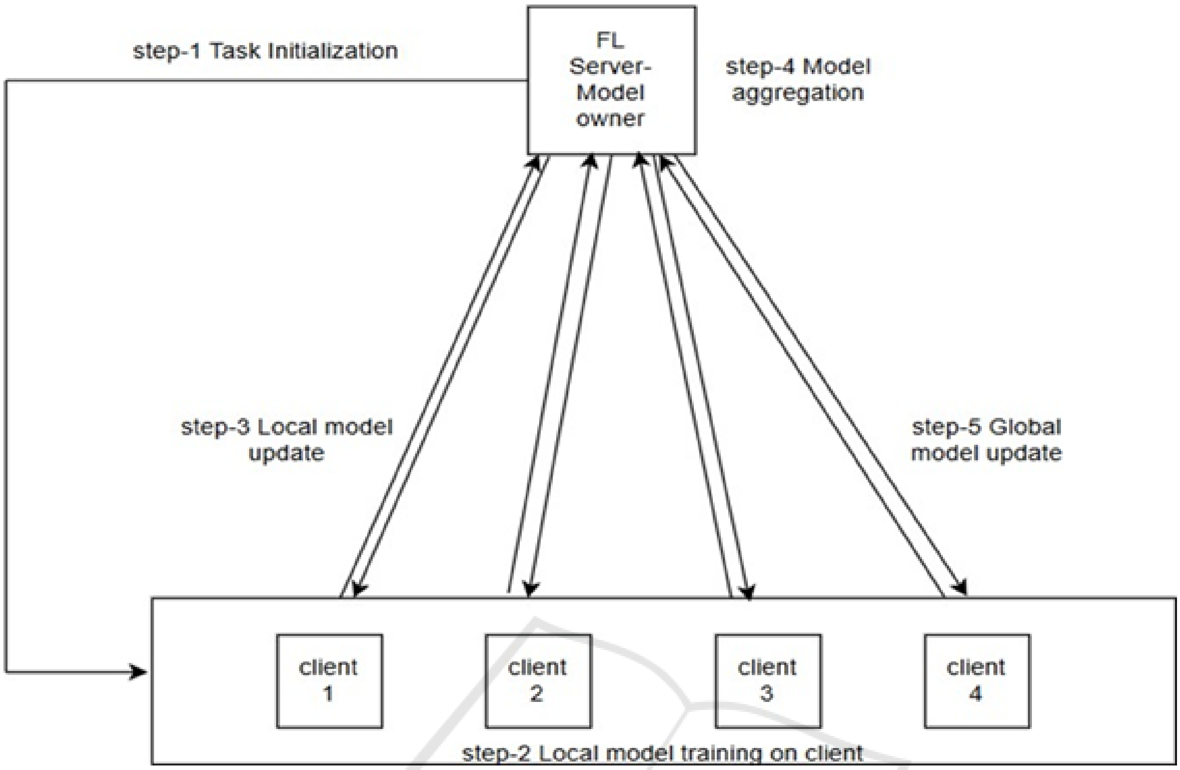

Figure 1: Federated Learning Architecture

of any size. Figure 1 depicts the proposed FL architecture.

3.2 Federated Averaging

The foundation of FL is an algorithm called Federated Averaging (FedAvg), which makes it possible to create machine learning models that are trained across different clients using their own private data. In our work, we use FedAvg to develop the global model. The crux of FedAvg lies in getting clients to train their local models on their data and then send the model updates, i.e., weights, to the server instead of sending raw data, thus keeping sensitive information within the client. The average weight updates are done as in Equation (1).

$$W = \frac{1}{N}\sum_{i=1}^{k} n_i \omega_i \tag{1}$$

Where,

- ω_i is the model weights for clients i.
- n_i is the amount of data for clients i.
- k is the total number of clients.
- N is the total number of data points across all clients.
- W is the global model weight after aggregation.

The process starts with each client training a local model on their own data for several rounds. Once the training is complete, the clients send their model weights to a central server. The server combines these weights to create a new global model, which is then shared back with the clients. The clients use this updated global model as a starting point for the next round of local training.

This cycle repeats until the model reaches the best possible performance. The FedAvg method reduces communication costs by sharing weights instead of gradients, making it efficient for low-bandwidth situations and ideal for applications that require strong privacy.

3.3 Experiments

To demonstrate the purpose and performance of FL, we conduct the following experiments.

3.3.1 First Experiment

In first experiment, we train local models based on CNN on 100% of the ISIC 2018 training data. To test the generalizing capability of the local models, we run the model on ISCI 2019 dataset.

3.3.2 Second Experiment

In second set of experiments, we use MobielNetV2 for training the local models. These models are trained on 100% of the ISIC 2018 training data. MobileNetV2 is efficient in computation footprint besides retaining good accuracy. The generalizing capability of the models are tested using ISIC 2019 dataset.

3.3.3 Third Experiment

Four clients are locally trained with the CNN and aggregated globally using FedAvg. In this third experiment, FL, integrated over four local clients, led to two clients trained by ISIC 2018 dataset while the remaining two were trained with ISIC 2019 dataset, to solve the overfitting phenomena observed in the first two experiments. Common diseases were taken and trained. After each local training, the weights of the models were forwarded for global averaging using the Federated Averaging Algorithm. The further updated weights were then sent back to each client.

Thus, the federated learning approach enables the models to be trained using multiple datasets without training the models on each dataset. Although Client 1 trained on the ISIC 2018 dataset, the updated global model could be used for new images from the ISIC 2019 dataset and vice versa. Hence, the models are generalized well concerning previously unseen data by accumulating learning evolved from both datasets into the federated averaging process.

3.3.4 Fourth Experiment

Here, four clients are locally trained with the MobileNetV2 and aggregated globally using FedAvg. The fourth experiment was basically the same as the third, except that the CNN model was substituted for local training with MobileNetV2. MobileNetV2 is built to give high accuracy while being light on the number of parameters and computations. Four local clients were set up: two clients trained the ISIC 2018 dataset and the other two the ISIC 2019 dataset. Similar to the previous experiments, each local model was independently trained on its respective datasets. Subsequently, the model weights were sent to a central server for federated averaging using the Federated Averaging Algorithm. This algorithm averaged the weights from the local models and updated them, after which the global model weights were sent back to each client, thus enabling the clients to benefit from the knowledge learned by other clients.

4 RESULTS AND DISCUSSION

4.1 Local Models

In Experiment 1, a CNN model is trained and tested on the ISIC 2018 datasets and achieved 83% accuracy. This accuracy drastically fell to 62% when applied the models on the ISIC 2019 datasets, which means that the model has less generalizability. As the model is trained by 2018. It is not suitable for 2019 images.

4.1.1 Classification results for ISIC 2018 using CNN

Table 1 shows the performance metrics of the developed models for each class. CNN achieved an accuracy of 83% on the test dataset of 938 samples. CNN exhibited a good performance among the classes with an F1-score of 0.93 for class 5. Nearly 39000 images was trained by CNN model as a single client.

Table 1: Classification report for ISIC 2018 using CNN

Class	Precision	Recall	F1-Score	Support
0	0.53	0.35	0.42	26
1	0.58	0.50	0.54	30
2	0.41	0.37	0.39	75
3	0.13	0.33	0.19	6
4	0.34	0.51	0.41	39
5	0.94	0.92	0.93	751
6	0.61	1.00	0.76	11
Accuracy	**0.83**			**938**
Macro Avg	0.50	0.57	0.52	938
Weighted Avg	0.84	0.83	0.83	938

Figure 2 visually represents the classification performance of the CNN model on the ISIC 2018 dataset, highlighting the model's strengths and weaknesses across different classes.

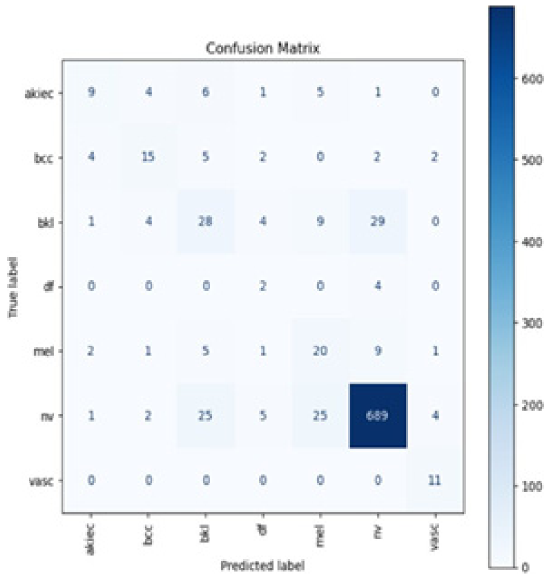

Figure 2: Confusion Matrix for ISIC 2018 using CNN

4.1.2 Classification results for ISIC 2019 using CNN

In Table 2, performance metrics of CNN is shown for all the classes. The model gives an accuracy of 62% to the dataset of 5,074 samples. Of all the classes, Class 4 showed the best performance, with an F1-score of 0.79. Since the model is trained using ISIC 2018 dataset, it gives the minimal performance while testing with the 2019 dataset. The model is not well suited for other datasets rather than the trained dataset. Thus, it shows a limited capability of the model in adapting to new forms of data distributions.

Table 2: Classification report for ISIC 2019 using CNN

Class	Precision	Recall	F1-Score	Support
0	0.31	0.14	0.19	175
1	0.49	0.59	0.53	665
2	0.33	0.28	0.30	526
3	0.60	0.06	0.11	49
4	0.76	0.82	0.79	2576
5	0.50	0.50	0.50	905
6	0.28	0.06	0.10	127
7	0.61	0.37	0.46	51
Accuracy		**0.62**		**5074**
Macro Avg	0.48	0.35	0.37	5074
Weighted Avg	0.60	0.62	0.60	5074

The classification performance of the CNN model on the ISIC 2019 dataset is shown in Figure 3.

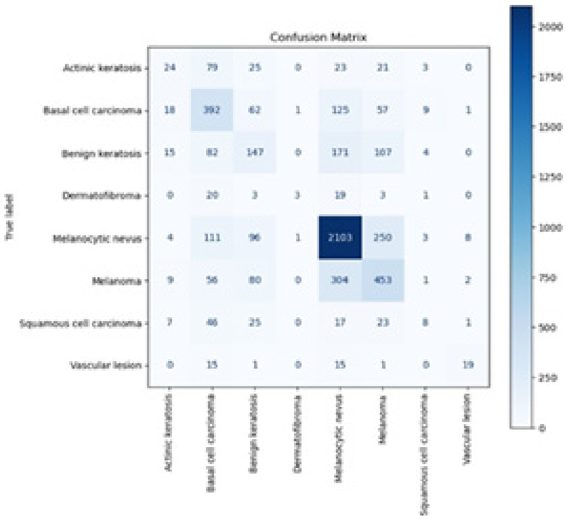

Figure 3: Confusion Matrix for ISIC 2019 using CNN

Experiment 2 showed a slight improvement using the MobileNetV2 model, with the ISIC 2018 dataset around 89% accuracy. MobileNetV2 proved to have better trade-off between precision and recall in all the classes, reducing the false positives and negatives. Despite being highly accurate on the ISIC 2018 dataset, it fell short with its generalization ability and large accuracy at 72% when tested on the ISIC 2019 dataset. This might not be much as it was better than the performance of the CNN model on ISIC 2019, but it still points to some difficulty in generalizing across datasets with very different distributions.

4.1.3 Classification results for ISIC 2018 using MobileNetV2

Table 3 provides an overview of model performance over all classes. The accuracy obtained is 89% for test dataset. Apart from class 5, which gives an F1-score of 0.96, making it the most prominent class in the dataset, others stand out due to their excellent performance on F1 scores: class 6 with 0.91 and class 1 with 0.71. Since the CNN model is not generalized, MobileNetV2 is used. This model gives the better accuracy in testing the 2018 dataset but while testing with 2019, the accuracy is not much defined. But it has some improvement compared to CNN model's performance.

Table 3. Classification report for ISIC 2018 using MobileNetV2

Class	Precision	Recall	F1-Score	Support
0	0.80	0.15	0.26	26
1	0.60	0.87	0.71	30
2	0.76	0.56	0.65	75
3	0.60	0.50	0.55	6
4	0.41	0.62	0.49	39
5	0.96	0.97	0.96	751
6	0.91	0.91	0.91	11
Accuracy	**0.89**			**938**
Macro Avg	0.72	0.65	0.65	938
Weighted Avg	0.90	0.89	0.89	938

Classification performance of the MobileNetV2 model for ISIC 2018 is shown in Figure 4. The findings indicate that yet powerful architecture of MobileNetV2 would really fit skin cancer classification tasks provided that training and testing are performed on similar datasets.

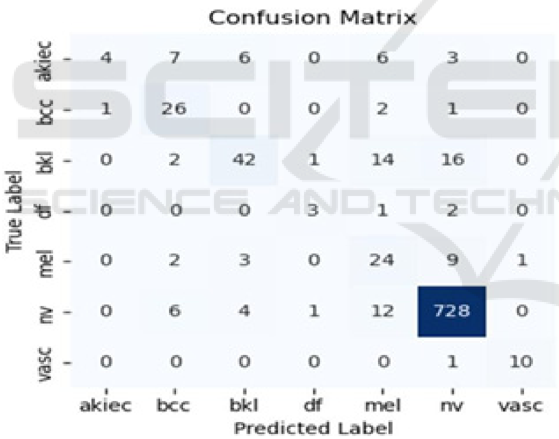

Figure 4: Confusion Matrix for ISIC 2018 using MobileNetV2

4.1.4 Classification results for ISIC 2019 using MobileNetV2

Table 4 gives the performance of MobileNetV2 on a dataset comprising 5,074 samples, with the overall accuracy of 72%. Class 4 was the best class performance with an F1 score of 0.86. Figure 5 shows the performance of MobileNetV2 on ISIC 2019 dataset.

Table 4: Classification report for ISIC 2019 using MobileNetV2

Class	Precision	Recall	F1	Support
0	0.50	0.18	0.27	175
1	0.58	0.86	0.69	665
2	0.63	0.36	0.46	526
3	0.50	0.02	0.04	49
4	0.83	0.88	0.86	2576
5	0.64	0.58	0.61	905
6	0.32	0.23	0.26	127
7	0.47	0.65	0.55	51
Accuracy	**0.72**			**5074**
Macro Avg	0.56	0.47	0.47	5074
Weighted Avg	0.71	0.72	0.70	5074

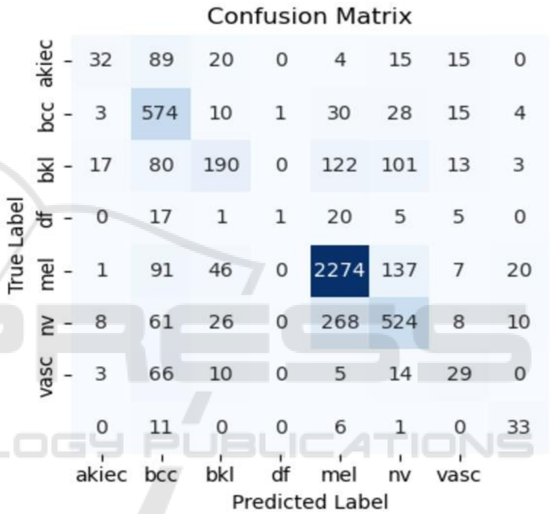

Figure 5: Confusion Matrix for ISIC 2019 using MobileNetV2

4.2 Federated Models

To combat the generalization problem, federated learning CNN was used in Experiment 3, for instance. All four local clients, trained on ISIC 2018 and ISIC 2019 datasets, have achieved 82% for ISIC 2018 and 76% for ISIC 2019 overall with better generalization across datasets.

4.2.1 Classification results for ISIC 2018 using Fed-CNN

From Table 5, we can see that the performance of CNN and it gives 82% accuracy. Four clients trained their local CNN models using their own data and shared their updated weights with a central server. The server aggregated these weights by calculating their weighted average and redistributed the updated weights back to the clients. This iterative process allowed the global model to benefit from diverse client datasets while preserving data privacy. The global model achieved 82% accuracy on ISIC 2018 and 76% on ISIC 2019, demonstrating improved generalization compared to standalone training.

Table 5: Classification report for ISIC 2018 using Fed-CNN

Class	Precision	Recall	F1-Score	Support
0	0.14	0.02	0.04	40
1	0.70	0.44	0.54	153
2	0.68	0.70	0.68	124
3	1.00	0.28	0.44	20
4	0.35	0.51	0.42	185
5	0.60	0.63	0.61	385
6	0.51	0.43	0.47	31
Accuracy		**0.82**		938
Macro Avg	0.57	0.43	0.46	938
Weighted Avg	0.56	0.54	0.54	938

Figure 6 shows that the model performs best for nevus category, with 243 correct predictions, but also shows some misclassifications.

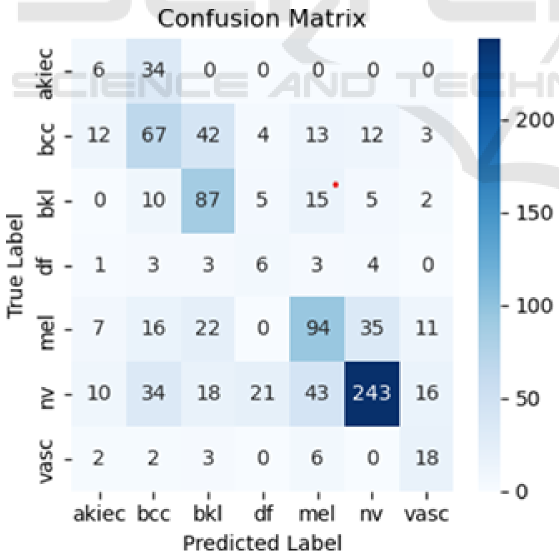

Figure 6: Confusion Matrix for ISIC 2019 using Fed-CNN

4.2.2 Classification results for ISIC 2019 using Fed-CNN

Next, we present the performance of CNN using ISIC 2019 dataset with FL in Table 6. Compared to the standalone CNN model trained only on ISIC 2018 data (Experiment 1), this approach demonstrated improved performance on the ISIC 2019 dataset. The iterative process of weight aggregation and redistribution enhanced the ability of the models to generalize to datasets from different distributions. This aggregation step allowed the global model to benefit from the knowledge acquired by all clients, effectively combining their individual learning outcomes. This is visually represented in Figure 7

Table 6: Classification report for ISIC 2019 using Fed-CNN

Class	Precision	Recall	F1-Score	Support
0	0.74	0.50	0.59	172
1	0.62	0.89	0.73	619
2	0.63	0.44	0.51	419
3	0.50	0.01	0.03	75
4	0.84	0.90	0.87	2798
5	0.73	0.58	0.65	869
6	0.30	0.23	0.26	122
Accuracy		**0.76**		**5074**
Macro Avg	0.60	0.52	0.52	5074
Weighted Avg	0.75	0.76	0.74	5074

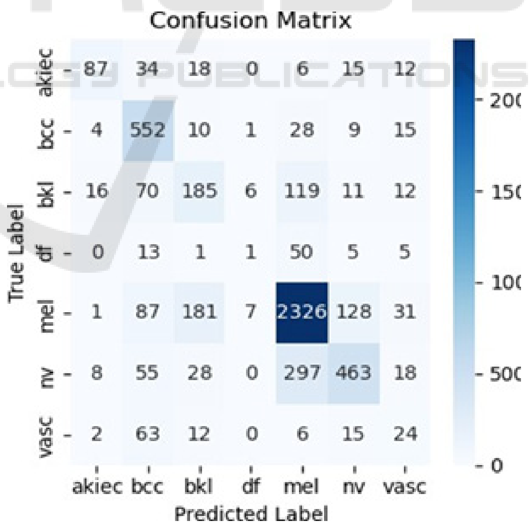

Figure 7: Confusion Matrix for ISIC 2019 using Fed-CNN.

4.2.3 Classification results for ISIC 2018 using Fed-MobileNetV2

Experiment 4 has shown that the Federated Averaging (FedAvg) method can be used with MobileNetV2 as a local model architecture. Each client was training its local MobileNetV2 model on its data and sending the updated weights to a central server.

The server, in turn, weighted these updated weights for aggregation before sending the distributed updated weights back to the clients. This collaborative approach can iterate, where the global model learns diverse data without privacy loss.

The MobileNetV2 Global model has been able to achieve an accuracy of 80% in ISIC 2018 and 87% in ISIC 2019. This can be referenced in table 7. During these tests, the study achieved significant improvements in generalization-performance. The results were particularly significant for ISIC 2019. The improvements show the power of combining the FedAvg algorithm and using MobileNetV2 architecture in distributed skin cancer classification tasks.

Table 7: Classification report for ISIC 2018 using Fed - MobileNetV2

Class	Precision	Recall	F1-Score	Support
0	0.14	0.02	0.04	21
1	0.04	0.04	0.04	52
2	0.26	0.41	0.32	49
3	1.00	0.39	0.56	8
4	0.82	0.85	0.84	534
5	0.56	0.51	0.53	259
6	0.51	0.48	0.49	15
Accuracy		**0.80**		**938**
Macro Avg	0.48	0.39	0.40	938
Weighted Avg	0.66	0.66	0.66	938

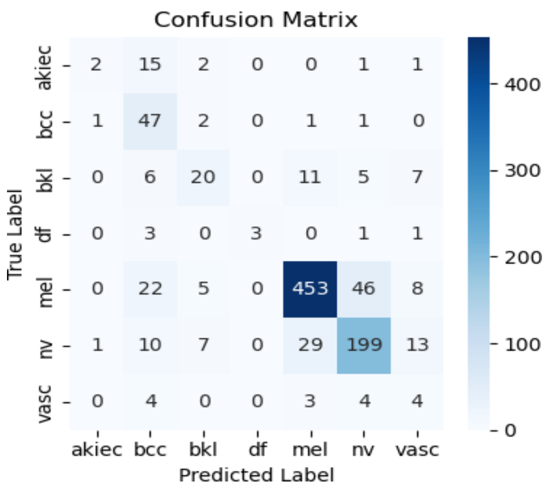

Figure 8: Confusion Matrix for ISIC 2018 using Fed-MobileNetV2

It is shown in Figure 8 that MobileNetV2 performed best for class 4 with 453 correct predictions, demonstrating that it has a very good identification ability for that particular class.

4.2.4 Classification results for ISIC 2019 using Fed-MobileNetV2

As shown in Table 8, Class 5 achieves an excellent performance with its F1-score of 0.97 and with good precision and recall, denoting that the class is clearly the most represented class by a strong classification of itself. Thus, the model has an overall accuracy of 87%, justifying its high competence in classifying most cases correctly.

Table 8: Classification report for ISIC 2019 using Fed - MobileNetV2

Class	Precision	Recall	F1-Score	Support
0	0.16	0.14	0.15	122
1	0.60	0.67	0.63	170
2	0.64	0.52	0.57	354
3	0.23	0.43	0.30	32
4	0.36	0.50	0.42	209
5	0.97	0.97	0.97	4043
6	0.59	0.30	0.40	144
Accuracy		**0.87**		**5074**
Macro Avg	0.51	0.50	0.49	5074
Weighted Avg	0.87	0.87	0.87	5074

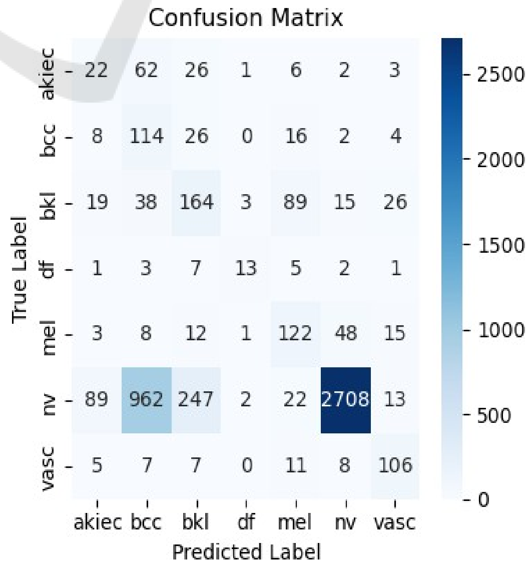

Figure 9: Confusion Matrix for ISIC 2019 using Fed-MobileNetV2

Figure 9 shows that class 5 has the highest correct predictions, with 2708 samples accurately classified. This shows that the model performs exceptionally well for this class. Class 2 also performs well, with 164 correct predictions, indicating good discrimination for this class.

4.3 Discussion

The CNN model built under Experiment 1 with the ISIC 2018 dataset achieved an accuracy of 83% when deployed as a test on the same dataset. The model's application on the ISIC 2019 dataset, recorded an accuracy of only 62%. It indicates the limited ability of the model to generalize the assigned task in data from different distributions such as ISIC 2019. Next, the MobileNetV2 model was trained on the ISIC 2018 dataset, and it performed better, achieving a high accuracy of 89% when tested on the test dataset. When tested using the ISIC 2019 database, this model showed a higher level of generalization than the CNN, at 72%. However, the performance gap shows that the model is not entirely prepared for classifying images from the 2019 database with training focusing only on the 2018 data. FL method aggregated model weights of different clients and redistributed the new weights to each client for refining the local models training. It proved to be much more effective in building the models that generalizes well to a wider variety of datasets other than the ISIC 2018 dataset.

By applying this methodology, we noticed the improved performance in both models. The local CNN model with global FedAVG'S performance for the classification of 2019 images increased to 76% from 72% whereas for 2018 images the performance slighted reduced to 82%. However, the model is well suited for the different datasets. To have an efficiency in classification, MobileNetV2 was used as a local client model under the FedAvg algorithm. This configuration achieved its highest accuracy, with an 80% for ISIC 2018 and an impressive score of 87% for the ISIC 2019 dataset. This model is well suited for both datasets since the model weights are aggregated globally and the updated weights are sent back to all the four clients.

5 CONCLUSION AND FUTURE WORK

In this work, we have designed a skin cancer classification system using the federated learning approach with the MobileNetV2 model. This method has the potential to perform efficient, privacy-preserving training on decentralized devices while maintaining high performance. The final accuracy of the model was 87% for ISIC 2019 dataset and 80% for ISIC 2018 dataset, making it a promising candidate for use in real-world applications such as skin cancer detection. MobileNetV2 is a lightweight architecture and, thus, more suitable for an edge device with a balance between performance and computational efficiency. We ensured that there was no sensitive medical information leaving the user's device by using federated learning to preserve privacy. Future work would involve improving the dataset by applying SMOTE , model optimization along with federated learning methods used, and would allow continuous learning, which makes the system faster on real-time skin cancer detection on mobile devices. Federated learning techniques could also be extended to make this process better in terms of efficiency as well as accuracy while training models. Such techniques as Federated Averaging could be combined with even more advanced techniques such as differential privacy or secure multi-party computation to further enhance the privacy and security of the model updates.

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