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RESEARCH ARTICLE

Federated Deep Learning for Monkeypox Disease Detection on GAN-Augmented Dataset

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ABSTRACT After the coronavirus disease 2019 (COVID-19) outbreak, the viral infection known as monkeypox gained significant attention, and the World Health Organization (WHO) classified it as a global public health emergency. Given the similarities between monkeypox and other pox viruses, conventional classification methods encounter difficulties in accurately identifying the disease. Furthermore, sharing sensitive medical data gives rise to concerns about security and privacy. Integrating deep neural networks with federated learning (FL) presents a promising avenue for addressing the challenges of medical data categorization. In light of this, we propose an FL-based framework using deep learning models to classify monkeypox and other pox viruses securely. The proposed framework has three major components: (a) a cycle-consistent generative adversarial network to augment data samples for training; (b) deep learning-based models such as MobileNetV2, Vision Transformer (ViT), and ResNet50 for the classification; and (c) a flower-federated learning environment for security. The experiments are performed using publicly available datasets. In the experiments, the ViT-B32 model yields an impressive accuracy rate of 97.90%, emphasizing the robustness of the proposed framework and its potential for secure and accurate categorization of monkeypox disease.

INDEX TERMS Cycle GAN, deep neural network, federated learning, WHO, convolution neural network, monkeypox detection, vision transformer, datasets, data analysis.

I. INTRODUCTION

Monkeypox is an infectious disease originating from wildlife and affecting humans. Its symptoms closely resemble those observed in smallpox patients. Since the eradication of smallpox in 1980 [1] and the cessation of smallpox immunizations, monkeypox has emerged as the primary orthopoxvirus of public health concern. Although its main impact is in Central and West Africa, the disease has extended to urban areas and is prevalent near tropical rainforests. This global public health significance is not limited to African regions but extends worldwide, as evidenced by instances of monkeypox appearing in non-endemic countries as recently as May 2022 [2]. The COVID-19 pandemic has underscored the critical need to swiftly isolate confirmed viruses to contain their spread [3], [4]. Delaying the identification process not

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only hampers treatment but also elevates transmission rates, potentially leading to pandemics. Thus, finding practical ways to enhance early identification is imperative for curbing the dissemination of this fatal ailment. Researchers have turned to various machine learning (ML) techniques, particularly deep learning methods, for medical image analysis to effectively differentiate the monkeypox virus from other pox diseases [5].

Given that monkeypox disease shares symptomatic similarities with other conditions like chickenpox and smallpox, the differentiation of pox viruses solely based on symptoms can be challenging. In this context, automated detection emerges as a pivotal factor. Implementing automated detection methods through image processing and leveraging ML or Deep Learning (DL) offers a viable solution [6], [7]. However, the training and testing of DL models necessitate a substantial volume of data. Hence, the early detection of monkeypox disease using neural networks faces some challenges. One of the biggest challenges, in this case, is the limitation of the dataset [8], [9]. As it is a very rare disease, a lack of data might cause the neural network training process to overfit. In such a circumstance, models trained with a small dataset fail to perform adequately.

Generative Adversarial Networks (GAN) can be used to add more data, which is a useful way to deal with the problems that come up when training deep neural network models with small or uneven datasets. This strategy aims to create a balanced dataset, thus enhancing the efficacy of model construction. The purpose of this study is to develop a unique framework for the classification of monkeypox virus lesions using medical image data that blends federated learning (FL) with CycleGAN [10]. CycleGAN serves as a proficient tool for generating synthetic image data, while federated learning is a decentralized machine learning strategy that facilitates collaborative work across various entities without exposing private data. Integrating deep neural networks that excel in image recognition and classification tasks with the federated learning environment enhances the classification approach's efficiency. This combination not only ensures robust classification capabilities but also enforces additional security measures [11], [12]. Based on the preceding context, the primary contributions of this study are as follows:

- We consider FL and the Vision Transformer to build a secure framework for the categorization of Pox virus skin lesions. In particular, we use the Flower FL and investigate several vision transformer models, such as ViT-B16 and ViT-B32.
- We augment the Pox virus image dataset by incorporating the Cycle GAN data augmentation method.
- The proposed framework achieves higher accuracy in the FL-DL environment with the vision transformer model, ViT-B32, and with augmented data.

The rest of the paper is organized systematically, with the following major sections: Table 1 represents the technical terminologies used in this work, with their descriptions in alphabetical order. Section II reviews related research work and identifies gaps in the current literature. Section III describes the research methodologies and procedures used for the study and explains the rationale behind their choice. After that, Section IV discusses experimental setup and data collection, and provides experimental results. Further, Section V interprets the results in the context of the research questions, and provides a discussion; and finally, in Section VI, the key findings are summarised, the research question's significance is reiterated, the contributions are highlighted, and a final assessment with a recommendation is made.

TABLE 1. Some terminologies with their description in alphabetically ordered.

Terms	Definition
AI	Artificial Intelligence
COVID-19	Coronavirus disease 2019
CNN	Convolutional Neural Network
DL	Deep Learning
FL	Federated Learning
GAN	Generative Adversarial Networks
GPU	Graphical Processing Unit
ML	Machine Learning
NN	Neural Network
TPU	Tensor Processing Unit
VIT	Vision Transformer
WHO	World Health Organization

II. LITERATURE REVIEW

Recently, medical professionals have been utilizing technological advancements to aid in disease identification. The healthcare sector is significantly advantaged by the integration of deep learning methodologies in computer vision for computer-aided diagnosis. Many researchers have suggested the integration of deep learning models with image analysis in the domain of skin diseases, particularly in the accurate detection of the pox virus within skin lesions.

Altun et al. [13] presented a Convolutional Neural Network (CNN) with transfer learning that achieved 96% efficiency. The models offered in this paper include MobileNetV3, ResNet50, VGG-19, DeneNet121, and Xception where MobileNetV3 outperformed the others. Pramanik et al. [14] suggested a collaborative approach for the detection of the monkeypox skin lesion with a five-fold evaluation procedure. Their approach received an accuracy score of 0.93. Sitaula and Shahi [15] performed a comparative analysis among thirteen different DL models for the classification of monkeypox skin images. The best accuracy achieved in this work is 87% with 85% precision and recall. To explain and ensure the transparency of the predicted model, Azar et al. [5] proposed several methods like LIME and Grad-CAM for model explainability with a DenseNet model for the classification task and achieved an accuracy of 97%. Again, Ahsan et al. [16] proposed six models with explainability for comparative analysis of the performance of different models for the classification of monkeypox.

As a related study shows, Jaradat et al. [17] used a comparative analysis of different models, such as VGG-16, EfficientNetB3, and others, to find the best and most efficient model for classifying monkeypox skin diseases. MobileNet got the best results, with an accuracy of almost 98%. However, the work discussed above used a dataset that is from an open-source repository [18] that includes 228 images of monkeypox skin lesions and other Pox virus skin sores. Because the images of the monkeypox skin lesions are limited, additional measures are necessary for the training of the models for disease classification. Ahsan et al. [19] implemented generalization and regularization-based transfer learning models for monkeypox detection and showed that their proposed optimized ResNet-101 can achieve the best performance for multiclass classification with an accuracy of 99%. Saleh and Rabie [20] proposed the Human Monkeypox Detection (HMD) system for monkeypox detection using a blood test dataset. They introduced an Improved Binary Chimp Optimization (IBCO) algorithm for feature selection in the ensemble model designed for monkeypox detection. Their proposed HMD strategy achieved an accuracy of 98.48% with 350 training data samples. Privacy is a major concern in medical diagnosis. Blockchain technology can ensure the privacy and integrity of user's data. In [21], Gupta et al. proposed a blockchain-embedded monkeypox detection and classification framework using transfer learning. Their proposed RssNet50 model achieves an accuracy of 98.80%.

Researchers proposed several ways for synthetic image generation, like applying GAN for data augmentation or transforming the existing images. Among them, GAN is an efficient process that has been widely used in synthetic image data generation that uses ML and DL models. Rashid et al. [22] analyzed several works and pointed out the challenges of the application of deep Neural Networks (NN) in the medical domain as the number of available datasets is limited. The authors investigated the GAN technique for synthetic image generation to create a robust model for the skin lesion classification task. Qin et al. [23] augmented skin images using style-based GAN and then trained and tested the images using deep neural networks with transfer learning, and this process improved the accuracy of the system by 1.6%. To overcome the shortcomings and imbalances of melanoma skin cancer images, Zhao et al. [24] implemented Style GAN for the generation of a balanced and vast amount of data. Sedigh et al. [25] presented a CNN-based skin cancer detection framework that integrated GAN for the processing of synthetic images from the available image dataset. However, in [26], the author augmented data using GAN and showed that the augmented data can be the same as the real image data, but on the other hand, the hardware and software specification required by the GAN-based model can sometimes be challenging to implement in the medical sector as this can impose an extra cost to the user. Although these methods are chosen for producing synthetic images, the collection of medical images across several medical centers or hospitals is still challenging as these images contain sensitive information about a patient. Due to security concerns, patients sometimes show less interest in sharing data with third parties.

In the literature, the majority of research on detecting monkeypox is confined to the utilization of traditional deep-learning techniques. Some authors have advocated for ensemble learning [14], [15] to maximize the accuracy of their developed models, and certain methods have been carefully adapted for specific tasks [5], [16]. Most papers have employed standard data augmentation techniques due to the scarcity of training data [13], [27]. However, standard image augmentation techniques have limitations, as they may not cover all possible variations that a model might encounter in real-world scenarios. Moreover, advanced augmentation techniques, such as GANs have been explored to generate more realistic and diverse augmented data. However, the existing literature only involves a few applications of GAN [23], [26]. Only a few papers have addressed privacy concerns related to data [28]. To our knowledge, there is no existing research that has introduced methodologies for detecting monkeypox using federated learning.

In summary, this article has proposed a secure framework in response to the challenges mentioned earlier. This framework eliminates the necessity for data sharing among parties by fusing FL with DL techniques. Given the limited dataset on monkeypox skin lesions, we generated synthetic images using CycleGAN.

III. PROPOSED METHODOLOGY

The proposed approach is divided into two parts. First, we assessed our deep learning models independently, and then we incorporated our deep learning models in a federated learning environment to gauge their efficiency in both cases. Due to the limited dataset, our primary step involved generating enhanced images using GAN. Following that, we employed a deep NN model for image classification. We then split the images into two batches for training. One batch received datasets for monkeypox and normal skin images, while the other was provided with datasets for other diseases like measles and chickenpox. A detailed explanation of our approach is presented in this section. In Fig. 1, the proposed system architecture is depicted.

A. DATA AUGMENTATION WITH CYCLEGAN

Without the need for paired training data, the Cycle Consistent Generative Adversarial Network, or CycleGAN, is a model developed using machine learning that creates synthetic images from sample data. Two NNs, a generator and a discriminator, are used in this system to output images concurrently. The translation is performed bidirectionally, as suggested by the name of the architecture. Furthermore, the discriminator's role is to assess the excellence of the image generated by the translation process between the domain of healthy skin images and the domain of monkeypox skin images, and vice versa. This approach is suggested to be

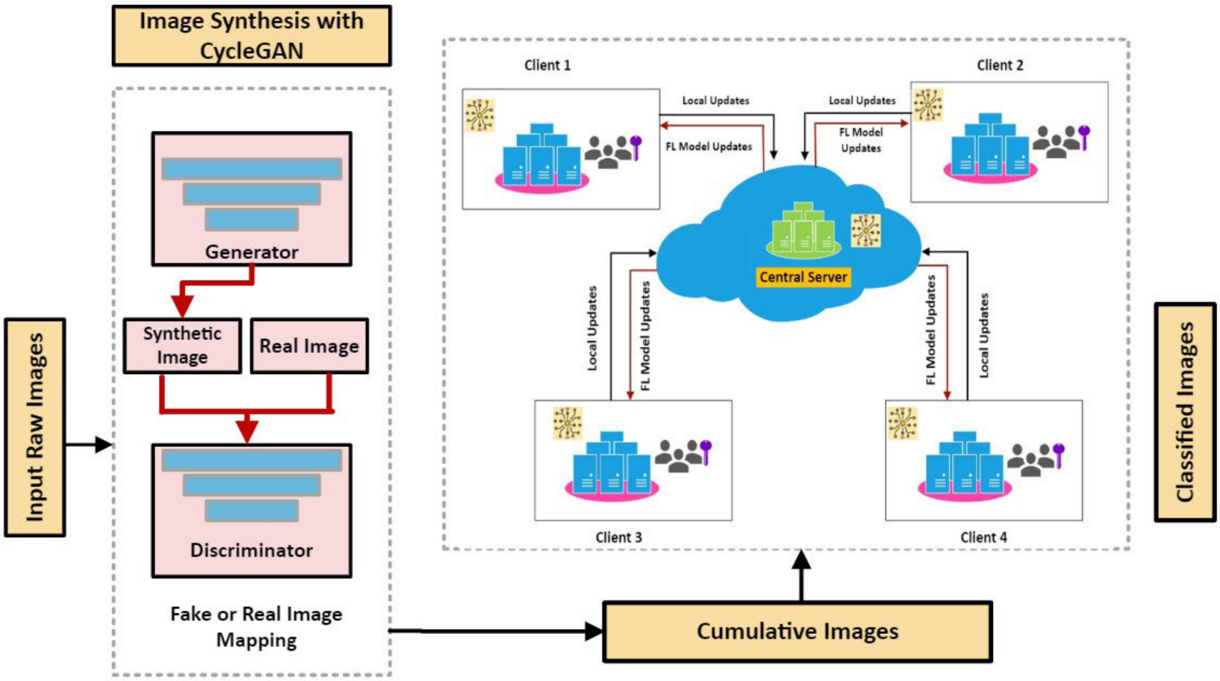


FIGURE 1. Proposed architecture with GAN and federated learning model.

TABLE 2. The hyperparameter settings of the proposed model.

Hyperparameters	*Values*
Optimizer	SGD
Learning Rate	0.0009
Loss	sparse_categorical_crossentropy

utilized in this study to generate synthetic images so that the framework can function with unpaired data. CycleGAN is appropriate since the dataset for this field of monkeypox detection or Pox virus classification is small and obtaining the necessary images is challenging. Fig. 2 presents the architecture of CycleGAN [29].

B. DEEP LEARNING MODEL FOR IMAGE CLASSIFICATION

In this study, to address the challenge of training with the limited dataset, we leverage a pre-trained deep neural network model combined with transfer learning, enhancing the system's performance. Through transfer learning, knowledge from the extensive ImageNet dataset can be applied to our smaller, domain-specific dataset [30]. We have assessed both heavyweight and lightweight DL models to measure the models' effectiveness. The pre-trained models we utilized include MobileNet, the vision transformers (ViT-B16, and ViT-B32), and ResNet50 [31]. The description of the model's hyperparameters is given in Table 2.

C. FEDERATED LEARNING WITH DEEP LEARNING MODEL FOR IMAGE CLASSIFICATION

The federated learning environment used in this study is implemented using the Flower federated learning framework. Four deep learning models: MobileNet, ResNet50, ViT-B32, and ViT-B16, have been chosen for the federated learning image categorization task. The classification task's core is based on these deep neural models. The server, or central server, then initialized the global model. This global model awaits client information. The clients connect to the global server, then download the global model, and the local training process using local datasets begins. The clients send their changes to the global model without their datasets. Once the central server has received all of the updates, it uses the FedAvg method, which is shown in Equation 1 [32], to combine them.

$$p_{t+1}^{g} = \frac{1}{c_i} \sum_{i=1}^{c_i} \delta_i * p_t^i \tag{1}$$

Here p_{t+1}^{g} is the global model update at the time (t+1), c_i is the number of clients that take part in the averaging, δ_i is the weights added to each client during the averaging process and p_t^i is the local model parameter on device i at time t.

1) MOBILENET

MobileNet is a compact, deep artificial neural network variation that is mostly utilized in embedded computers for image-related procedures. The depthwise convolutions enable this neural model's neural network to have fewer parameters, which lowers the cost of computation. The process of Mobilenet is first the depthwise convolution

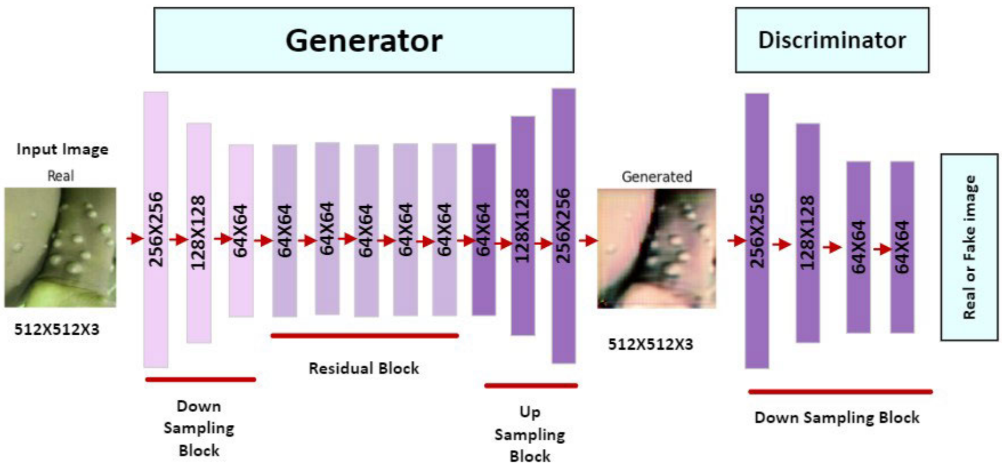


FIGURE 2. **CycleGAN architecture with generator and discriminator.**

followed by the point-wise convolution [33].

$$T * K = \sum_{i}^{Ci} T_i * K \tag{2}$$

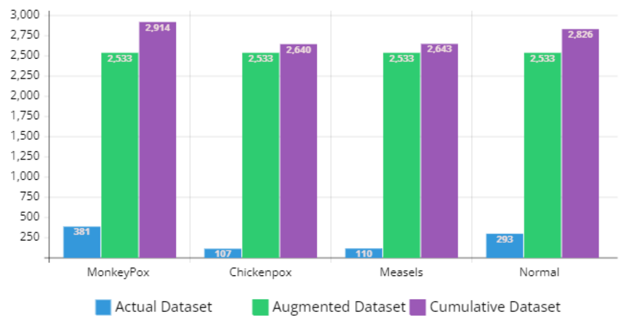
In Equation 2, the convolution process is shown where T is the tensor as input, and T_i and K) which is the Kernal represent the i-th element of the tensor T, the kernel or the filter, respectively, and * represents the convolution operation. After doing the element-wise product and sliding the kernel over the input tensor in the convolutional layer, the output of the convolution operation is found by adding the two.

2) VISION TRANSFORMER MODEL (VIT-B16 AND VIT-B32)

The Transformer, which is the basis of ViT models, excels in visual classification tasks that leverage self-attention. This method allows the model to consistently focus on diverse sections of image data. To capture the attributes of the entire image, it is segmented into patches, which are then fed to the encoder. For the transformer model known as ViT-B32, an image patch size of 32 is utilized. Conversely, the B-16 model comprises 16 layers and uses a patch size of 16. Both the ViT-B32 and ViT-B16 transformer versions are designed for image processing. ViT-B32 uses larger patches (size 32), while ViT-B16 uses smaller patches (size 16). Additionally, ViT-B16's ability to capture local and global properties may suffer from having 16 fewer layers than ViT-B32. Both of these models represent basic designs [34].

3) RESNET50

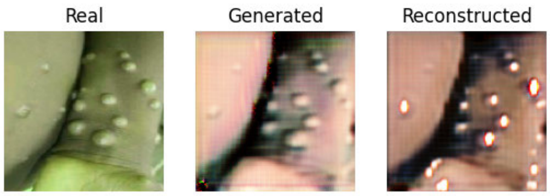
ResNet50 belongs to the residual network family and is a deep convolutional neural network. Because of its deep architecture, which consists of 50 layers, it can capture complex patterns and characteristics in images. The word "residual" refers to the utilization of residual blocks, a crucial component of design that aids in resolving issues with training extremely deep networks, including the vanishing gradient issue. The model performs well in situations where comprehending complicated feature hierarchies is essential, such as object identification and image classification, because of the depth of its design [35].



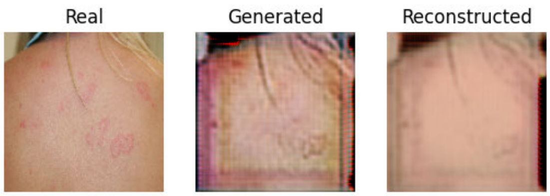
(a) Data Distribution (Original, Augmented and Cumulative)

(b) Sample images from Dataset

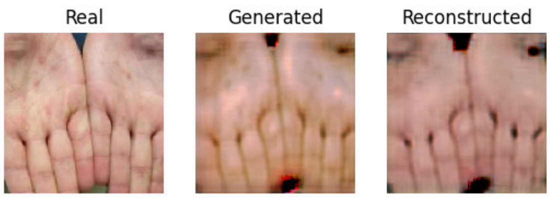
FIGURE 3. **Data distribution and sample images.**



(a) Augmented Monkeypox Data



(b) Augmented Normal Skin Images



(c) Augmented Measles Images

FIGURE 4. Three sample of data augmentation through cycle GAN.

IV. EXPERIMENTAL DESIGN AND ANALYSIS OF THE RESULTS

A. DATASET DESCRIPTION

A dataset of skin lesions [36] is used in the experiments. We combine this dataset with a dataset from [37] to make the classification of Pox viruses into four classes. Digital color photographs of skins are the main images that were used in this research. Monkeypox, chickenpox, measles, and normal skin images are four types of skin lesions available in the collected data. The combined dataset consists of a total of 381 images of monkeypox, 102 images of chickenpox, 110 images of measles, and 293 images of normal skin. All the color images in the open-source collection were specifically focused on capturing the afflicted portions of the patient's skin. Since the digital input consists of RGB-colored images, each image contains three channels. The images exhibit diverse formats and sizes due to their collection from many sources, hence making them inappropriate for use in predictive analytics. To address this problem, all of the images have been resized to meet the exact requirements set by the models. We have included images of normal skin as well as images obtained from other data sources to create disease images. The CycleGAN is used to generate augmented images. After applying CycleGAN to our dataset, the dataset size increased significantly. In Fig. 3a, the image dataset distribution of each class for Original, Augmented, and Cumulative is shown. Fig. 3b shows some samples of image data. Fig. 4a, 4b, 4c represent the sample of augmented data images of monkeypox, normal, and measles, respectively. For experiments, we split the dataset into 80 percent and 20 percent of the train and test datasets for both cases (augmented and without augmentation). Further, for validation purposes, we kept from the original dataset (without augmentation) only 38 images of monkeypox, 10 images of chickenpox, 10 images of measles, and 29 normal skin images; these images were not used in training or testing. In the case of augmentation, 110 samples from 2914 images of monkeypox, 79 from 2640 images of chickenpox, 65 from 2643 of measles, and 127 from 2826 of normal were used for validation, and these images were not used for training or testing.

B. PERFORMANCE INDICATORS

The accuracy score, recall, specificity, then F1-score, and curve of ROC are the performance metrics for the assessment of monkeypox identification using image categorization. The values of true positive (TruePos), true negative (TrueNeg), rate of false positive, and rate of false negative are used to compute each of these metrics using the following equations.

$$\text{Precision(P)} = \frac{\text{True Pos}}{\text{True Pos + False Pos}} \tag{3}$$

$$\text{Recall(R)} = \frac{\text{True Pos}}{\text{True Pos+ False Neg}} \tag{4}$$

$$F1_S = \frac{2 * P * R}{P + R} \tag{5}$$

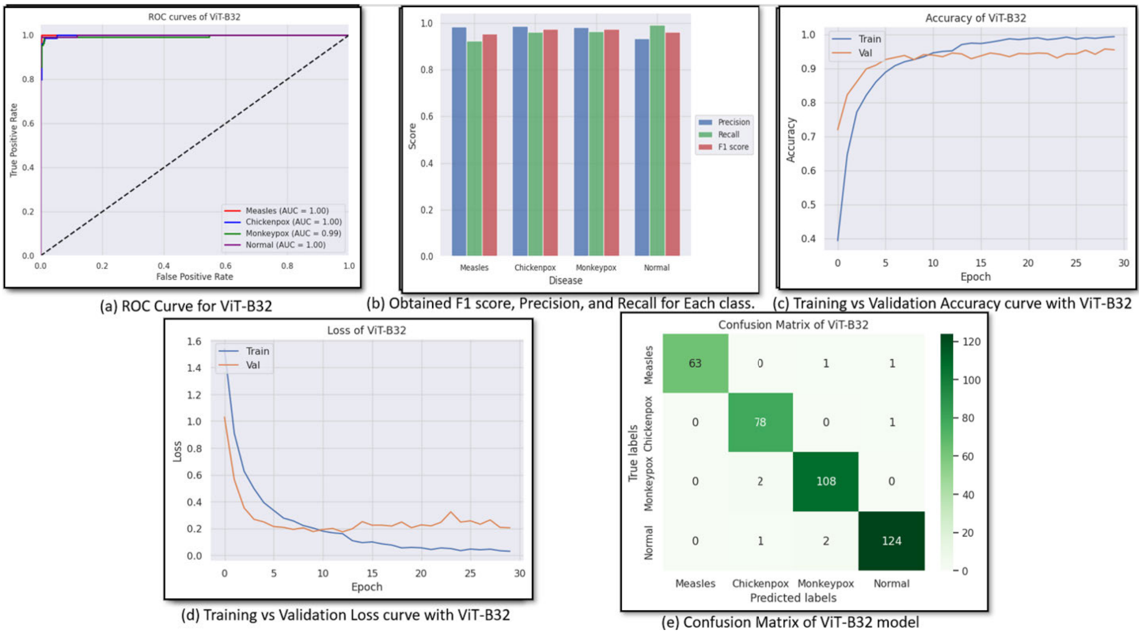
In 3 here P is referred to as Precision, in 4 R is referred to as Recall, and in 5 the $F1_S$ is refereed as F1 score.

C. EXPERIMENTAL ENVIRONMENT

In this section, we describe the environment where the classification task was experimented. In this study, we used TPU over GPU among the several hardware accelerators accessible in Colab since TPU is thought to be more energy-efficient and also specifically made for tensors. To make use of TPU, we use the Colab Pro version. Due to the use of both heavy and light models in this work as well as the need for energy economy, we used TPU as the hardware accelerator with High RAM in the Python 3 environment. The proposed federated learning framework was implemented using the Flower framework, proposed in [43].

D. ANALYSIS OF THE RESULT

In this proposed method, four DL models MobileNetv2, ViT-B16, ViT-B32, and ResNet50 have been utilized for the classification task. Table 3 shows the accuracies under the FL environment, and for comparison purposes, it also shows the accuracies without the FL environment. In both cases, model accuracies when trained with and without augmented datasets are also shown. We used four clients, each having different datasets. The best accuracy obtained by the global model is 97.90% by leveraging ViT-B32 under the secured FL framework. Fig. 5 shows the performance matrix graphs of the ViT-B32 model. Fig. 5 (a) shows the ROC curve for four classes, obtained F1-Score, recall, and precision



(a) ROC Curve for ViT-B32

(b) Obtained F1 score, Precision, and Recall for Each class.

(c) Training vs Validation Accuracy curve with ViT-B32

(d) Training vs Validation Loss curve with ViT-B32

(e) Confusion Matrix of ViT-B32 model

FIGURE 5. **Performance indicators of ViT-B32.**

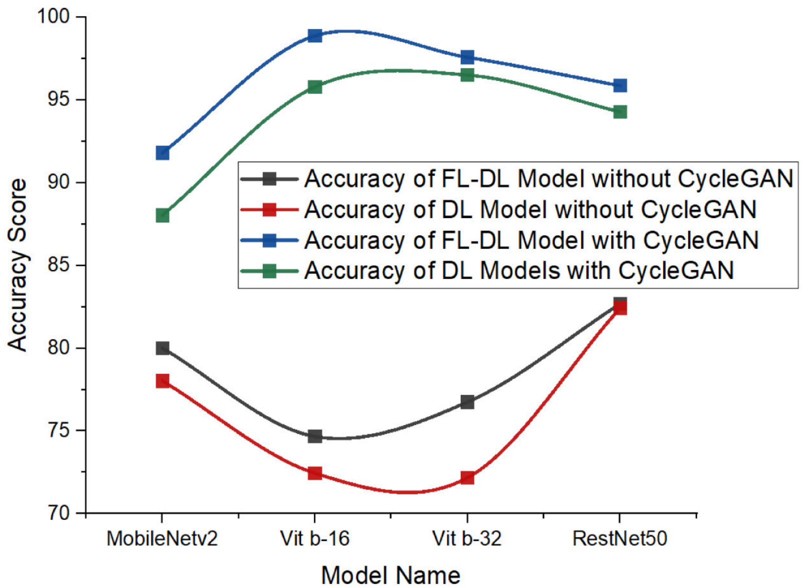


FIGURE 6. **Comparative result analysis.**

values are also depicted in Fig. 5 (b) and the corresponding values are presented in Table 5, and the training vs validation accuracy, loss curve against epochs and confusion matrix are shown in Fig. 5(c), 5 (d), and 5 (e), respectively. Again, we have added a dropout layer and considered running the model up to 30 epochs with early stopping to the Vit-B32 model that reserved the validation loss, and this model stopped after 30 epochs to ensure the model does not overfit.

As indicated in Fig. 6, the performance of the ViT model is notably poorer without data augmentation when compared to the other deep learning models. Yet, with an increased number of datasets, the ViT model showcases remarkable accuracy improvements beyond the other models. Conversely, the RestNet 50 performs well in scenarios involving both augmented and unaugmented datasets. Nevertheless, due to its computational complexity, the model might not always be suitable, especially within interconnected systems featuring

TABLE 3. Calculated system accuracy with and without FL environment.

Model	Without CycleGAN Augmentation		With CycleGAN Augmented Dataset	
	Clients=4, Accuracy (FL-DL)	Accuracy (DL)	Clients=4, Accuracy (FL-DL)	Accuracy (DL)
MobileNetV2	80	78.02	91.80	88.02
Vit-B16	74.66	72.45	96.86	95.77
Vit-B32	76.74	72.17	97.90	96.75
ResNet50	82.68	82.42	95.85	94.27

TABLE 4. A comparative assessment of the proposed framework to various cutting-edge models.

Works	Dataset Size	Method	Class Type	Hyperparameter	Accuracy
Pramanik et al. [14]	228	Ensemble learning (Inception V3, Xception and DenseNet169)	Binary	Batch Size:16 LR:1e-4	93.39
Lakshmi et al. [38]	835	VGG16, VGG19, ResNet50, ResNet101, DenseNet201, and AlexNet + LIME for explainability	Binary	Classifier: Softmax	94.25 (ResNet50)
Gupta et al. [21]	1905	Modified RestNet + Blockchain (BC)	Binary	Classifier: Softmax Loss Function: Categorical cross-entropy Optimizer: Adam LR: 0.001	98.80
Nayak et al. [39]	2283	GoogLeNet,SqueezeNet,ResNet18	Binary	Mini Batch Size: [16,32,64] , LR: [0.01 0.001]	97.87 (Best)
Gairola et al. [40]	2187	VGG+ AlexNet	Binary	Batch Size:16 LR: 0.001	95.55
ÖRENÇ et al. [41]	2548	EfficientNetB3, ResNet50and InceptionV3.	Binary Class	Batch size: 32 Optimizer: Adam LR: 0.001	94 (ResNet50)
Bala et al. [27]	6800	modified DenseNet-201	MultiClass	Batch size: 32 LR: 0.003	98.91
Alharbi et al. [42]	770	GoogleNet+ Dipper throated optimization algo	Binary	Classifier: Softmax	94.35
Yasmin et al. [7]	3192	PoxNet22	Multi Class	Batch size: 8 Optimizer: Adam LR: 0.001	87
Jaradat et al. [17]	1328	MobileNetV2	Binary	LR: 0.001 Loss Function: binary crossentropy	98.0
Proposed Method	11023	FL+ DL +CycleGAN	Multi-Class	Optimizer: SGD LR: 0.0009 Loss Function: Sparse categorical Crossentropy	97.90

TABLE 5. Obtained score of the three metrics.

Metric	Measels	Chickenpox	Monkeypox	Normal
Precision	0.98	0.98	0.98	0.93
Recall	0.92	0.96	0.96	0.99
F1 Score	0.95	0.97	0.97	0.96

sensor devices [39]. Based on the results, it becomes evident that the models specified exhibit superior performance when augmented with CycleGAN-generated data, as opposed to utilizing an unaugmented dataset. However, it's worth noting that the ResNet50 model requires more time compared to the others, necessitating higher configuration memory for computation.

V. DISCUSSION

This study proposes a monkeypox detection approach based on federated learning coupled with CycleGAN data augmentation. This approach allows the classification of skin images into either monkeypox or other conditions across various clients, all the while maintaining the confidentiality of image data. By adopting this method, the necessity for data sharing is reduced, thereby addressing concerns related to data breaches. Particularly within the medical industry, our suggested approach holds the potential to enhance imaging-related tasks with greater precision. By confining user data to the local network, we ensure data security [44]. Throughout this study, deep learning models [45], including MobileNetV2, Vision Transformers (ViT-B16 and B32), and ResNet50, were employed for training and calculating the global model's parameters. Furthermore, a comparison was drawn between the federated learning environment and the deep learning network model without security measures. The comparative outcomes reveal that the model's accuracy remains consistent while user data confidentiality is safeguarded within the federated learning environment. Again, a comparative analysis of existing work with the model used and the accuracy achieved has been presented in Table 4. From the table, it is visible that our proposed model can achieve higher accuracy while ensuring security. In extending the application to other predictive tasks in healthcare, this proposed framework can be utilized to safeguard patient data privacy and construct robust models for critical illness prediction tasks.

To the best of our knowledge, the FL+DL and FL+DL+CycleGAN approaches that have been suggested are the first to be used in recent years to identify monkeypox. Furthermore, no study that we compared in this research addressed the application of a federated learning strategy. Only the deep technique was compared in Table 4 to draw comparisons between approaches that are comparable or nearly equivalent and have previously been employed for the diagnosis of monkeypox. Furthermore, when this comparison assessment was designed, the same number and model were not taken into account.

VI. CONCLUSION

This paper introduces a secure Federated Learning and deep learning-based framework for monkeypox virus detection using skin lesion images. The primary objective is to enhance classification performance while maintaining the confidentiality of medical images. By aggregating model parameters during training, data privacy is ensured, as sensitive information remains undisclosed. Given the limited data availability, the CycleGAN generator plays a crucial role in augmenting training and test data. The resulting synthetic images are partitioned into four groups, each corresponding to a client, and utilized to train local models using classifiers such as MobileNet, ViT-B16, ViT-B32, and ResNet50. Among these, ViT-B32 excels with an impressive accuracy of 97.90. To validate the effectiveness of the proposed deep learning-based Federated Learning approach, the DL models are also assessed individually outside the FL environment, and they perform nearly as well. The adoption of Federated Learning not only ensures user data privacy within the local network but also accomplishes the categorization task effectively. This approach is especially relevant in medical contexts where limited datasets and data privacy concerns are prevalent. In the future, further security measures, such as Blockchain, could be incorporated to enhance the security of the skin lesion images.

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Conflict of Interest The authors declare no competing financial and non-financial interests.

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