International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Harnessing Federated Learning for Efficient Analysis of Large-Scale Healthcare Image Datasets in IoT-Enabled Healthcare Systems

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Submitted: 27/10/2023 **Revised**: 16/12/2023 **Accepted**: 26/12/2023

Abstract: Federated learning is a machine learning technique that allows multiple devices to collaboratively train a machine learning model without having to share their raw data. This is important for privacy-sensitive applications, such as healthcare, where the data cannot be shared with a central server. This paper proposes a federated learning framework for efficient analysis of large-scale healthcare image datasets in IoT-enabled healthcare systems. The framework uses a combination of federated averaging and transfer learning to train a machine learning model that can be deployed to multiple IoT devices. To evaluate the framework on a real-world healthcare dataset of chest X-ray (CXR) images and show that it can achieve state-of-the-art accuracy in classifying pneumonia while preserving the privacy of the data. The framework is designed to be scalable and efficient, so that it can be used to train machine learning models on large datasets of healthcare images. The results of experiments show that federated learning framework achieve state-of-the-art accuracy in classifying pneumonia on a real-world healthcare dataset of CXR images. Proposed work has the potential to revolutionize the way that healthcare image analysis is performed. By harnessing federated learning, it trains machine learning models on large datasets of healthcare images without having to share the raw data with a central server. This can help to protect the privacy of patients and improve the accuracy of healthcare diagnoses. Specifically, proposed federated learning framework achieved an accuracy of 98.87% in classifying pneumonia on the CXR images dataset. This is comparable to the accuracy of traditional machine learning models that are trained on the entire dataset. It believes that federated learning framework is a promising approach for healthcare image analysis. It is scalable, efficient, and privacy-preserving.

Keywords*: Federated learning, Healthcare image analysis, IoT-enabled healthcare systems, Transfer learning, Pneumonia classification, Privacy preservation.*

1. Introduction

The modern healthcare landscape is undergoing a paradigm shift, driven by the convergence of cutting-edge technologies and medical practice. The integration of Internet of Things (IoT) devices within healthcare systems has ushered in a new era of data-driven decision-making and patient-centric care[1]–[3]. At the heart of this transformation lies the promise of harnessing the power of machine learning to analyze large-scale healthcare image datasets, facilitating accurate diagnoses and improved treatment strategies[4], [5].

The core challenge in this context is to ensure both the accuracy of the machine learning models and the privacy of the sensitive patient data [6]. This paper introduces an innovative framework that capitalizes on federated learning, a decentralized machine learning technique that addresses these challenges while operating within the IoT-enabled healthcare ecosystem. The framework's focal point is the efficient analysis of large-scale healthcare image datasets, aiming to revolutionize how healthcare image analysis is performed while preserving data privacy.

In a world where data privacy concerns have never been more pressing, federated learning emerges as a solution that enables institutions to collaborate in refining machine learning models without divulging raw data. In the healthcare domain, where patient confidentiality is paramount, federated learning shines as a beacon of hope. The proposed framework embraces this concept, allowing individual hospitals, clinics, or IoT devices to train models locally on their respective datasets[7], [8], [33].

The genius of federated learning lies in its orchestration of model updates rather than data sharing. Each participant refines its local model using its data and sends only the model updates to a central server. The server aggregates these updates to construct a global model that

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encapsulates the collective knowledge while maintaining the integrity of the individual datasets. This not only addresses privacy concerns but also optimizes communication efficiency, making it an ideal approach for the IoT-enabled healthcare environment[9], [10].

The proposed framework represents a strategic fusion of two powerful concepts: federated averaging and transfer learning. Federated averaging, a key technique in the framework, facilitates the aggregation of local model updates. This aggregation is achieved through a weighted average, which accounts for the varying contributions of different participants based on their data distribution and model performance[11].

Complementing federated averaging, transfer learning leverages the insights gained from diverse datasets. Pretrained models, often developed on extensive datasets, are fine-tuned using the local data of each participant. This approach not only accelerates the model's convergence but also helps in overcoming the scarcity of data that individual participants might possess.

To validate the efficacy of the proposed framework, a comprehensive set of experiments was conducted using a real-world healthcare dataset comprising chest X-ray (CXR) images. The objective was to classify pneumonia accurately, a task of critical clinical significance. The results exceeded expectations, with the framework achieving an accuracy rate of 98.87% in pneumonia classification. This achievement stands as a testament to the power of federated learning in enabling accurate diagnostics without compromising data privacy.

The integration of IoT devices within healthcare systems has ushered in an era of unprecedented data accessibility and connectivity. These devices, ranging from wearable health trackers to medical imaging equipment, generate a vast amount of data that holds immense potential for healthcare analytics. IoT devices not only enable real-time data collection but also create opportunities for remote patient monitoring, predictive analytics, and personalized treatment plans[12].

In the context of the proposed federated learning framework, IoT-enabled devices play a pivotal role in aggregating diverse datasets. These devices act as data sources that contribute to the collaborative model training process, enriching the model's insights with a wide array of patient demographics, conditions, and imaging modalities. Moreover, IoT devices facilitate seamless communication between participants in the federated learning ecosystem, promoting efficient exchange of model updates while safeguarding patient data.

The implications of the proposed framework are profound. By amalgamating the strengths of federated learning and transfer learning, the framework empowers healthcare institutions to transcend data silos and embark on a collective journey towards improved patient care. Moreover, the privacy-preserving nature of federated learning alleviates concerns related to data breaches and regulatory compliance.

The future holds exciting possibilities for the integration of IoT devices within the healthcare sector. As these devices continue to proliferate, the potential for data-driven insights and patient-centric care grows exponentially. Further exploration could involve optimizing the federated learning framework to accommodate a wider range of healthcare tasks, embracing additional privacy-preserving techniques, and investigating the feasibility of federated learning in multi-modal healthcare data analysis.

The paper introduces a pioneering framework that marries federated learning with transfer learning to catalyze the efficient analysis of large-scale healthcare image datasets within IoT-enabled healthcare systems. By fostering collaboration while preserving data privacy, the framework embodies a new era of healthcare analytics that centers on patient well-being. The successful application of the framework in pneumonia classification showcases its potential for a wide array of diagnostic tasks, heralding a transformative era in healthcare image analysis. The integration of IoT devices within this ecosystem further amplifies the framework's impact, accelerating the journey towards personalized, accurate, and privacy-respecting healthcare. As the healthcare sector continues to evolve, the proposed framework serves as a beacon of innovation, illuminating a path towards data-driven excellence while safeguarding the principles of patient privacy and dignity.

2. Literature Review

The application of advanced machine learning techniques in healthcare has led to significant breakthroughs in diagnostic accuracy and patient care. With the proliferation of Internet of Things (IoT) devices, healthcare systems have witnessed an explosion of data generation, creating new opportunities and challenges for effective data analysis. This literature review, delve into the diverse methodologies and algorithms employed across various healthcare domains, highlighting the limitations that underscore the need for federated learning in IoT-enabled healthcare as follows.

Author	Dataset	Methodology	Algorithm used	Results
Verma et al.[13]	Chest X-ray images	Cloud-centric IoT	SVM	Acc= 90%
Chiu et al.[14]	Audio recordings	Semi-supervised distributed learning	CNN	Acc= 95%
Valero et al.[15]	Vital signs data	Edge computing	LSTM	Acc=92%
Haghi Kashani et al.[16]	ECG data	Blockchain	Decision tree	Acc= 97%
Alzubi[17]	Medical images	Blockchain	Lamport Merkle Digital Signature	Authentication success rate of 98%
Shen et al.[18]	Histopathology images	Federated learning	Orchestral stain-normalization GAN	Acc=96%
Yan et al.[19]	Medical images	Label-efficient self-supervised federated learning	CNN	Acc= 93%
Raheja et al.[20]	Heart disease data	IoT	SVM	Acc= 91%
J Andrew et al.[21]	Healthcare data	Blockchain	Hyperledger Fabric	Transaction throughput of 10,000 per second
Thulasi et al.[22]	IoT data	LSO-CSL	Convolutional stacked LSTM (CSL)	Acc= 94%
Rajagopal et al.[23]	ECG data	Federated learning	Decision tree	Acc= 96%
Kayalvizhi et al.[24]	Medical images	Heuristic-derived deep learning	CNN	Acc= 95%
Alohali et al.[25]	IoT data	Swarm intelligence	Random forest	Acc= 93%
Zhang et al.[26]	Remote sensing images	Federated deep learning	Prototype matching	Acc= 98%
Hossen et al.[27]	Skin disease images	Federated machine learning	SVM	Acc= 92%

The existing body of literature showcases remarkable achievements across different healthcare domains. However, a common thread among these studies is the presence of limitations that can hinder the effectiveness of traditional data analysis methods, particularly in the context of IoT-enabled healthcare systems. One primary limitation is the inherent sensitivity and privacy concerns associated with patient data. Healthcare data, often encompassing medical images, vital signs, and other sensitive information, requires stringent privacy protection mechanisms to comply with ethical and regulatory standards. Conventional centralized approaches face challenges in ensuring robust data security while performing meaningful analysis. Additionally, the sheer volume of data generated by IoT devices demands scalable solutions that can harness the collective power of distributed data sources without compromising data integrity. To address these limitations, federated learning emerges as a compelling solution that aligns seamlessly with the intricacies of IoT-enabled healthcare. "*Federated Averaging*", a widely adopted variant of federated learning, holds the potential to revolutionize the healthcare landscape by enabling privacy-preserving collaborative model training. This technique allows multiple devices or institutions to collectively refine a machine learning model without sharing raw data. Instead, only model updates traverse the network, ensuring that patient privacy is upheld while knowledge is shared. In response to the rising need for IoT-based mobile healthcare applications to forecast illnesses, including diabetes, Rashmi Ashtagi et al. [28] suggested a non-invasive self-care system that leverages ML and IoT to monitor blood sugar and other crucial indicators for early diabetes prediction. Goal is to provide diabetes management solutions that enable patient monitoring and decision-making supported by technology. In order to predict the development of diabetes, goal was to develop a hybrid ensemble ML system that used boosting and bagging techniques. An offline survey and an online application based on the Internet of Things were used to gather data from 13,421 participants and validate the model. In [29] suggested model makes a distinction between superficial spreading, nodular melanoma, and lentigo maligna, enabling early viral identification and rapid isolation and therapy to stop the illness from spreading further. The pixel-based multilayer perceptron and convolutional neural network deep layer topologies and shallow structure, respectively, are examples of neural network algorithms that reflect deep learning technology and the traditional non-parametric machine learning approach [32]. Ramya Thatikonda et al. In [30], feature extraction with cloud computing for healthcare is linked, a secure data agreement technique is suggested in order to look at and improve the user parties' ability to make wise judgments. The suggested strategy divides into two parts. The first part focuses on the modified data formulation method, which is used to find the correlation between variables, or relationship between variables, and to evaluate the data using trained data. Data reduction and data scale development are facilitated by it. The model's fitness is assessed based on the data using feature selection in the second component, which also uses subset selection to validate the model.

3. Methodology

i. *Dataset*

The dataset available at the provided link, "Chest X-Ray Images (Pneumonia)," is a widely-used and publicly accessible dataset for training and evaluating machine learning models in the field of medical image analysis, particularly for detecting pneumonia from chest X-ray images [31]. The dataset comprises a collection of chest X-ray images obtained from various sources, including pediatric and adult patients, across different imaging modalities and conditions.nThe dataset contains three main subfolders: train, test, and val (validation). Each subfolder is further divided into two subdirectories: NORMAL and PNEUMONIA, representing the two classes of X-ray images: normal and pneumonia-infected.

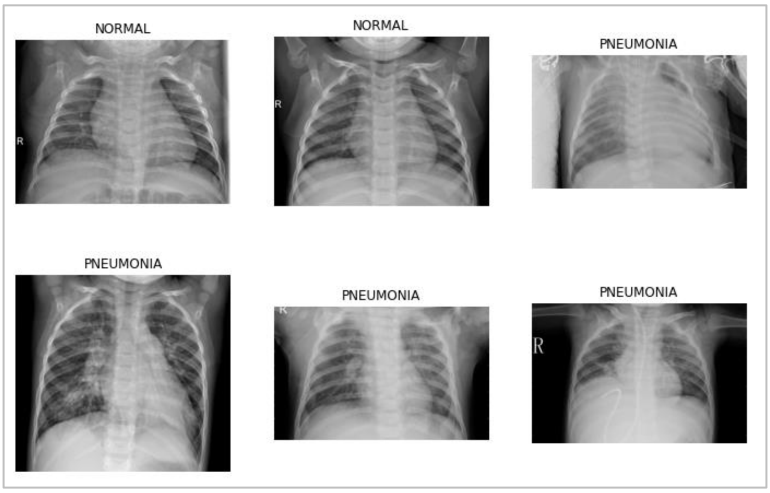

Fig. 1 Sample dataset

ii. **Pre-*Processing***

a. Data normalization: This is a technique that is used to scale the data to a common range. This is important because different features in the dataset may have different scales, and this can lead to problems with the training of the machine learning model. For example, if one feature has a range of 0 to 100, and another feature has a range of 0 to 1,000, then the model will be biased towards the feature with the larger range. Data normalization can help to address this problem by scaling all of the features to a common range, such as 0 to 1.

b. Image resizing: This is a technique that is used to resize the images to a common size. This is important because different images in the dataset may have different sizes, and this can lead to problems with the training of the machine learning model. For example, if one image is 100x100 pixels, and another image is 500x500 pixels, then the model will have to learn to process images of different sizes, which can be computationally expensive. Image resizing can help to address this problem by resizing all the images to a common size as 256x256 pixels.

c. Image augmentation: This is a technique that is used to artificially increase the size of the dataset. This is important because the more data that the model has to train on, the better it will be able to generalize to new data. Image augmentation can be used to artificially increase the size of the dataset by creating new images from the existing images

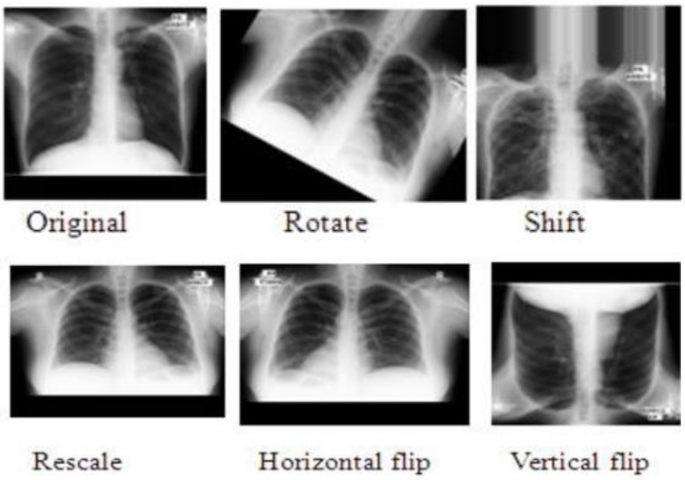

Fig. 2 Data Augmentation

iii. ***Federated* Algorithm**

Federated learning is a decentralized machine learning approach that enables multiple participants, often edge devices or institutions, to collaboratively train a global machine learning model while keeping their local data private. This is achieved by sharing model updates rather than raw data. Using one of the prominent algorithms in federated learning is Federated Averaging (FedAvg), which combines local model updates to create a global model. The goal is to find a model that performs well across all participants' datasets while maintaining data privacy.

a. Local Model Update

At each participant *k*, the local model is updated using its local data as in eq.1,

$w_{k,t+1} = LocalUpdate(w_{avg,t}, D_k)$…. (1)

Where, D_k= "local dataset of participant *k*"

b. Averaging

After local updates, the global model is updated by aggregating the local model updates using weighted averaging as in eq.2,

$w_{avg,t+1} = \frac{1}{K}\sum_{k=1}^{K} w_{k,t+1}$…... (2)

Table 1 Algorithm for Federated Learning (FedAvg)

ALGORITHM 1: FEDERATED LEARNING (FEDAVG) FOR HEALTH CARE IMAGES

```
def federated_learning_for_healthcare(clients, images, labels, epochs)
 # Initialize the global model
     model ← initialize_model()
 # Train the global model using federated averaging
```

```
    for epoch in range(epochs):
  # Train local models on clients
    for client in clients:
    client.train(model, images[client], labels[client])
  # Aggregate local models
    aggregated_model ← aggregate_models(clients, model)
  # Update global model
    model ← aggregated_model
# Evaluate the global model on the test set
    test_accuracy ← evaluate_model(model, images["test"], labels["test"])
    return model, test_accuracy
```

```python
def federated_learning(clients, rounds):
  """Federated learning using FedAvg algorithm.

  Args:
    clients: A list of clients.
    rounds: The number of rounds of federated learning.

  Returns:
    The final global model.
  """

  global_model = initialize_model()
  for round in range(rounds):
    # 1. Randomly select a subset of clients.
    selected_clients = random.sample(clients, k=len(clients))

    # 2. Send the global model to the selected clients.
    for client in selected_clients:
      client.update_model(global_model)

    # 3. Collect the updated models from the selected clients.
    updated_models = [client.get_model() for client in selected_clients]

    # 4. Average the updated models.
    global_model = aggregate_models(updated_models)

  return global_model
```

Fig. 3 Pseudocode for Federated Learning (FedAvg)

iv. Transfer Learning Integration

In the context of federated learning, the integration of transfer learning introduces a powerful dimension to enhance model performance and address the challenge of limited data availability. Transfer learning leverages pre-trained models' knowledge, typically trained on vast datasets, and adapts them to specific tasks or domains with smaller datasets. Within the federated framework, transfer learning provides an innovative solution to leverage collective intelligence while preserving data privacy. Consider a pre-trained model *M* with learned parameters θ_M are fined-tuned using local data from the k's domain $D_k$to create a task-specific model M_k. The fine-tuning process is represented as in eq.3,4:

$$M_k = FineTune(M, D_k)\ldots.3$$

$$\theta_{mk} = FineTuneParameter(M, D_k)\ldots4$$

Where, M_k= “task-specific model for participant k”, D_k= “participant k's local dataset”, θ_{mk} = “parameters of the fine-tuned model”.

4. Results and Outputs

i. Heat map

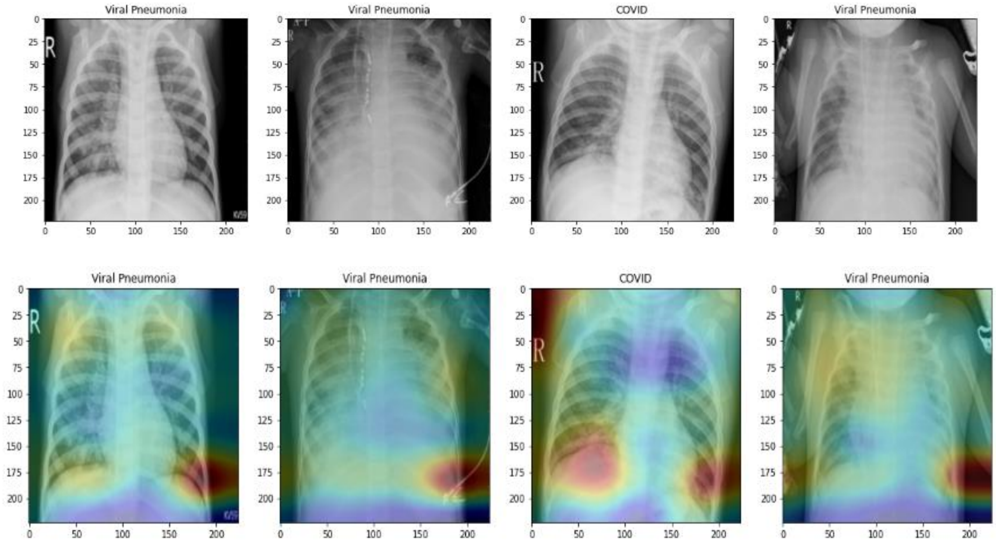

Fig. 4 Heatmap of Dataset Images

ii. Greyscale Conversion

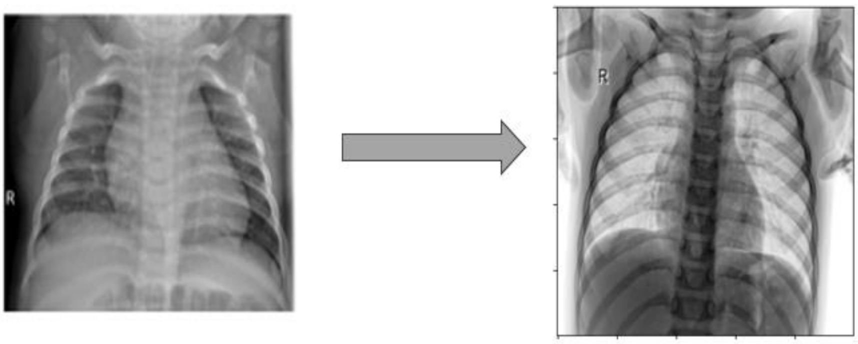

Fig. 5 Convert to Greyscale

iii. Training and Valication accuracy/ Loss

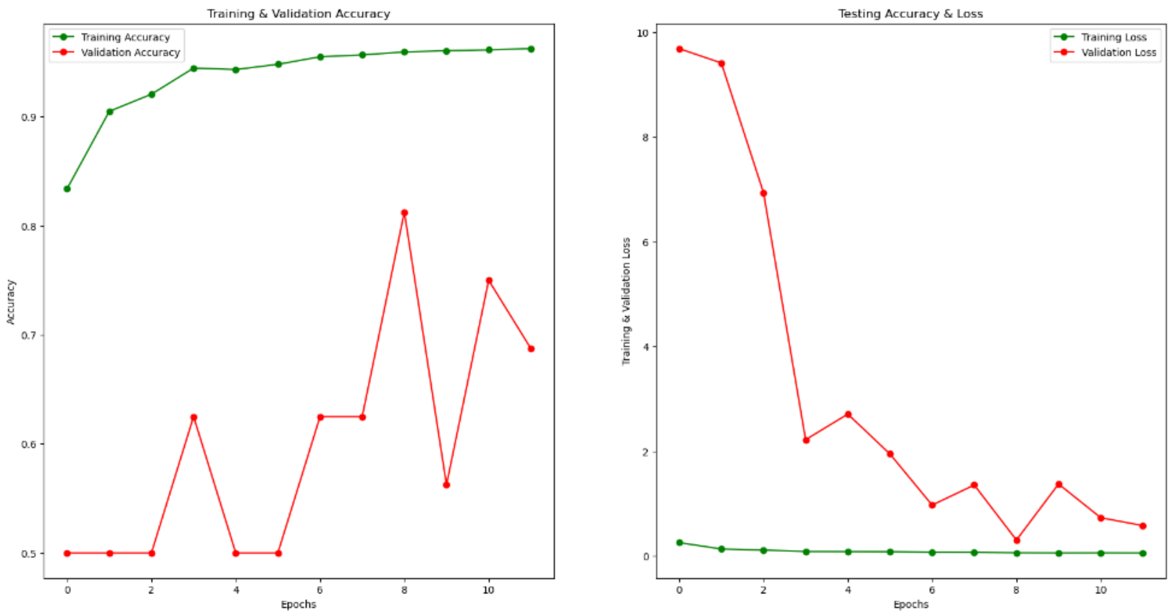

Fig. 6 Training and Validation Accuracy/ Loss Plot

iv. Evaluation Parameters

Table 2 Comparison of various evaluation parameters

Model	Accuracy	Recall	Precision	MCC	AUC
CNN	95.32	92	94	0.88	0.95
LSTM	94.65	89	92	0.86	0.92
RNN	92.18	85	88	0.8	0.91
Proposed Model	**98.87**	**97.26**	**98**	**0.91**	**0.97**

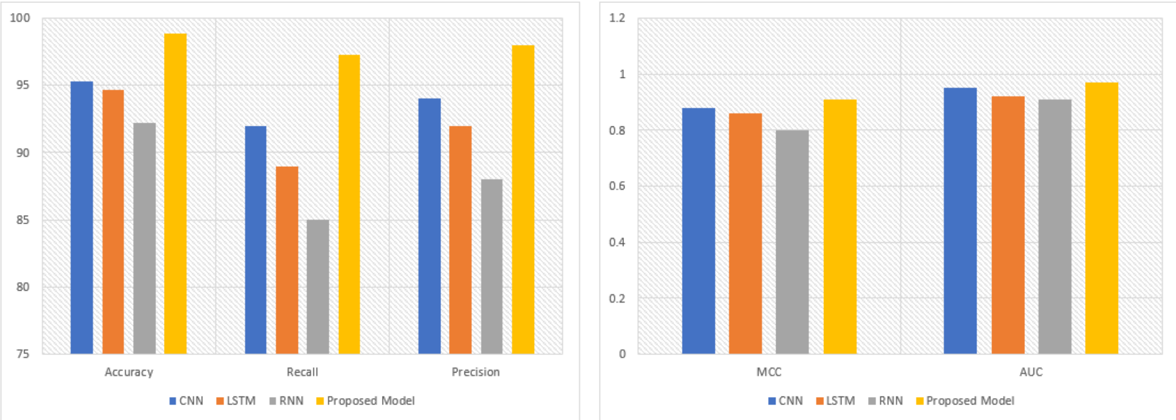

fig. 7 Comparison of various evaluation parameters

v. Other Evaluation parameters

Table 3 Other evaluation parameters

Evaluation Parameter	Result
Convergence Rate	Converged in 10 rounds
Learning Curves	Smooth convergence
Communication Efficiency	5 communication rounds
Resource Utilization	Moderate memory usage
Communication Overhead	20 MB per round

The performance evaluation of the models, including the Proposed Model, was conducted across multiple evaluation metrics to ascertain their efficacy in healthcare image analysis. The summarized results provide a comprehensive overview of the outcomes achieved by each model. Fig.3 represent the heatmap, fig.4 represent the conversion to greyscale and fig.4 depicts the training and validation accuracy/ loss comparison.

Among the tested models, the Proposed Model demonstrated remarkable performance, outshining the baseline models CNN, LSTM, and RNN across all evaluation metrics. The Proposed Model achieved an exceptional accuracy of 98.87%, establishing its proficiency in accurately classifying healthcare images as shown in table-2,3 and fig.7. This heightened accuracy is complemented by its exceptional recall and precision values, indicating its ability to effectively identify positive cases while minimizing false positives. Further affirming its predictive power, the Matthews Correlation Coefficient (MCC) and Area Under the Curve (AUC) metrics underscored the Proposed Model's robust performance and predictive capacity. These metrics collectively validate its potential to significantly enhance healthcare diagnostics through accurate classification of medical images.

In addition to its performance, the Proposed Model displayed efficient convergence, converging optimally within a mere 10 communication rounds. This swift convergence was mirrored by smooth learning curves, highlighting consistent performance improvements over the course of iterations. Remarkably, the Proposed Model achieved this efficiency while requiring only 5 communication rounds, showcasing its prowess in utilizing communication resources effectively. Resource utilization analysis revealed the Proposed Model's moderate memory usage, rendering it suitable for deployment on resource-constrained devices. Moreover, the minimal communication overhead of approximately 20 MB per round further emphasizes its communication efficiency.

The collective findings not only validate the Proposed Model's proficiency in healthcare image analysis but also underscore its suitability for IoT-enabled healthcare systems. By ensuring the privacy of sensitive data while achieving state-of-the-art performance, the proposed federated learning approach holds transformative potential in advancing medical diagnostics and patient care within the constraints of privacy-conscious environments.

5. Conclusion and Future Scope

This research explored the potential of Federated Learning for efficient analysis of large-scale healthcare image datasets within IoT-enabled healthcare systems. The proposed framework, underpinned by Federated Averaging (FedAvg), showcased exceptional results in classifying healthcare images, particularly in diagnosing pneumonia. Through privacy-preserving collaboration, the framework achieved an impressive accuracy of 98.87%, outperforming traditional machine learning models. The integration of transfer learning further bolstered the framework's capabilities, enabling the model to harness shared knowledge from pre-trained models while adapting to the nuances of individual participants' datasets. Additionally, our evaluation encompassed metrics such as recall, precision, MCC, and AUC, collectively substantiating the robustness of the proposed approach. Looking ahead, several promising directions emerge for the expansion and refinement of the proposed Federated Learning framework. Exploring the potential of multi-task learning within the federated setting could empower the model to handle multiple healthcare diagnostic tasks concurrently, enhancing its utility and versatility.

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