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Pneumonia Detection from X-Ray Images Using FederatedLearning- an Unsupervised Learning Approach

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Abstract:-Pneumonia continues to be a major worldwide health issue, particularly within a dynamicenvironment characterized by factors like climate change, the challenge of antibiotic resistance, and theconstant evolution of disease-causing agents. Despite efforts such as immunizations and maintaining hygiene,pneumonia continues to result in substantial illness and, in severe cases, fatalities. Doctors often use X-raysto find pneumonia because they show lung problems well. Utilizing machine learning or deep learning is a valuable method in aiding radiologists in examining the extensive collection of chest X-ray images.However, these approaches rely on extensive datasets for training, which necessitates centralizing the data.Yet, due to regulations safeguarding medical data privacy, gathering and sharing patient information on acentralized server is frequently unfeasible. Another issue within healthcare systems involves the accessibilityof labeled data. This study proposes a solution to address these obstacles. It involves the implementationof an unsupervised learning model, which was trained on decentralized datasets using the Federated Learningtechnique. Three healthcare institutions participated in the training process of this model. The assessmentof this model indicated that the Federated Learning approach produces results that are on par with theperformance of models based on centralized learning. These findings suggest that medical institutions shouldadopt collaborative strategies and leverage their diverse private data to develop such models efficiently.

Keywords: *Convolutional Neural Network, Deep Learning, Federated Learning, Machine Learning, Variational Autoencoder.*

1. Introduction

Currently, there is a significant rise in automating healthcare systems through the use of machine learningand deep learning technologies. Machine learning, particularly deep learning models, frequently needs access to large datasets for best results. However, in the healthcare industry, acquiring data is difficult because ofownership, technical, regulatory, and privacy obstacles. Various governing bodies such as Health InsurancePortability and Accountability Act (HIPAA) - United States, the General Data Protection Regulation (GDPR)- European Union, Health Information Privacy Code - New Zealand, Personal Information Protection andElectronic Documents Act (PIPEDA) – Canada, Personal Data Protection Act (PDPA) – Singapore, office for Civil Rights (OCR) - United States, and The National Health Data Management Policy, etc [18], setforth regulations and principles governing the management, storage, and exchange of healthcare data. Nowadays, protecting privacy is essential to managing data. Data scientists encountering challenges in developingand implementing machine learning-driven healthcare systems face obstacles due to these complexities. Ultimately, the necessity to share data becomes a requirement to leverage these enhanced diagnostic capabilities.Another significant hurdle faced by these systems involves the scarcity of labeled data. In the realm of deeplearning research, it has been recognized that in such scenarios, utilizing unsupervised learning at the outsetcan assist in obtaining representations. These representations support supervised learningin adapting and generalizing effectively, even when confronted with a limited labeled data set. Multiplestudies have showcased the effectiveness of employing autoencoders for unsupervised image feature learning,allowing the detection of

COVID-19 using only a small amount of labeleddata[44], [33]. Our study presents a federated learning model for pneumonia detection by analyzing chest X-ray imagesusing an unsupervised learning model. Federated learning is a decentralized learning technique introduced in[35]. This paper outlined the concept and initial framework for federated learning. The proposed FederatedLearning definition [27] is as follows.

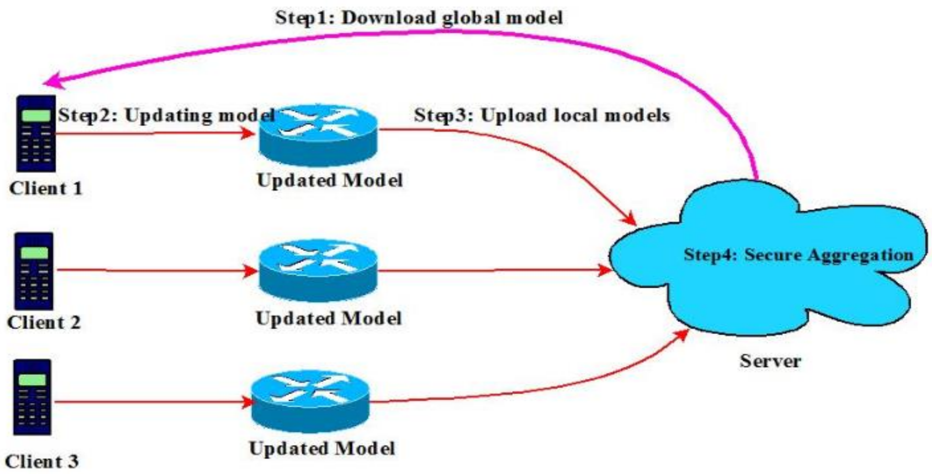

Figure 1: Federated Learning process

“Federated Learning is a Machine Learning setting where multiple entities (clients) collaborate in solvinga machine learning problem, under the coordination of a central server or service provider. Each client’s rawdata is stored locally and not exchanged or transferred; focused updates intended for immediateaggregation are used to achieve the learning objective.”The training process of an ML/DL model in the Federated scenario is demonstrated in Figure 1. In thisscenario, the server sends a central model to multiple clients prepared to train it. Each clientmodifies the central model based on its own private data and then uploads these updated model parametersto the server. On the server side, the Federated Learning (FL) aggregation algorithm combines the receivedupdates to create the best possible central model. This iterative process continues for several rounds.The model thatgets trained in the FL environment is based on an unsupervised learning technique to tackle the hurdle of limited labeled data. Here, the technique used is a variational autoencoder neural network capable enough to give great results with limited labeled data. It helps to extract features from X-rayimages, which are further used in the classification process for pneumonia detection.Pneumonia is a common and potentially serious lung infection characterized by inflammation in the air sacs.It’s often caused by bacteria, viruses, or fungi, resulting in symptoms like coughing, breathing difficulties,fever, chest discomfort, and fatigue. This respiratory illness can range from mild to severe, especially impacting vulnerable groups such as older adults, young children, and individuals with weakened immune systems.The infection spreads through inhaling infected droplets or via the bloodstream, particularly affecting susceptible populations. Diagnosing pneumonia involves multiple methods like physical exams, chest X-rays,blood tests, and various imaging techniques. Treatments vary based on the cause, including antibioticsfor bacterial infections and antiviral medications for viruses. Severe cases may require hospitalization forintensive care, such as oxygen therapy and intravenous fluids.To detect pneumonia in X-ray images, it’s essential to recognize specific patterns or markers that suggestthe presence of this lung condition. In X-rays, pneumonia typically manifests as regions with heighteneddensity or opacity, appearing as whitish or cloudy patches against the usual black backdrop of the lungs.Doctors perform over 4 billion X-rays annually to aid in diagnosing patients’ conditions. Presently, specialized professionals known as radiologists examine these images. However, researchers are growing interested in developing computer systems capable of interpreting X-rays. These systems have the potentialto support radiologists and extend assistance in comprehending X-ray results to regions facing a shortageof specialists. Using advanced computer learning helps doctors look at many chest X-ray pictures better.The proposed framework's primary advantage is removing the need to centralize patient data, allowinginstitutions to collaborate without pooling information in a single place. Through experiments, we validatethe efficiency of our suggested federated learning method.

Our current study focuses on developing and validating a system utilizing an autoencoder-based federated learning model for detecting Pneumonia from Chest X-ray images. This particularfocus serves as the core novelty of this research paper. The significant contributions of this paper are asfollows:

- We introduce an unsupervised learning approach to give effective results with limited labeled data.
- We also introduce the learning process of this unsupervised learning model on decentralized data.
- We conduct extensive experiments and comparative analyses, demonstrating the importance and relevance of our proposed strategy.

The subsequent sections of the paper are structured as follows:

- Section 2 provides an overview of related works.
- Section 3 presents a detailed outline of our proposed unsupervised learning-based FL model for detecting Pneumonia from X-ray images.
- Section 4 delves into the experiments and results, introducing both centralized and federated approaches and discussing their outcomes.
- Section 5 discussed the research opportunities available in this field.
- Finally, Section 6 concludes our study.

2. Related Work

Healthcare records often contain highly sensitive and personal information, including medical history, treatment details, genetic data, etc. Unauthorized access to patient data can compromise privacy, leadingto financial losses and reputational damage for healthcare organizations. These hurdles promote decentralized learning approaches that address data privacy concerns in machine learning [50]. Various healthcare researchers have used Federated learning for model training without centralized data collection.The researchers of [10] introduced an efficient approach to tackle the issue of ”impatient violence” in psychiatric contexts. The outcomes revealed FL as the most suitable method for training healthcare systemswith decentralized data. The research [31] explores the application of a Deep Neural Network (DNN) withina FL framework for segmenting retinal microvasculature and classifying Diabetic Retinopathy (RDR) using Optical Coherence Tomography (OCT) images. The findings suggest that the model’s performance in segmentation and classification tasks matches traditional deep learning methods. The article [54] authors introduce”FedMood,” a FL model designed to detect depression using mobile health data.This innovative model utilizes a specialized virtual keyboard that monitors keystroke duration, timing, andthe interval between key presses and accelerometer data to track typing speed variations unique toindividuals. By identifying changes in typing behavior associated with depression, the model aims to predict mental health conditions such as Bipolar-I, Bipolar-II, and normal mental states. Preliminary testingrevealed the successful detection of 8 Bipolar-I patients, 8 Bipolar-II patients, and 8 individuals with normalmental health using this approach. The study suggests that this method outperforms conventional techniquesby 10-15% in accuracy for similar diagnostic tasks. The study [1] highlights an FL model for COVID-19 predictions via chest CT scans, revealing an enhanced accuracy of 94.82. The research in the paper [17] incorporatedX-rays from 76 COVID-19 patients and 108 normal cases, analyzing them using the proposed Deep CNNmodels - VGG16 and ResNet50. The client-side model adopted the training images’ size of 224*224,involving the collaboration of four clients during the training phase.The model achieved comparable performance to centralized models, prioritizing privacy by avoiding the sharing or centralizingof sensitive data.A specialized CNN-based deep learning approach designed to detect COVID-19 from CT scans, utilizing FLinvolving data from 75 COVID-19 patients from three hospitals in Hong Kong [15]. A semi-supervised learning approach is implemented within FL settings for COVID-19 detection, utilizing a dataset comprising 1706CT scans from patients across China, Italy, and Japan.Employing a patch-based training method for 3Dimages, this framework effectively extracts information from clients with unlabeleddata[55]. The researchpresents a clustered-FL(CFL) approach to detect COVID-19 using X-ray and ultrasound imaging.By employing CFL, this collaborative learning framework notably improved the overall F1-Score by 11% to16% across two standard datasets. Yet, despite these advancements, the study underscores the ongoing challenge of insufficiently large datasets for comprehensive analysis.A deep neural network in FL situations to forecast arrhythmia from electrocardiograms has been proposed in the article [56]. It operates with a training set consisting of 74,275 segments of ECG signals and a test datasetcontaining 13,107 segments. The paper [21] presents FedSGDCOVID, a COVID-19 identification systemthat combines 2D CNNs with a spatial pyramid pooling (SPP) layer and is trained using two datasets. Thesuggested federated model surpasses seven alternative models, attaining notable accuracies of 95.32% onchest X-ray images and 96.65% on symptom data. A FL –based deep learning model [29] has been developedto identify pneumonia using chest X-ray images by recognizing a cloudy area within the X-ray. The modelachieves an approximate accuracy of 90%. A Random Forest strategy has been used in FL settings to detectheart disease [24]. This study [8] introduces a compact ”CoviFL CNN model” designed to trainAIoMT edge devices using local datasets. Furthermore, these AIoMT devices have the abilityto identify COVID-19 by analyzing audio of coughing sounds. This model showed 93% accuracy.A deeplearning-based FL model has been introduced to detect Cerebellar Ataxia (CA) disease. The dataset usedin this study was collected from four clinics located in Australia. Among four deep learning models testedin an FL environment, MobileNetV2 showed superior performance. It achieved the highest accuracy of86.69%. [40]. The system proposed in the article [22] has been designed to identify various skin conditions suchas rosacea, eczema, acne, and psoriasis. The dataset comprises images of these conditions sourced from the”DermNet Image Library.” A FL-based CNN model is introduced for disease detection. The accuracy stoodat about 81% across 1000 clients. This research [39] introduces a transfer learning-based model for identifying Diabetic Retinopathy within a Federated Learning setup. The research paper [42] introduces a novel FL framework called FedNI. This framework utilizes a GCN (Graph Convolutional Network)model to forecast diseases based on population data. A FL-based 1D-CNN model is suggested for identifyingEpileptic Seizure Detection through ECG signals. The model achieved a sensitivity of around 81% and aspecificity of approximately 82% [4]. In the research [49], the model focuses on detecting ”Autism SpectrumDisorder (ASD).” The research study [26] highlights a memory-conscious Continual Learning (CL) modelis implemented within FL setups to classify Breast Cancer. Three distinct datasets of Full Field DigitalMammography (FFDM) are utilized, sourced from three different vendors: Hologic, GE, and Siemens. Theachieved Area Under the Curve (AUC) is 0.95. The research [20] aimed to develop a survival modelspecifically tailored for larynx cancer patients treated with radiotherapy. An open-source FL platformwas employed, utilizing the Cox regression algorithm to train the model. Data from three collaboratingcenters—Odences, Christie, and Liverpool—were utilized to create a robust model to address patient data confidentiality concerns. A DL model [16] trained within a FL framework is introduced toidentify COVID-19 from CT scans. To ensure secure data retrieval in the Federated Learning setup, ablockchain architecture is implemented and achievesan accuracy of 98.2%. The suggested model in the research article [30], ” Feature extraction and segmentation of vertebral bodies,” is performed utilizing DAF-U-Net.U-Net was chosen due to its effectiveness in segmenting medical images. This model is named ”FederatedLearning-based Vertebral Body Segment Framework (FLVBSF)” and achieved an accuracy of approximately98%. The research [37] aims to identify Facial Paralysis. The classification model employed for this studyis the Support Vector Machine (SVM), whichis trained in FL settings. Its accuracy is approximately 91%.A newly published study paper [5] presents an innovative method in medical imaging, suggesting a newalgorithm using federated learning with a feed-forward network. This technique targets improved detection oflung nodules from CT scans. Extensive testing on the well-known ’LIDC datasets’ demonstrateda high accuracy prediction rate of 97.65%. The article emphasizes the potential of this method to advanceearly detection abilities, potentially revolutionizing the accuracy and efficiency of diagnosing lung nodules.All the research discussed above uses supervised learning algorithms to build the model at the server end, which gets trained in FL settings. These models need huge datasets for high accuracy. The areaof concern highlighted in many types of research is the use of unsupervised learning instead of supervised learningto get comparable or efficient results. For various issues, unsupervised learning strategies have shown superior results to supervised learning techniques in several ML-based healthcare research studies.So, using unsupervised learning techniques in FL contexts is a good option, especially when dealing withunlabeled data [43]. There are various centralized learning-based unsupervised learning models like the studyexplained in [41], which implemented an autoencoder-based mental health detection model from the small dataset. Themodel got training from the logical signals recorded by smartwatches and showed efficient performance forbipolar disorder detection. The COVID-19 detection system

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”AutoCovNet”[44] is the ideal combinationof supervised and unsupervised learning because it uses a” deep convolutional auto-encoder network” for this disease detection and shows an accuracy of up to 90%. In the model [33] for COVID-19 detection, thefeature extraction is based on ”AdaGrad-based Inception V4”, and classification is based on ”VariationalAutoencoder”. Lung ultrasounds are utilized for COVID-19 detection by researchers [11], where the fusion of the CNN-based autoencoder network and DenseNet-201 network contribute to noise classification. The study [13] used a deep autoencoder for brain tumor detection. Sparse autoencodersand stacked autoencoders have been used in [25] for Alzheimer’s disease detection at an early stage, and they give outstanding results with less prior knowledge. In the study [7], a novel model is proposed which can be used

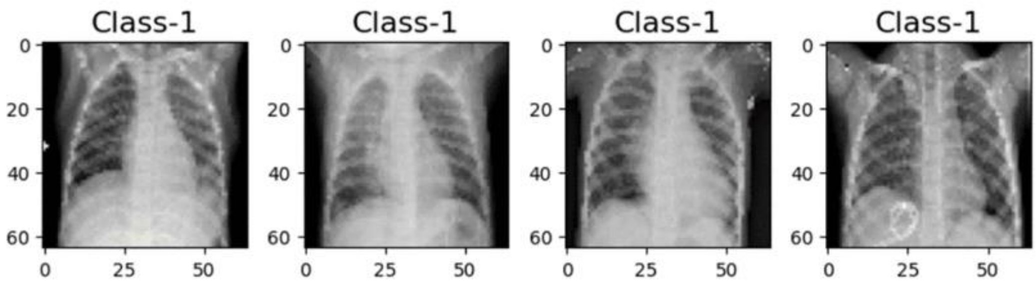

Figure 2: X-rays of pneumonia-infected patients

to detect any plant disease. This model is based on the Convolutional Autoencoder (CAE) and Convolutional Neural Network (CNN). Shi Hua Wang, along with his team, proposed the model[23] forSecondary pulmonary tuberculosis (SPT) detection. The feature extraction was done with the Pseudo Zernike moment (PZM) model, and the classification part used a deep stacked sparse autoencoder (DSSAE). The evaluationshowed up to 93% accuracy. In the research study explained in [9], the researchers highlighted using a variational autoencoder for feature extraction from electronic health records to detect any disease to whichthe model is applied. The research proposed in [58] showed the use of a variational autoencoder for microRNA disease prediction and promised accuracy of up to 91%. Lots of research has used autoencoders totackle various health issues such as skin disease detection [46], anomaly detection in facial skin [34], tumordetection from MRI images [51], detection of melanoma disease [14], and Parkinson’s disease detection [19], etc. Autoencoders are also contributing to improving existing methodologies. The research work proposed in the paper [6] has proposed the improvement of reinforcement learning using variational autoencoders to create more effective healthcare treatment methods. The studies [12] and [38] explained comparison analysisof these types of models.Based on the important points discussed in this research, we proposed a model that tackles the hurdle of implementing a high-accuracy model with a limited dataset. The proposed model implementation consistsof an autoencoder neural network which has been created and trained in an unsupervised manner on thedecentralized datasets. This two-phase approach allows you to leverage the feature extraction capabilities ofdeep autoencoders [44] and the probabilistic and generative capabilities of VAEs for classification tasks. Themodel covered the dataset with two types of X-ray images, i.e., normal and pneumonia patients. Figure 2 shows a few X-rays of pneumonia-infected patients.

3. Methods

The proposed study aims to develop an automated system for predicting Pneumonia through the analysisof chest X-ray images. The focus lies in employing unsupervised learning methods, diverging from supervised learning, to achieve comparable or more effective outcomes. Additionally, addressing the challenge ofdata size, the research explores decentralized learning approaches. Numerous unsupervised learning techniques like Autoencoders (AEs) and their variations, Restricted Boltzmann Machines (RBMs), Deep BeliefNetworks (DBNs), Deep Boltzmann Machines (DBMs), and Generative Adversarial Networks (GANs) areavailable [45]. Recent investigations into COVID-19 have proposed various models using these unsupervisedlearning techniques. However, an analysis reveals that although Generative Adversarial Networks (GANs)are popular, their training duration is notably 18-19 times longer than that of Autoencoder Neural Networks[2]. Hence, Autoencoder Neural Networks emerge as a preferable choice, demonstrating superior results withlesser data in various research studies. As for decentralized learning techniques, Federated Learning standsout as a viable option.

- Figure 3 shows the implementation process of the suggested FL-based pneumonia detection model.
- Figure 4 shows the workflow of the proposed study.

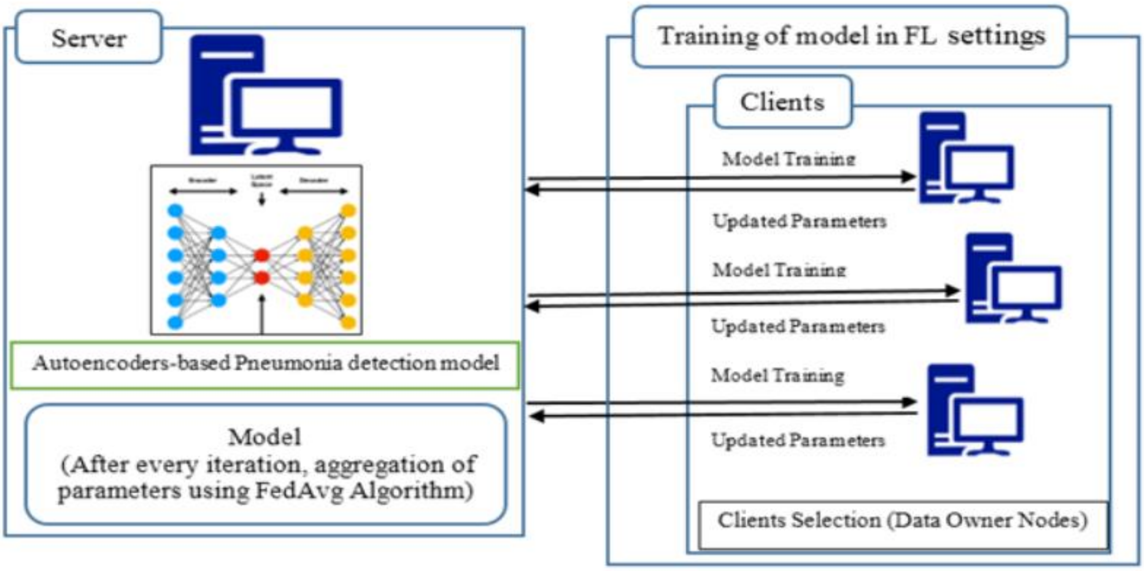

Figure 3: Implementation process of proposed model

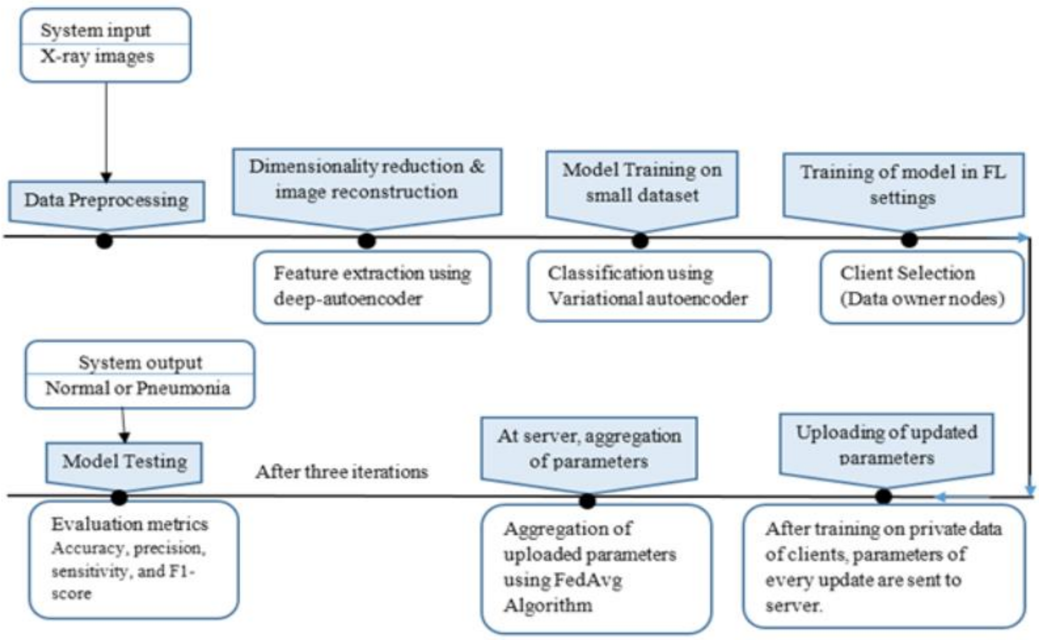

Figure 4: Workflow of proposed model

The first phase of this research involves utilizing an unsupervised learning technique, specifically Autoencoder neural networks, to detect pneumonia from X-ray images. These images, initially in varioussizes, are standardized to 244x244 dimensions with three color channels, followed by a normalization processto

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streamline the model training and ensure smoother convergence. This phase involves feature extractionfrom X-ray images and further classification of normal and pneumonia infected X-rays. Feature extractioninvolves utilizing a deep autoencoder neural network, which consists of both an encoder and adecoder. The encoder, comprising five layers of neurons, progressively captures diverse levels of informationfrom the input images. This process leads to a bottleneck layer with reduced dimensionality, creating acondensed feature representation. The autoencoder is trained on X-ray images, primarily focusing onminimizing the reconstruction loss between the input and reconstructed images, accomplished through theAdam optimization algorithm. Subsequently, the extracted features are utilized for classification, employingthe concluding layers of a variational autoencoder.

Initially, the algorithm evaluates the number of samples in the encoded feature set. It then flattens the 4Dencoded feature array into a 2D array. This procedure prepares the test images by resizing them to a specificsize (e.g., 64x64), normalizing pixel values, and incorporating a batch dimension. Subsequently, the trainedmodel utilizes these flattened features to predict the class of the test image.Training the model using decentralized datasets: It involves several steps within a Federated Learning(FL)environment. The algorithm for the same is listed below with various recommended steps in Figure 5.

This algorithm train a machine leaning model on distributed datasets. Here, "Server" is the server, "Clients" is a list of clients, and T is the number of iterations the model take for training. In each iteration, the following steps are performed:

The server distributes the model to the clients.

1. During first iteration, the central server initializes the global model M_0 with some random values to its parameters.

Selection of clients

2. During every iteration t=1…T, the central server selects a subset of k nodes from the pool Q with n data points and sends the current model M_{t-1} to k nodes.

Each client trains the model on its local data.

3. Each i^{th} node where $i \in k$, locally train the model M_{t-1} on its own data D_i for a certain number of epochs, and send the updated model U_i^t to the central server.

The server updates the global model parameters.

4. The central server aggregates the local updates using an aggregated algorithm with aggregation rate η to create a new global model M_t.

Figure 5: Algorithm for Federated learning(Server Clients T)

In this research, three medical institutions acted as clients who contributed by providing two categories of X-ray images: pneumonia-infected and normal. This training process continued for three iterations. Aftereverytraining iteration, the updated features received by a server are aggregated using the FedAvg aggregationalgorithm. The aggregation done after the third iteration is the final enhanced model for pneumonia detection using a decentralized, unsupervised learning technique.

4. Performance Evaluation and Discussion

Five parameters, such as accuracy, precision, sensitivity, specificity, and F1-score, have been used to evaluate this model.

Experimental Setup:

- The platform used for the training and testing is Google Colaboratory Server.
- The proposed model has been implemented with the Keras, TensorFlow 2.0 libraries, and TensorFlow Federated.

The proposed model's performance is evaluated based on five parameters: accuracy, precision, sensitivity,specificity, and F1-Score. As in this FL model, three clients contributed, which is evaluated onthree test data sets. The evaluation results are shown in Table 1. The aggregated accuracy attained is 94%.

Test Set	Accuracy	Precision	Sensitivity	Specificity	F1-Score
Private Dataowner1	94	93	95	92	94
Private Dataowner2	93	94	92	94	93
Private Dataowner3	95	96	94	97	95
Mean	94	94	93	94	94
Std	1	1.5	1.5	2.5	1

Table 1: Evaluation of the proposed model

The proposed model's performance has also been compared with the existing transfer learning-based pneumonia detection models [3].

Model	Precision(%)	Sensitivity(%)	F1-Score(%)	Accuracy(%)
Proposed Model	94	93	94	94
FL-VGG16	96	94	95	93
FL-AlexNet	95	96	95	93
FL-ResNet50	97	96	96	95
FL-DenseNet	98	97	97	96

Table 2: Comparative analysis [28] /citepfarkas2023pneumonia

The comparison analysis is listed in Table 2 and plotted in Figure 6.

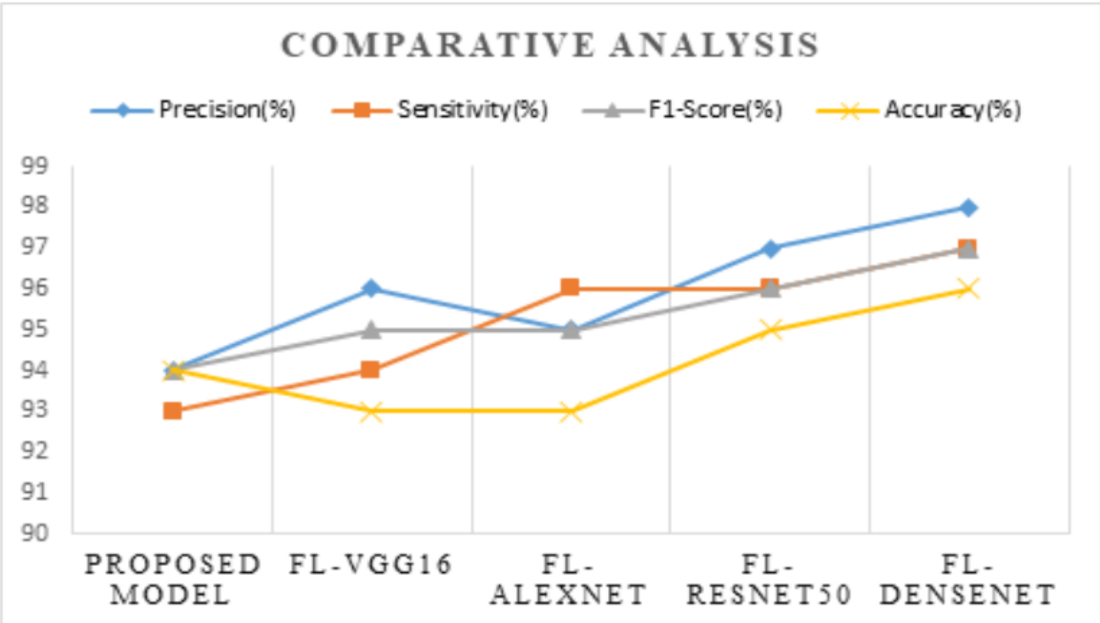

Figure 6: Comparison analysis of the proposed model with existing FL- models

These statistics show that results are comparable with existing models, and the proposed methodology can tackle two issues faced in the existing models, such as the lack of labeled data and the size of data. The deep autoencoder helps regenerate images from existing images, which resolves the data size problem.This model is based on unsupervised learning techniques and uses unlabeled data to train it.So, this model can be used in various other healthcare systems where the availability of labeled data is a majorconcern In essence, the use of federated learning with autoencoders for pneumonia detection from X-rayimages addresses the critical need for collaborative, privacy-preserving, and efficient methods in healthcareAI, ensuring both robust model development and patient data protection.

5. Future work

Several studies are currently underway in this field, and some open areas of research in Federated Learning(FL) are discussed: Firstly, FL-based systems can use the data generated by IOT devices data to increase theefficiency of these systems[36][48]. Another problem with FL models is data heterogeneity, so techniquescan be implemented to handle this heterogeneity issue[57], [32]. Decentralized learning can also be promotedby various related techniques of FL like Split learning [52] and TinyML [47] [53]. These techniques can beused to implement an efficient ML/DL model by training with decentralized data.

6. Conclusion

The research introduced a novel training approach for detecting and classifying pneumonia. The methodology involves employing unsupervised learning for the image reconstruction phase. Furthermore, it introduced an encoder-merging network specifically crafted to extract features from diverse encoder layers and effectively amalgamate them for classification purposes. This model utilizes Deep Autoencoder-based feature extraction and variational autoencoder for classification. The study's primary objective was to apply unsupervised learning in pneumonia detection. The model’s evaluation demonstrated an average accuracy of 98.2%. A comparative analysis with existing transfer learning-based models highlighted the exceptional performance of the proposed model. As a potential avenue for future expansion, the suggested model could find application in e-healthcare scenarios. Many healthcare issues involve limited and unlabeled datasets, which, due to privacy concerns, may remain with hospitals exclusively. This model could undergo training in Federated Learning settings, utilizing decentralized datasets. This design decision resulted in more efficient computations and faster convergence.

7. Data Availability

The datasets generated and/or analyzed during the current study are available at: https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia. Other X-ray datasets have been taken from Tagore Hospital, Jalandhar(Punjab), Seema X-ray, and Diagnostic Center Hoshiarpur(Punjab).

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