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ADVANCED METHOD FOR DETECTING CHEST DISEASE USING FEDERATED LEARNING MODELS

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Abstract— An important part of any nation's economy is the healthcare sector. This clearly defined practice began a number of years ago. As time has gone on, the healthcare industry has advanced to new heights, and technology has undoubtedly always been a major factor in this. Every stage of the evolution of healthcare has its own set of problems. In the prehistoric age, healing with herbs and other natural resources was a drawn-out procedure that may take years to finish because drugs had not yet been invented.

Even if treatment times have shortened in the modern era due to technological and mechanical advancements, storing patient data and records, records, therapies, and many other things has become more difficult.

The detection of various chest conditions, including lymphoma disease, is the main goal of this study project. We have used FL models, including as VGG-16, MobileNet V2, and VGG-19, to speed up and simplify the prediction process.

Since we now know that chest diseases are so common, it is essential to properly predict and analyze them. 112,120 chest x-ray images from the study's dataset were examined. A total of 14, including atelectasis, consolidation, infiltration, and pneumothorax, as well as a class called "No findings" if the condition was not discovered, were represented in the study's 30,805 images.

The highest accuracy of 96.71% was attained by VGG-19 using federated transfer learning. As a result, the classification report said that the best transfer-learning model for correctly diagnosing chest disease was the VGG-16 model.

Index Terms—Chest Diseases, Federated Learning, X-ray Image, Lymphoma disease, VGG-19, etc.

I. INTRODUCTION

Chest disease, often known as lung disease or chest disease, is a broad category of medical conditions that impact the organs and tissues inside the chest cavity. These illnesses mostly affect the heart, lungs, esophagus, diaphragm, chest wall, and other related systems. Chest disease can have a wide range of causes, symptoms, and severity. There are a number of other chest ailments that should put forward-thinking doctors to the test. A wide enough category and a sufficiently complex set of challenges are presented by conditions affecting numerous organs and tissues in the chest to fully utilize the expertise of the medical specialists involved. It is easier to become competent and efficient in managing these problems when they are studied as connected topics. Because of the strong anatomical and functional relationships between the organs that may be impacted, chest problems can only be diagnosed and treated with a comprehensive understanding of each issue. A thorough medical examination is typically necessary for the diagnosis and treatment of chest diseases. This includes a physical examination, imaging tests (such as CT or X-rays), lung function tests, and, on occasion, biopsies or laboratory blood testing. Each condition has a variety of treatment options, such as medication, lifestyle modifications, breathing exercises, surgery, and other procedures [1–3].

Physicians employ a variety of diagnostic procedures referred to as "chest detection methods" in order to identify and assess illnesses that impact the heart and lungs, among other organs and tissues found in the chest cavity. These methods frequently make use of various forms of medical imaging, such as radiography, CT (computed tomography) scans, and MRIs (magnetic resonance imaging), which provide exact visual details regarding the inner workings of the chest area. EKGs, or electrocardiograms, track the electrical impulses in the heart, whereas PFTs, or pulmonary function tests, evaluate lung function. Furthermore, in some circumstances, more advanced diagnostic techniques like bronchoscopy and cardiac catheterization may be employed. Biopsies, sputum analysis, and blood testing can all aid in the diagnosis of underlying conditions [4].

As a potent tool to increase speed and accuracy, artificial intelligence (AI) is being used more and more in chest illness diagnosis methods. Medical imaging, such as CT scans and X-rays, can be reliably evaluated by AI-driven algorithms, which aids in the early identification of anomalies or illnesses. Neural network models can also help with risk assessment by forecasting the likelihood of particular diseases associated to the chest based on patient data and disease history.

Federated Learning Models in Chest Disease Detection

In 2016, McMahan et al. introduced federated learning (FL), which became a revolutionary concept in deep learning (DL) and machine learning (ML). It was a significant breakthrough because of its decentralized architecture, which allowed for cooperative model training across mobile and edge devices. FL facilitates the training of ML and DL models in distributed computing systems by eliminating the need to centralize data. This aids in addressing concerns about dependability, privacy, and data integrity in compliance with regulations such as the HIPAA Act. [5].

In recent years, FL has become more and more prominent as a research topic for developing privacy-centric frameworks in the healthcare sector. Researchers are looking on decentralized methods to safeguard data privacy and allow data centers and other clients to share parameters without jeopardizing personal information. This approach eliminates the requirement for central data gathering by distributing the computational work among multiple edge devices while DL models are trained locally. As part of the procedure, local model training is carried out on the clients' devices, and modifications are subsequently transmitted to a central server to facilitate collaborative efforts to enhance a collective learning model. This method is quite useful for dealing with problems like segmenting data resources, access privileges, and limited data availability. It has uses in a wide range of industries, including traffic control, medical imaging, telecommunications, and autonomous driving [6].

Given the sensitivity of patient data and the need to protect privacy, FL is crucial to healthcare for illness prediction. It enables servers and devices to work together smoothly, protecting data locally and sharing a global model with clients. A procedure that begins with the server sending an initial global model to clients—which could be a new deep learning model or a pre-trained model obtained through transfer learning—is an example of this decentralized FL architecture. Clients safeguard privacy and security by storing critical information on their property and using their own local data to train this model autonomously. Client devices transmit updated model weights and biases to a central server after local training, and the server aggregates these updates.

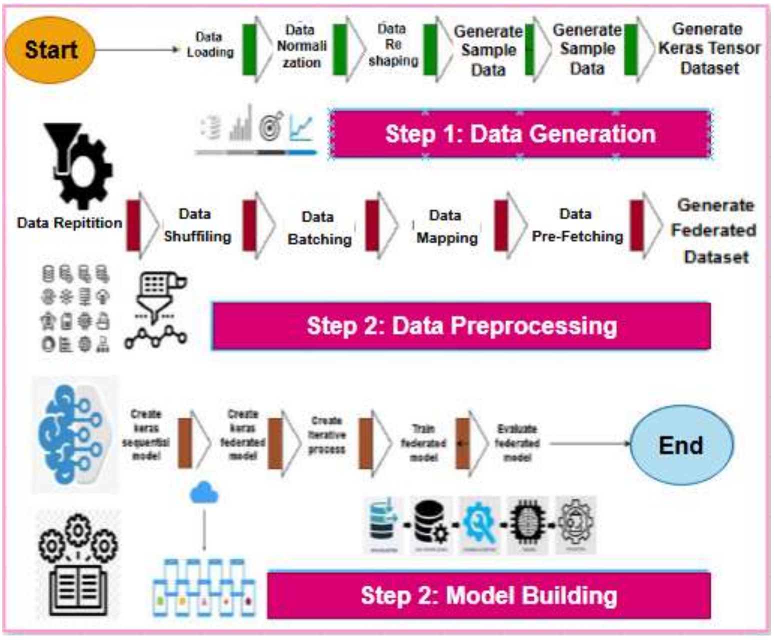

Figure 1: Federated Learning Models Work Flow

In contrast to traditional distributed learning, federated learning aggregates user data in one place and then distributes it to agents uniformly and independently. In federated learning, a central model is started by the server, which then distributes the current global model to a random number of clients for each cycle. After utilizing their local data to train the model, clients upload the finished product to the central server. These updated models are combined by the server to create a new, enhanced global model. The communication cost between the server and clients is usually the main bottleneck in federated learning since the server distributes the global model to several clients and uploads the updates from these clients back in each cycle. There are basically two ways to deal with this problem: one lowers the communication cost by reducing the number of communication rounds, and the other uses compression techniques to minimize the model size without sacrificing accuracy.

An extremely rare subtype of lymphoma, Mucosa Associated Lymphoma Tissue (MALT) lymphoma is found in less than 3% of patients with primary Sjögren's Syndrome (pSS), a chronic autoimmune disease that primarily affects the body's moisture-producing glands. Because of this rarity, it is extremely difficult for researchers and medical professionals to find and examine the risk factors linked to the development of MALT lymphoma in this patient population. Traditional studies have had difficulty gaining the statistical power required to make significant inferences regarding MALT lymphoma in the context of pSS because of their narrow focus and the inconsistent quality of patient data [7].

In one study, data harmonized from 17 different databases was used to create and train models particularly for diagnosing MALT lymphoma among patients with pSS using a federated AI strategy. This substantial variety of data sources offers a strong basis for determining trends and risk factors linked to MALT development with previously unheard-of precision and dependability.

II. Literature Work

During the COVID-19 pandemic, Muhammad Umair Ali et al. (2023) [8] created a 19-layer convolutional neural network (CNN) model to detect chest infections in X-ray scans. Stochastic gradient descent and momentum were used to optimize the model, which produced remarkable classification accuracies of

97% in four-class subclassification and 98.85% in binary classification. On a new dataset, the model also showed an accuracy rate of 98.5%. The model required substantially less training time than other pretrained models, making it a useful asset for medical experts in clinical undertakings. In pulmonary medicine, this technology has the potential to enhance patient care and diagnostic procedures.

The use of deep learning in healthcare is examined by Sudipta Modak et al. (2023) [9], who concentrate on applying medical picture analysis to identify lung conditions. The prevalence of lung disorders and non-invasive imaging techniques make them essential. The identification and classification of lung disorders has been revolutionized by deep learning methods such as CNNs, autoencoders, and graph convolutional networks. The most recent techniques, publicly available databases, and cutting-edge deep learning strategies are all included in the paper. It also encourages a culture of continuous improvement in healthcare by highlighting the significance of continued research and development in the application of deep learning techniques to the detection of lung diseases.

AI integration was used in a study by Saad M.M. et al. (2023) [10] to evaluate the severity of Chronic Obstructive Pulmonary Disease (COPD). They examined a group of 80 patients using non-contrast CT scans and Coreline Soft's AVIEW identification software. To diagnose parenchymal illness, they employed sophisticated density mask techniques, such as the D-value and inspiratory LAA-950%. Inspiratory LAA-950% and the Tiffeneau index were found to be significantly correlated with the severity of COPD. The study demonstrates the potential of AI in increasing the accuracy and efficiency of COPD severity evaluation, giving a promising alternative to existing spirometry-based approaches. AI combined with chest CT imaging may help patients with COPD receive better care.

Al-Sheikh M.H. et al. (2023) [11] created a brand-new automated system that uses CT and X-ray scans to identify a variety of lung conditions. To increase the accuracy of image categorization, the system combines deep learning models with a convolutional neural network (CNN) and image enhancement. An inventive image enhancement algorithm is used in the pre-processing step to improve the visual quality and diagnostic usefulness of images. A customized CNN architecture and pre-trained CNN models AlexNet and VGG16Net are used in the classification stage. High levels of classification accuracy, sensitivity, and specificity were attained when the system's effectiveness was assessed using publicly accessible image datasets. The study demonstrates the benefits of including an image enhancement model in the processing pipeline and suggests potential for major improvements in diagnostic accuracy and patient care in pulmonary medicine.

To enhance chest radiography diagnosis, Nawaz M. et al. (2023) [12] created a deep learning method utilizing the EfficientDet model. With a high recall rate, the model improves diagnosis by identifying and classifying eight different kinds of chest anomalies in X-ray pictures. The CXray-EffDet model, based on the EfficientNet-B0 model, achieved an Area Under the Curve (AUC) score of 0.9080 and an Intersection Over Union (IOU) of 0.834, proving its competency and efficacy in chest illness detection and classification. This study demonstrates the potential of cutting-edge deep learning methods for medical diagnostics.

Because major lung disorders like cancer and COVID-19 are so common, Ahmed et al. (2021) [13] highlight the significance of chest imaging diagnostics in the medical industry. With an emphasis on the most recent developments in the diagnosis of lung diseases, they examine deep learning methods applied to X-ray and CT scan datasets. The paper draws attention to issues in the field, including the dearth of varied standardized datasets, large training sets, high-dimensional data complexity, and issues with feature independence. In spite of this, the most popular methods for managing picture collections in chest imaging diagnostics are Convolutional Neural Networks (CNNs). The study emphasizes how important it is to keep improving deep learning techniques for medical imaging.

The study by Priya S.B. et al. (2021) [14] examines how pollution and unhealthy eating habits affect public health, with a particular emphasis on diseases of the chest such as atelectasis, cardiomegaly, effusion, edema, lung consolidation, mass, nodule, pneumothorax, pneumonia, pleural thickening, infiltration, fibrosis, and emphysema. The study integrates a Convolutional Neural Network (CNN) with the InceptionV3 architecture to predict chest illnesses using machine learning techniques. The study uses transfer learning to extract features from a pre-trained network, offering measurable diagnoses in percentage terms.

Chaudhary et al. (2019) [15] developed a deep convolutional neural network (CNN) especially designed for the study of chest disorders, leading to a major advancement in medical imaging. The extensive Chest X-Ray 14 dataset, a collection of radiographic pictures that depict a variety of chest diseases, was used to train this network. The study team's deep CNN demonstrated an outstanding average accuracy rate of 89.77% in differentiating between different chest diseases. This degree of accuracy highlights how deep learning can support and enhance the diagnostic process in clinical settings by offering a tool that can accurately identify diseases from chest X-rays, thereby cutting down on diagnostic times and enhancing patient outcomes.

Shakeel et al. (2022) [16] developed a state-of-the-art lung cancer detection technique that leverages the power of an ensemble classifier and a deep neural network, building on the search for more precise diagnostic tools. Their method improved imaging quality, skillfully divided lung regions of interest, and focused on the most important characteristics for cancer identification. They significantly improved the accuracy of lung cancer detection by amplifying the identification of aberrant cancer features through the use of an ensemble classifier. This novel approach marks a major advancement in the application of machine learning to medical diagnosis.

LungNet, a hybrid model that combines data from wearable sensor-based medical Internet of Things (IoT) devices with deep-convolutional neural network architecture, was presented by Faruqui et al. (2021) [17] in yet another creative investigation. The goal of this merger was to take advantage of the vast amounts of data that were available from both wearable healthcare technologies and sophisticated medical imaging. With an overall accuracy of 96.81%, LungNet showed an exceptional ability to diagnose lung cancer after being painstakingly trained on a large dataset that included more than half a million photos. Furthermore, with an accuracy of 91.6%, the model demonstrated exceptional precision in differentiating between stage-1 and stage-2 lung tumors. Through earlier intervention and individualized treatment programs, such precision in early-stage cancer identification could have a substantial impact on the field of oncological diagnostics and dramatically improve patient prognoses. The achievement of LungNet sets a new standard for the early detection and classification of lung cancer and represents a significant advancement in the fusion of deep learning models with real-world clinical application.

III. Research Methodology

More advanced, precise, and effective diagnostic instruments are desperately needed in the medical field, especially for the diagnosis of cancer and chest problems. Although somewhat successful, traditional diagnostic techniques frequently lack speed, scalability, and occasionally accuracy because of the subjectivity of human analysis and the increasing complexity of medical data. As a result, there is an urgent need for creative solutions that might enhance diagnostic procedures by utilizing the enormous volumes of medical imaging data.

One promising approach to overcoming these obstacles is the application of deep learning and federated learning models. By evaluating medical images with a level of accuracy and speed that is not possible with human capabilities alone, these models have the potential to greatly improve illness identification and categorization. However, creating machine learning models that can reliably recognize and categorize a variety of chest conditions and lymphoma from medical images presents a number of difficulties, such as the need for large amounts of training data, data privacy issues, and the need for models to be both extremely accurate and processing and analysis-efficient [18].

The medical sector is in dire need of more sophisticated, accurate, and efficient diagnostic tools, particularly for the diagnosis of cancer and chest issues. Due to the subjectivity of human interpretation and the growing complexity of medical data, traditional diagnostic procedures, while partially successful, often lack speed, scalability, and occasionally accuracy. Therefore, innovative solutions that could improve diagnostic processes by using the massive amounts of medical imaging data are desperately needed.

The use of deep learning and federated learning models is one possible strategy to get over these challenges. These models have the ability to significantly enhance sickness diagnosis and classification by analyzing medical images with a speed and accuracy that is not achievable with human capabilities alone. Nevertheless, there are several challenges in developing machine learning models that can accurately identify and classify a range of chest conditions and lymphoma from medical images. These challenges include the requirement for substantial training data, concerns about data privacy, and the requirement that models be both highly accurate and processing and analysis-efficient.

The following illustrates the contribution given to the study work (figure 2) in order to diagnose different chest diseases:

- The information was gathered from two datasets, including the Malignant Lymphoma Classification and the NIH Chest X-ray.
- To efficiently classify chest diseases, the study used a unique approach that blends deep and federated learning approaches with transfer learning.
- To guarantee data integrity, alignment with the.csv dataset, management of missing values (NAN), and data encoding, preparation operations were carried out.
- Following preprocessing, a graphic summary and visual representation of the data were created. This made it easier to extract characteristics from the data, including solidity, area, perimeter, and aspect ratio.
- The dataset was divided into subsets for testing and training, with 25% going to testing and 75% going to training. Flipping, rotation, and other augmentation techniques were used to increase the diversity of the dataset.
- Lastly, for classification tasks, pre-trained models like VGG16, DenseNet-161, MobileNet V2, and VGG19 were used. Precision rate and recall rate criteria were used to assess these models' performance.

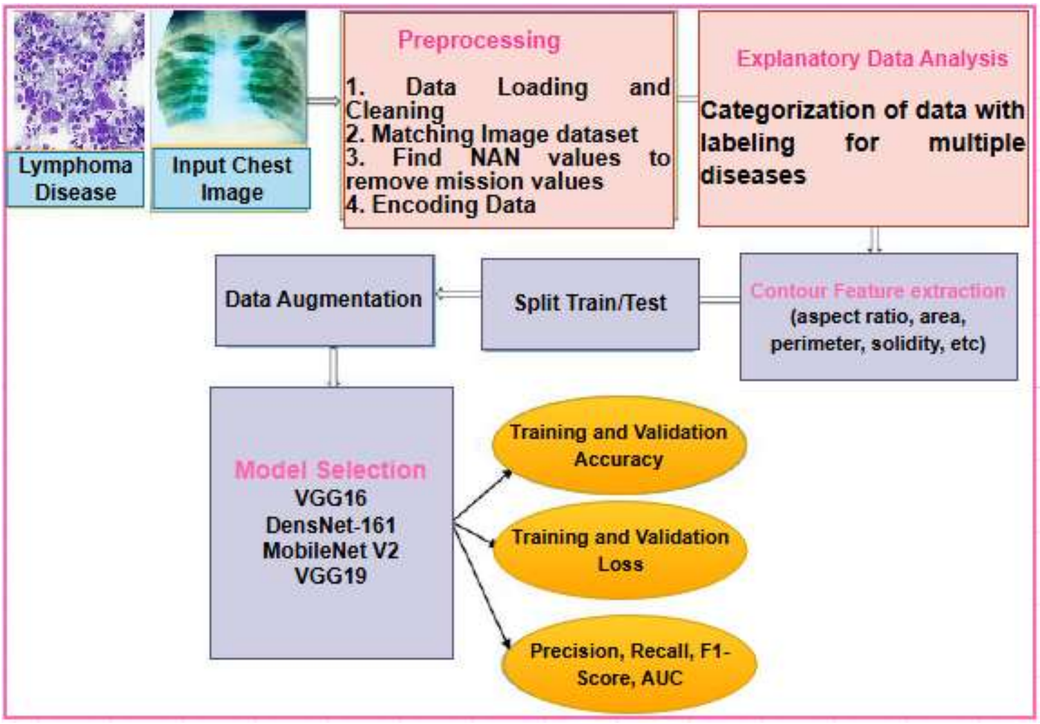

Figure 2: Block Diagram of Proposed System

IV. Material and Methods

Dataset: Historically, there have been few publicly available datasets for chest X-rays. In the past, Openi was a well-known source with 4,413 photos. However, the National Institutes of Health (NIH) chest X-ray collection, which includes 112,120 pictures and disease annotations for 30,805 people, was used for this investigation. In order to obtain precise information from disease classifications, these annotations were created using Natural Language Processing (NLP) techniques [19].

Similarly, the "Malignant Lymphoma Classification" dataset, which is accessible on Kaggle, has been utilized for lymphoma. There are 5400 photos in all, along with specimens created by different pathologists in different places. This dataset includes three different types of lymphoma: mantle cell lymphoma (MCL), follicular lymphoma (FL), and chronic lymphocytic leukemia (CLL). This dataset can identify different forms of lymphoma from sectioned samples that have been stained with hematoxylin and eosin (H+E), which makes the identification of the disease easier and more compatible. Among the features of the dataset are 5400 photos altogether, each measuring 1388 x 1400 pixels, organized into three folders called CLL, FL, and MCL, and offered in.tif format. Finally, the images are in a standard RGB color scheme.

Data Pre-Processing: Preprocessing the chest X-ray pictures to improve their quality is the first step. First, the dataset is loaded into the system, and each column's textual data is converted into floating-point representations. Using distinct picture index numbers, photographs are linked to related CSV files to accomplish this conversion. Any missing values (NAN) are then found and fixed using imputation methods like mean or mode replacement or by removing columns that contain unnecessary data. Lastly, to make analysis easier, categorical variables are encoded into numerical representations.

Feature Extraction: By creating new attributes from the existing ones and removing the original features, the suggested approach uses feature extraction to reduce the dataset's feature set. Since the CSV file only contains image height and width values, many contour features are extracted to improve classification accuracy.

A sampling of chest X-ray pictures is shown in Figure 3. Natural Language Processing (NLP) was used to annotate these photos, which could occasionally lead to inaccurate labeling. Despite the existence of a few bounding boxes defining disease-affected regions, the overall accuracy of NLP-based tagging is thought to be higher than 90%. The public release of chest x-ray radiology results is not anticipated. If users use this public dataset in their future study, they are urged to contribute their "updated" image descriptions and new bounding boxes, perhaps through human annotation.

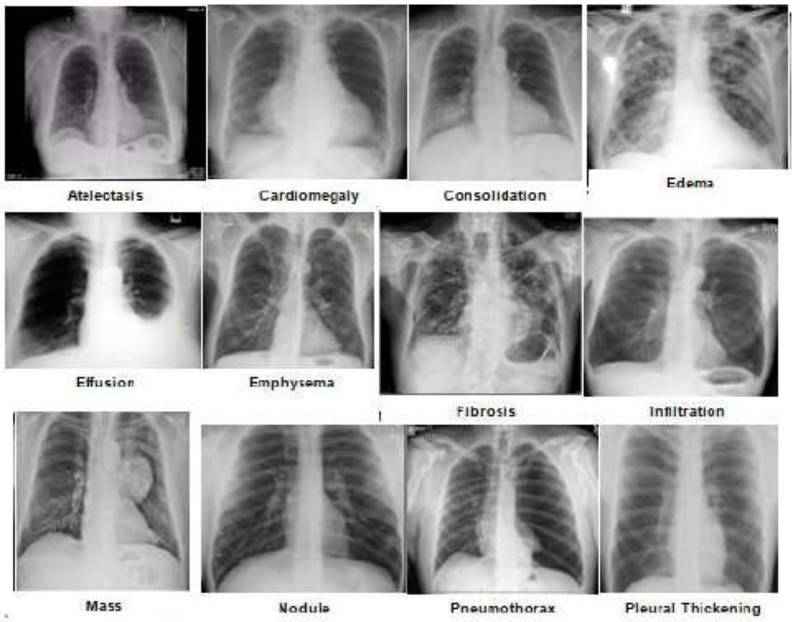

Figure 3: Chest x-ray images

Models Applied: VGG19

The advent of new technology has led to notable progress in the field of computer vision in recent years. Due to these advancements, computer vision models are now able to outperform humans in a number of tasks, including object identification, image categorization, face recognition, and image recognition. In this context, the development of deep convolutional neural networks, or CNNs, is significant. It is common knowledge that these networks can accurately evaluate visual imagery.

The Visual Geometry Group at the Department of Engineering Science at the University of Oxford is the source of the trained Convolutional Neural Network VGG-19. The number of trainable layers is 19. Three fully connected layers and sixteen convolutional layers are present. Winning the ILSVRC imagenet competition was the main objective of the VGG network [20].

The VGG19's picture input size is 224224. The convolutional layers of VGG use a small open field, specifically 33, which is the smallest size that truly captures left/right and up/down. A ReLU initiation capability comes next. ReLU stands for rectified straight unit enactment capability; if the information is positive, a piecewise direct capability returns it; otherwise, it returns zero. After convolution, the step is fixed to 1 pixel to maintain the spatial aim. Three fully connected layers make up the VGG19. The whole classes in the imagenet dataset are represented by the first two layers, which each contain 4096 hubs, and the third layer, which has 1000 hubs [21].

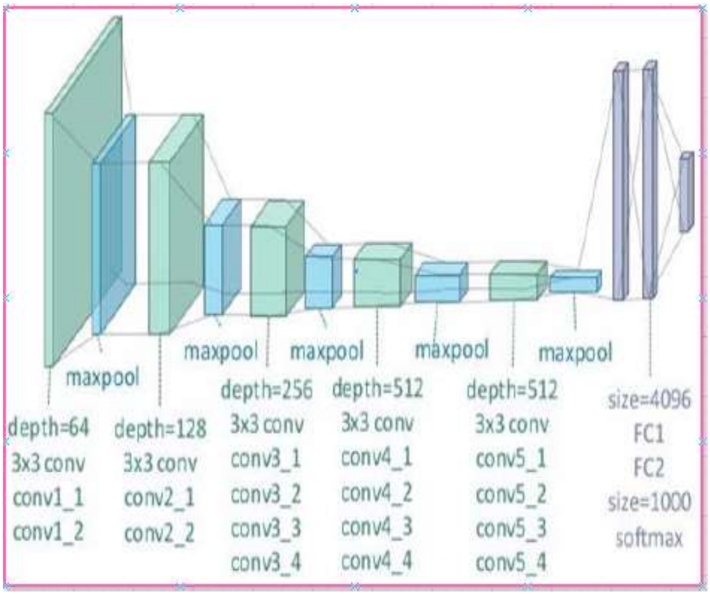

Figure 3: VGG19 architecture [21]

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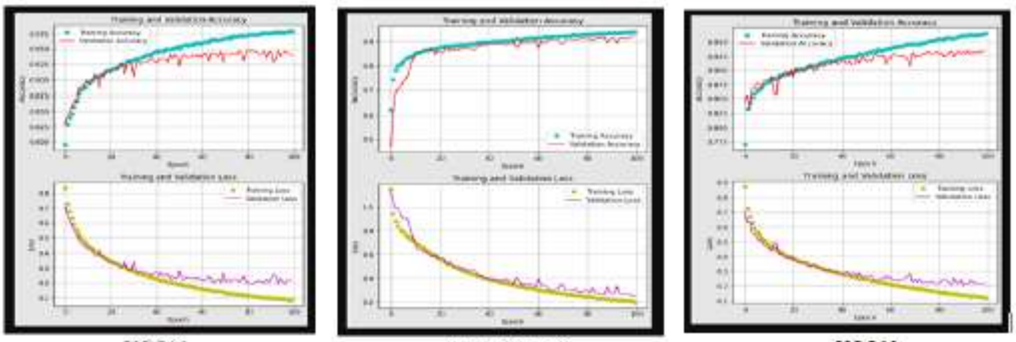
V. Results

The mean ideal metrics attained by the transfer learning models using federated-learning strategies are shown in Table 1. While deep transfer learning primarily deals with huge datasets, federated transfer learning solves privacy issues such traffic flow prediction, data attack avoidance, and management of extensive datasets. Accuracy, loss, and root mean square error (RMSE) values for the training and validation stages are among the metrics assessed. The VGG19 had the best precision throughout the training phase (94.23%), whereas MobileNetV2 has the lowest RMSE and loss values (0.124 and 0.358, respectively). In a similar vein, Inception V3 recorded the lowest loss and RMSE values (0.168 and 0.418, respectively) and the highest precision (97.11%) during the validation phase.

Table 1: Evaluation of Federated Learning Algorithms

Models	**Training**			**Validation**		
	Accuracy	**Loss**	**RMSE**	**Accuracy**	**Loss**	**RMSE**
VGG16	78.85	0.124	0.358	76.61	0.211	0.459
MobileNet V2	79.19	0.121	0.341	78.91	0.185	0.437
VGG19	94.23	0.229	0.471	97.11	0.168	0.418

VGG-19 from federated learning algorithms performed the best when compared to the other models of deep learning algorithms, according to an analysis of pre-trained models using both deep transfer learning and federated learning algorithms. Federated learning algorithms actually received the top scores when evaluated in terms of accuracy, loss, and root mean square error throughout the training and validation phases.



VGG16 MobileNet V2 VGG19

Figure 4: Analysis of models based on their accuracy and loss values

The training and validation losses of VGG16 and VGG19 in Figure 4 illustrate overfitting. It only occurs when the validation loss plot decreases to a certain point before rising once more, whereas the training loss plot keeps decreasing with experience. The training and validation loss curves shown by VGG16 and MobileNetV2 are much closer to being characterized as perfect fit learning curves since the plot of validation loss falls to the end of stability and has a tiny gap with the training loss. The training accuracy curve is higher than the validation accuracy curve for both follicular lymphoma and chronic lymphocytic leukemia, suggesting that the training dataset is easier to predict than the validation dataset.

VI. CONCLUSION

The topic of AI-based chest illness detection is expanding quickly in the medical sector. AI algorithms are trained to search for patterns or abnormalities in medical pictures, such as CT scans or chest X-rays, that may indicate the existence of a chest illness. One of the most widely used AI techniques for identifying chest conditions is convolutional neural networks (CNNs). CNNs are deep learning algorithms that look for patterns in an image by analyzing its pixels. SVMs are another AI technique that can be used to detect disorders of the chest. SVMs are machine learning algorithms that can classify images into different groups based on information extracted from the images. By using these AI techniques, doctors and other medical professionals can detect chest conditions more rapidly and precisely, perhaps leading to better patient outcomes. In this section, we looked at how the suggested model, VGG19, differs from the methods that researchers have employed to differentiate between various chest conditions. The correlation has been used in two scenarios: the first case relies on the comparable dataset, while the second case considers other datasets according to their correctness.

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