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Chest Disease Detection Using Deep Learning Models

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Abstract- DL models automate the analysis of medical images through techniques like prediction, segmentation, and classification, often achieving accuracy levels that surpass human capabilities. This is particularly valuable in medical fields where early and accurate diagnosis can significantly affect treatment success rates. For instance, in breast cancer screening, DL models can identify subtle signs of cancer in mammograms more accurately and earlier than traditional methods. Similarly, in lung cancer and brain tumors, DL models facilitate the detection of minute lesions and abnormalities that might be overlooked in manual examinations. This research work focuses on the detection of several chest diseases including lymphoma disease. We have employed DTL and FL models to make the prediction procedure more accessible and faster such as VGG-19. The research's proposed system was developed to predict 14 different kinds of chest conditions, and a comparison between federated learning and deep learning models was made. The proposed study describes a system that can predict lymphoma cancer with reasonable accuracy using sample images taken by various pathologists at different locations. A dataset titled malignant lymphoma classification dataset, which contains more than five thousand images, was used to analyze this study. When the models were evaluated, it was discovered that the VGG-16 model that was suggested had the best accuracy. Consequently, the classification report states that the VGG-16 model is the most effective deep and federated transfer-learning model for lymphoma cancer classification.

Index Terms—Chest Diseases, Deep Learning, X-ray, lymphoma, VGG-19, DL models

I. INTRODUCTION

With the passage of time the technologies in Artificial Intelligence has significantly advanced in scientific engineering domains. Sub-domains of artificial intelligence (AI) like machine learning (ML) and deep learning (DL), as well as related statistical tools, have attracted more and more interest. [1].So for these reasons many ML models are created to make use of the data that is already accessible and complete tasks like automatic prediction, segmentation, classification, clustering, and anomaly detection. But in order to train models for tasks like classification, labelled data is required to ensure consistent correctness.

Deep Learning (DL) model integration in healthcare and medical diagnosis systems represents a transformative shift, leveraging the advancements in artificial intelligence to enhance patient care and treatment outcomes. DL models, with their sophisticated architectures, have been instrumental in processing medical images, offering significant improvements in the diagnosis and prognosis of various life-threatening conditions such as breast cancer, lung cancer, and brain tumors.

These conditions, which require precise and early detection for effective treatment, have traditionally been challenging areas due to the labor-intensive and error-prone nature of manual analysis by doctors and specialists. Despite these advancements, DL models

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in medical diagnosis are not without limitations. One of the primary challenges is the need for large datasets to train these models effectively. Medical data, especially annotated images, are often scarce and difficult to obtain due to privacy concerns and the complexity of medical conditions. Furthermore, DL models require extensive processing power, for training and inference and are being readily available in all healthcare settings, particularly in low-resource environments [2].

Another concern is the interpretability of DL models. Medical professionals need to understand the rationale behind a model's predictions to trust and act upon them. However, many DL models, especially those based on complex architectures. Recurrent neural networks (RNNs) and Convolutional neural networks (CNNs) function as "black boxes," making it difficult to understand how they arrive at their findings. Moreover, DL models are sensitive to the data they are trained on, which means that biases in the training data can lead to skewed or inaccurate predictions. This is particularly problematic in medical diagnosis, where incorrect predictions can have serious implications for patient care [3].

In response to these limitations, ongoing research in the field is directed towards developing more efficient, transparent, and equitable DL models. Efforts include creating models that require fewer data for training, improving model interpretability, and designing algorithms that can mitigate biases in the data. As these advancements continue, DL models' potential for use in healthcare systems and medical diagnosis is expected to grow, offering more accurate, efficient, and accessible solutions for patient care.

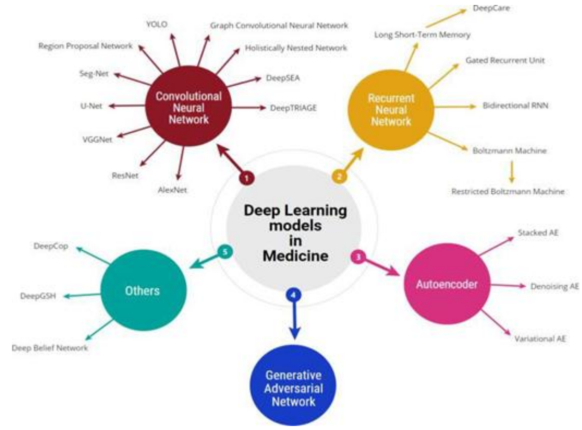

Figure 1: Deep Learning Models in Medical Science

Figure 1 representation categorizes the spectrum of DL models which are used in the medical arena into five distinct groups. Each group specializes in processing different types of data and is suited for specific tasks within medical diagnostics and research. Convolutional Neural Networks (CNNs) are primarily used for image recognition and segmentation tasks due to their proficiency in handling visual data. Recurrent Neural Networks (RNNs) are adept at dealing with sequential or time-series data, making them ideal for analyses where order and context are crucial. Auto-encoders are employed in unsupervised learning scenarios to reduce data dimensionality or clean noisy inputs, often used in imaging applications. Generative Adversarial Networks (GANs) have the unique capability to generate new, synthetic instances of data, which can be particularly useful for augmenting datasets where actual samples are scarce. Finally, the 'Others' category encompasses various alternative neural network architectures that are applied to diverse tasks in medical data processing, from predictive modeling to complex pattern recognition [4]. Collectively, these deep learning models are instrumental in advancing medical technology, improving patient care through enhanced diagnostic accuracy, and providing insights into disease characteristics and progression.

Two-dimensional (2D) CNN algorithms are primarily used in most applications in this area, and they take intensity patches as inputs [5]. Sometimes, post-processing calculations such as probabilistic graphical models are used to maintain spatial consistency in a secondary step. Nonetheless, the duration needed to hone patch-based techniques can make the process unworkable, particularly when dealing with a substantial quantity and size of patches.

In recent advancements within the field of computer vision, especially in medical imaging, Convolutional Neural Networks (CNNs) have undergone significant evolution to enhance their efficiency and effectiveness. Traditional CNN approaches often relied on the manual selection of representative patches from images, a process that not only required additional preprocessing efforts but also introduced the risk of missing critical information outside these selected areas [6]. Moreover, this patch-based approach led to redundant computations, particularly in regions where patches overlapped, resulting in inefficiencies in both processing time and computational resource usage.

Addressing these challenges, new CNN architectures have been developed with the capability to process entire images in a single pass. This innovation marks a significant departure from the patch-based methods, offering a more holistic approach to image analysis. By analyzing entire images at once, these advanced CNN models ensure that no potentially informative part of the image is overlooked due to selective patching. Furthermore, the direct processing of whole images eliminates the redundancies associated with overlapping patches, thereby streamlining the computational process [7].

An additional benefit of these evolved CNN architectures is their improved scalability with respect to image resolution. As medical imaging technology progresses, producing higher-resolution images, the ability to efficiently scale model performance without a corresponding increase in computational burden becomes increasingly important. These newer CNN models are designed with scalability in mind, enabling them to handle higher-resolution images more effectively. This not only enhances the accuracy of the analyses but also ensures that the models can keep pace with advancements in imaging technology without requiring exponential increases in processing power or time [8].

Although deep learning is part of the long-standing class of ML with image based ML, its usage has lately acquired prominence when "deep learning" is introduced. The two main models used in ML for medical imaging are CNN and MTANN, and they have a number of distinctions in addition to certain commonalities. In comparison with CNNs, we found that MTANNs required fewer training cases, performed better, and were significantly more efficient in their development. Medical imaging "deep learning," or machine learning with image input, is a rapidly expanding and exciting topic. In the coming decades, machine learning with image input is anticipated to become the dominant field in medical imaging [9-10]. Deep learning models are revolutionizing medical diagnostics by detecting a wide range of diseases. This study focuses on chest disease detection, aiming to improve precision and speed in diagnosing respiratory conditions.

II. LITERATURE WORK

Nasser A.A. et al. (2023) [11] developed a two-step approach for classifying chest-related diseases using X-ray images. The first step involves a multi-class classification process, sorting images into normal, lung disease, and heart disease categories. The second phase is a binary classification to identify seven specific diseases affecting the lungs and heart. The researchers used 26,316 chest X-ray images and introduced two unique deep learning models, DC-ChestNet and VT-ChestNet. The VT-ChestNet model outperformed other models, achieving an impressive AUC score of 95.13% in the multi-class classification phase and an AUC of 99.26% for heart disease diagnosis and 99.57% for lung disease identification.
Naveen et al. (2020) [12] study explores the potential for AI to worsen health disparities in clinical decision-making in healthcare. They argue that AI algorithms may use protected characteristics like race or biological sex, resulting from biases in historical training data. The study uses chest X-ray datasets, CheXpert and MIMIC-CXR, to analyze the performance of deep learning models across different subgroups, considering race and biological sex as influencing factors. Using analytical methodologies like transfer learning, test set resampling, comprehensive model inspection, and multitask learning, the study reveals disparities in true and false positive rates among subgroups. The study emphasizes the importance of accounting for statistical variations among subgroups when evaluating potential biases in

disease detection. The methodology provides a comprehensive framework for identifying performance disparities and contributing to the development of more equitable AI systems in healthcare.

Glocker, B. et al. (2023) [13] took the application of deep learning in chest disease diagnosis to a new level with the development of VDSNet, a hybrid deep learning framework that integrates the Visual Geometry Group (VGG) neural network with data augmentation and a spatial transformer network within a CNN architecture. This sophisticated combination was applied to the full National Institutes of Health (NIH) Chest X-ray dataset available on Kaggle, a popular data science platform hosting a variety of medical datasets. The hybrid model, VDSNet, excelled in its performance, surpassing existing methods by achieving a validation accuracy of 73%. Such a result is indicative of the potential that innovative deep learning frameworks have in refining the accuracy and reliability of medical imaging analyses, offering a promising direction for future research and application in clinical diagnostics.

Nandipati Sai Akash et al. (2023) [14] introduced LungNet, a hybrid model that integrates deep-convolutional neural network architecture with data gleaned from wearable sensor-based medical Internet of Things (IoT) devices. This fusion aimed to capitalize on the extensive data available from both advanced medical imaging and the growing field of wearable healthcare technology. LungNet was meticulously trained on a vast dataset comprising over half a million images, demonstrating an extraordinary ability to accurately diagnose lung cancer with an overall accuracy of 96.81%. Moreover, the model displayed remarkable precision in distinguishing between stage-1 and stage-2 lung cancers, with an accuracy of 91.6%. Such precision in early-stage cancer detection could significantly impact the landscape of oncological diagnostics, offering the potential to markedly improve patient prognoses through earlier intervention and customized treatment plans. The success of LungNet signifies a leap forward in the amalgamation of deep learning models with practical clinical application, setting a new benchmark in the early detection and classification of lung cancer.

Intense Leukemia is a bone marrow sickness that influences the two youngsters and grown-ups. In Digital Image Processing (DIP) and Deep Learning, clinical picture examination is used (DL). Deep learning's commitment to Big Data clinical exploration has been massively gainful, offering new roads and opportunities for disease analysis procedures. Deep understanding is now being used by medical specialists such as pathologists, hematologists, mammalogists, and researchers. The proposed methodology used by researchers (DD Sarpateet al. 2020) [15] is Leukemia identification utilizing the Apache Spark BigDL package and Convolutional Neural Network (CNN) architecture GoogleNet deep transfer learning using microscopic images of human blood cells. The proposed method can identify four distinct types of Leukemia: Acute Lymphocytic Leukemia (ALL), Acute Myeloid Leukemia (AML), Chronic Myeloid Leukemia (CML), and Chronic Lymphocytic Leukemia (CLL). Utilizing microscopic images of human blood samples, the study obtained a training accuracy of 97.33% and a validation accuracy of 94.78% with the recommended methodology and the Spark BigDL framework employing the Google Net architecture [16]. A comparison was made between the model with and without BigDLGoogleNet, resulting in training and validation accuracies of 96.42% and 92.69%, respectively. The BigDL model demonstrated superior efficiency and accuracy compared to the Keras model, providing more reliable outputs [17,18].

Guo, Y. et al. (2021) [19] address the urgent global challenge posed by the COVID-19 pandemic, emphasizing the critical need for early, non-invasive, and time-efficient diagnostic methods. With the spread of the virus accelerating research into its detection, the study highlights the current reliance on Computed Tomography (CT), Ultrasound (US) imaging, and X-Ray, alongside Polymerase Chain Reaction (PCR) tests, which are manually analyzed by medical specialists. Noting the widespread availability of CT scanners and X-Ray machines across healthcare facilities in Pakistan, from district to tehsil levels, the authors propose an automated detection system utilizing Convolutional Neural Networks (CNN) to manage the large volumes of medical imaging data generated [20]. The CNN model proposed in this study demonstrates significant diagnostic efficacy by

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incorporating three publicly available datasets along with a locally curated dataset from the Department of Radiology at MS Ramayya Hospital, Bangalore (MSRHB), India. It achieved an average accuracy of 96.68%, sensitivity of 96.24%, along with specificity of 95.65%. The model's robust training on extensive datasets underscores its utility and effectiveness in the Radiology Department at MSRHB, offering a promising alternative to manual diagnostic methods and contributing significantly to the efforts against COVID-19 [20].

III. RESEARCH DESIGN

In the context of healthcare, particularly in diagnosing chest disorders and lymphoma, there exists a critical need for developing more sophisticated, accurate, and efficient diagnostic tools. Traditional diagnostic methods, while effective to a degree, often fall short in terms of speed, scalability, and sometimes accuracy, due to the subjective nature of human analysis and the growing complexity of medical data. Consequently, there is a pressing demand for innovative solutions that can leverage the vast amounts of medical imaging data to improve diagnostic processes.

The utilization of deep learning and federated learning models presents a promising avenue for addressing these challenges. These models have the potential to significantly enhance the detection and classification of diseases by analyzing medical images with a level of precision and speed unattainable by human capabilities alone. However, developing machine learning models that can accurately identify and classify a wide range of chest disorders and lymphoma from medical images poses several challenges, including data privacy concerns, the need for extensive training data, and the requirement for models to be both highly accurate and efficient in processing and analysis.

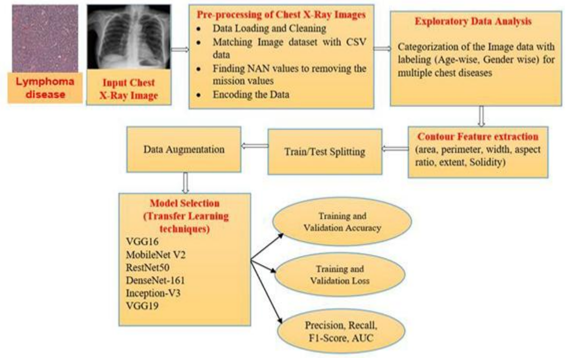

Figure 2: Proposed System

To detect various chest diseases, the contribution that has been made to conduct the research work (figure 3.1) has been shown as under:

1. The data has been collected from two datasets such as NIH chest xray and Malignant Lymphoma Classification.
2. The study employed a novel strategy that combines transfer learning with deep and federated learning techniques to effectively classify chest conditions.
3. Data preprocessing procedures were undertaken to ensure data integrity, alignment with the .csv dataset, handling of missing values (NAN), and data encoding.
4. After preprocessing, the data was visually represented and summarized graphically. This aided in extracting features such as area, perimeter, aspect ratio, and solidity from the data."
5. The dataset was partitioned into training and testing subsets, with a division ratio of 75% for training and 25% for testing. Various augmentation techniques, including flipping and rotation, were applied to enhance dataset diversity.
6. Finally, pre-trained models such as DenseNet-161, Inception V3, ResNet50,MobileNet V2, VGG16, and VGG19 were leveraged for classification tasks. The performance evaluation of these models was conducted using precision rate and recall rate metrics.

IV. MATERIAL AND METHODS

Dataset: Publicly accessible datasets for chest X-rays have historically been limited. Previously, Openi served as a prominent source, offering 4,413 images. "However, for this study, we utilized the National Institutes of Health (NIH) chest X-ray dataset, containing 112,120 images and disease annotations for 30,805 individuals. These annotations were developed using Natural Language Processing (NLP) methods to extract accurate information from disease classifications (Gilanie, G. et al., 2021).

Likewise, for lymphoma "Malignant Lymphoma Classification" dataset has been used which is available at Kaggle. There are a total of 5400 images available, as well as specimens generated by various pathologists at various locations. Three variants of Lymphoma are represented in this dataset namely, Chronic Lymphocytic Leukemia (CLL), Follicular Lymphoma (FL), and, Mantle Cell Lymphoma (MCL). This dataset has the capability of identifying types of lymphoma from biopsies that are sectioned plus tinted with Hematoxylin/Eosin (H+E) that aids in extra compatibility and less challenging disease diagnosis [22]. Some of the dataset features are such as 5400 total images of size: 1388 x 1400; consists of three folders named CLL, FL, and, MCL; the images are provided in .tif format and at last Images are in a standard RGB color space.

Data Pre-Processing: The initial step involves preprocessing the chest X-ray images to enhance their quality. This process begins by loading the dataset into the system and converting textual data into floating-point representations for each column. This conversion is achieved by linking images with corresponding CSV files using unique image index numbers. Subsequently, any missing values (NAN) are identified and addressed through imputation techniques such as mean or mode replacement, or by dropping columns containing unused data. Finally, categorical variables are encoded into numerical representations to facilitate analysis.

Exploratory Data Analysis: This step is mainly executed to examine and study the input dataset mainly for their critical characteristics by employing several techniques of data visualization. Utilizing exploratory data analysis (EDA) techniques, the proposed system conducts an in-depth examination of the dataset's characteristics.

Feature Extraction: The proposed system conducts feature extraction to diminish the dataset's feature set by crafting novel attributes from the existing ones while discarding the original features (Naveen et al., 2022) [23]. Given that the CSV dataset solely includes height and width values for images, numerous contour characteristics are derived to enhance classification precision.

V. MODELS APPLIED: VGG19

Recent years have seen significant advancements in the field of computer vision as a result of the introduction of new technologies. These developments have made it so that computer vision models can now perform better than humans at various tasks like image classification, object detection, face recognition, and image recognition. Developing deep convolutional neural networks or CNNs is noteworthy in this regard. The accuracy with which these networks have been used to analyze visual imagery is well known [24].

The Visual Geometry Group (VGG) is situated within the Department of Science and Engineering at Oxford University, as noted by Habeeb et al. (2022). Sundaralingam, A et al. (2020) focused on investigating the impact of convolutional network depth on the precision and accuracy of extensive image categorization and recognition in their study of VGG's convolutional network depth [25,26].

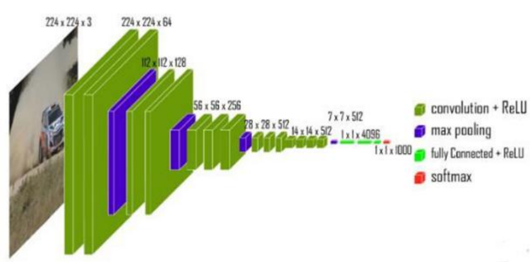

Figure 3: VGG16 architecture

A dimensioned picture as displayed in figure 3 is used as the organization's contribution of size (224, 224, 3). Every one of the first and second layers has 64 channels, cushioning of 1, and a 3*3 channel size. Two layers with convolution layers of 256 channel size and channel size are added after a maximum pool layer of step (2, 2). (3, 3). The following layer is a step (2, 2) max-pooling layer that is indistinguishable from the past layer [27]. The subsequent convolution layers comprise filters with dimensions of (3, 3) and a total of 256 filters. Following this, there are two groups of three convolution layers each, accompanied by a max-pooling layer. Each of these layers consists of 512 filters with identical padding and dimensions of (3, 3). Subsequently, the output from these layers is passed through a two-layer convolution stack. Unlike AlexNet and ZF-Net, which utilize 11*11 filters, the convolutional and max-pooling layers in this architecture employ 3*3 filters. Additionally, it adjusts the number of input channels by using 1*11 pixels in some layers. After each convolution layer, 1-pixel padding (the same padding) is applied to prevent the spatial feature of the image (geeksforgeeks/VGG16) [28].

VI. RESULTS

This part covers the performance of the deep transfer learning models during training and testing phase of chest diseases along with their computational time.

Table 1 illustrates the mean optimal values of assessment parameters associated with various transfer learning models. These metrics encompass accuracy, loss, and RMSE (Root Mean Square Error) values for both the training and validation stages. The proposed system is geared towards diagnosing chest infections in patients through analysis of chest X-ray images. Notably, DenseNet161 achieved the highest accuracy of 88.01%, while Inception V3 exhibited the lowest loss and RMSE values during training, registering at 0.324 and 0.569, respectively. Similarly, in the validation phase, MobileNetV2 demonstrated the highest accuracy of 88.09%, with Inception V3 recording the lowest loss and RMSE values, at 0.321 and 0.566, respectively.

Table 1: Evaluation of Deep Transfer Learning Algorithms

Models	Training			Validation		
	Accuracy	Loss	RMSE	Accuracy	Loss	RMSE
VGG-16	87.33	0.447	0.668	86.43	0.720	0.848
MobileNet V2	85.46	0.468	0.684	**88.09**	0.582	0.762
ResNet50	87.46	0.410	0.640	87.41	0.355	0.595

Table 2 presents the superior precision and recall rates observed in the VGG-16 model, culminating in the highest F1 score automatically. Thus, the classification report underscores the VGG-16 model's efficacy in accurately and efficiently classifying chest infections, affirming its status as the preeminent transfer learning model for this application.

Table 2: Classification using Deep Transfer Learning

Models	Precision	Recall	F1 Score
VGG-16	0.82	0.91	0.86
MobileNet V2	0.78	0.90	0.85
ResNet50	0.77	0.74	0.76
VGG-19	0.78	0.89	0.84

VII. CONCLUSION

The medical industry is seeing rapid growth in the field of AI-based chest disease detection. AI systems are taught to look for patterns or anomalies in medical images like chest X-rays or CT scans that might point to the presence of a chest disease. Convolutional Neural Networks are one of the AI methods for detecting chest diseases that are most frequently employed (CNNs). CNNs are deep learning algorithms that examine the pixels in an image to identify patterns. Another AI method that can be used to identify chest diseases is SVMs. Using features taken from the images, SVMs are machine learning algorithms that can categorise images into various groups. These AI methods allow physicians and other healthcare professionals to diagnose chest diseases more quickly and accurately, which can improve patient outcomes. In this part, we've examined about standing out the proposed model i.e VGG16 from the techniques that researchers have used to distinguish different chest diseases. The correlation has been acted in two situations where the primary case depends on the equivalent dataset and the subsequent case is for various dataset based on their accuracy.

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