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Enhanced Detection and Classification of Chest Diseases Using Modified VGG16 Deep Neural Network

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Abstract

For efficient medical diagnostics and patient care, prompt and accurate identification of chest disorders is required. Conventional techniques that depend on manual radiography picture interpretation are frequently hampered by time restrictions and human error. In order to improve the diagnosis of chest ailments, this research investigates the integration of deep learning techniques, particularly deep convolutional neural networks (CNNs). We investigate the possibility of VGG16, a well-known CNN architecture created by the Visual Geometry Group (VGG), to automate and enhance diagnostic accuracy. VGG16, characterized by its 16-layer architecture and use of small receptive fields, excels in recognizing complex patterns within medical images. Its application in detecting conditions such as atelectasis, cardiomegaly, masses, and nodules is discussed, highlighting its ability to discern subtle abnormalities and facilitate early diagnosis. Through a review of recent advancements and performance evaluations on benchmark datasets, this paper provides in- sights into VGG16's effectiveness, identifies key challenges, and outlines future research directions in lever- aging deep learning for medical imaging.

Keywords: Deep Learning, Convolutional Neural Networks, VGG16, Medical Imaging, Automated De tection.

1. Introduction

In medical diagnostics, the timely and precise identification of chest disorders is crucial since it has a direct impact on treatment strategies and patient outcomes. With their own diagnostic difficulties, chest disorders encompass a wide range of illnesses that impact the lungs and other thoracic structures. Common chest conditions such as atelectasis, cardiomegaly, masses, and nodules can have a serious negative effect on a patient's health if they are not identified and treated right once. The manual interpretation of radiographic pictures by radiologists is the mainstay of traditional di- agnostic techniques, and it can be laborious and risky. By automating and improving the precision of disease identification, the incorporation methods of deep learning specifically, deep convolutional neural networks, or CNNs—into the diagnostic procedure presents a viable way to address these issues. With the introduction of deep convolutional neural networks (CNNs), especially sophisticated models like VGG16, diagnostic efficiency and accuracy can be significantly improved.

Due to its ease of use and efficiency in image recognition applications, VGG16 has drawn a lot of interest among the many CNN designs. VGG16 was created by the University of Oxford's Visual Geometry Group (VGG) and is distinguished by its deep architecture, which consists of 16 weight layers, including 3 fully linked layers and 13 convolutional layers. To capture complex information in the input images, this network's design places a strong emphasis on the usage of deep networks and narrow receptive fields (3x3 convolutional filters). The architecture of VGG16 makes it especially well-suited for medical imaging applications where the capacity to identify intricate and delicate pat- terns is essential.

VGG16 is used to diagnose disorders of the chest by using datasets of labeled chest X-rays to train the net- work to identify patterns linked to particular conditions. On chest radiographs, for example, atelectasis, which is defined by the collapse of lung tissue, appears as areas of increased opacity that are difficult to identify. By learning to recognize these minute alterations, VGG16 can increase the likelihood of early diagnosis. Similar to this, cardiomegaly, which is characterized by an enlarged heart silhouette, calls for accurate measurement and analysis, which VGG16's powerful feature extraction capabilities may help with.

This study examines the automated detection of a number of chest conditions using the modified VGG16 architecture, highlighting new developments and the possibility of bettering clinical results. VGG16's incorporation into clinical procedures is a major step forward in using artificial intelligence to enhance radiologists' skills, improve diagnostic precision, and ultimately benefit patients. Our objective is to present a thorough analysis of VGG16's capabilities, pinpoint important issues, and talk about prospects for further study in this quickly developing area by looking at how well it performs on benchmark datasets. Our objective is to present a thorough analysis of how VGG16 and related deep learning architectures can influence medical imaging in the future by looking at recent studies and suggesting new lines of inquiry.

2. Related Work

A significant worldwide health burden, chest disorders must be identified early and accurately in order to be properly treated and managed. Deep learning methods have completely changed medical image analysis by offering reliable instruments for the automatic identification and categorization of different lung diseases from chest X-ray pictures. With an emphasis on methodology, datasets, and performance outcomes, this literature review examines current research efforts in applying deep learning for the identification of chest diseases.

Advances in deep learning, particularly deep convolutional neural networks (CNNs), have significantly enhanced the ability to identify and classify chest diseases from X-ray images. To improve the accuracy and efficacy of identifying chest ailments, a number of research studies have proposed novel strategies and architectures that leverage CNN capabilities.

The YOLO v5 algorithm was used by WenZe Fan et al. in 2021 [1] to offer an improper target identification approach in chest radiography. This method showed promise in combining CNNs and object detection algorithms for medical image analysis by finding anomalies in chest X-rays with strong performance.

The identification of lung illnesses from chest X-ray images using deep learning techniques has been extensively studied. Highlighting the advantages of pre-trained models and ensemble methodologies, Mostofa Kamal Sagor et al. 2021 [2] presented an effective model utilizing transfer learning and ensemble modling. Similarly, a CNN-based method for identifying thoracic disorders was developed by Siddhika Arunachalam and Prasenjit Bhavathankar et al. in 2021 [3], with notable improvements in detection rates. Labiba Fahad and Syed Krar Haider Bukhari et al. 2022 [9] showed how well CNNs recognize and categorize a range of lung conditions.

A number of studies concentrated on improving and optimizing CNN designs. A lightweight CNN architecture was created by Md. Rakibul Haque and Md. Al Mamun et al. in 2022 [6] with the goal of detecting lung disorders early on in contexts with limited resources. Siddiqua, Saba In order to integrate the advantages of both CNN and SVM for automatic lung illness identification, Sadique Ahmed Siddiqui et al. 2023 [13] did just that. Fatma A. Mostafa et al. 2023 [14] investigated fusion methods to improve diagnostic precision, emphasizing the possibilities of merging several CNN models.

There was additional research on particular lung disorders and severity evaluations. For determining the severity of lung disorders, Chathurika K.B.A.B. and Gamage A. et al. 2022 [7] created a deep learning-based risk level indicator. CNNs were utilized by Ryunosuke Maeda et al. in 2022 [8] and 2023 [12] to forecast the severity and progression of neonatal chronic lung illness, emphasizing the importance of early identification and treatment. CNNs' adaptability in diagnosing heart-related illnesses was demonstrated by Zahraa Ch. Oleiwe et al. 2023 [18], who devised a classification system for predicting cardiomegaly.

Mehedi Hasan Imran et al. 2023 [15] and Swati Patil et al. 2022 [10] were two studies that concentrated on using CNNs in conjunction with sophisticated image processing methods to accurately diagnose and localize lung illnesses. To promote effective clinical diagnosis, Archana D et al. 2023 [17] also suggested an automated classification technique for chest pictures.

Analyses of datasets and comparisons yielded important findings. A thorough assessment of public datasets of chest X-rays used to classify lung diseases was carried out by Sreena V. G. et al. in 2021 [4], who also identified useful data sources. Samuel Vasamsetti et al. 2023 [20] examined the advantages and disadvantages of deep learning models for predicting lung diseases. To enhance model training and validation, Yassamine Lala Bouali et al. 2021 [5]

presented an image dataset created especially for lung illness diagnosis.

The field got even more advanced thanks to innovative approaches. A genetic CNN technique, which combines CNNs and genetic algorithms to maximize performance, was presented by Amina Djoudi et al. Chest Disease Detection and Classification 2023 [23]. The efficiency of deep neural architectures for influenza classification from chest radiography was shown by T. Jemima Jebaseeli et al. 2023 [24]. For illness identification, Ashhadul Islam et al. 2024 [25] suggested a novel radon-based transform that improves feature extraction for higher diagnostic accuracy.

The significance of deep learning in managing viral infections was highlighted by research such as P.V. Naresh et al. 2023 [11] and Kosaraju Chaitanya et al. 2023 [21], which examined CNN-based models for COVID-19 detection and spread prediction.

Current research on chest X-ray-based disease detection faces several challenges. These include narrow dataset diversity resulting in biased predictions (Sreena et al. [4], Bouali et al. [5], Salma Sultana, Anik Pramanik, Md. Sadekur Rahman et al. [22]), overfitting in deep networks (Fan et al. [1], Fahad et al. [9], Vasamsetti et al. [20]), and striking a balance between model complexity and diagnostic accuracy (Haque and Al Mamun et al. [6], Mostafa et al. [14]). These issues hinder the successful implementation of deep learning models in healthcare environments.

Using one of the visual geometry group's convolutional neural networks aims to identify common chest conditions such as atelectasis, cardiomegaly, masses, and nodules. A computer vision technique called class activation maps (CAM) will be utilized to highlight the region of the x-ray picture that is used to detect the pathological condition in order to increase interpretability to improve the model's general functionality by adjusting a few VGG16 settings.

3. Proposed Methodology for Chest Disease Detection and Classification

The flow diagram for identifying certain disorders of the chest, such as masses, nodules, cardiomegaly, and atelectasis, is displayed in Figure 1. In the first step, the chest X-ray dataset is acquired, pre-processed, and divided into training and testing sets. Additionally, training will be conducted using a CNN architecture (VGG16) that has been modified as needed. The accuracy and loss of each disease will then be determined, and a test dataset will be used to make the disease prediction.

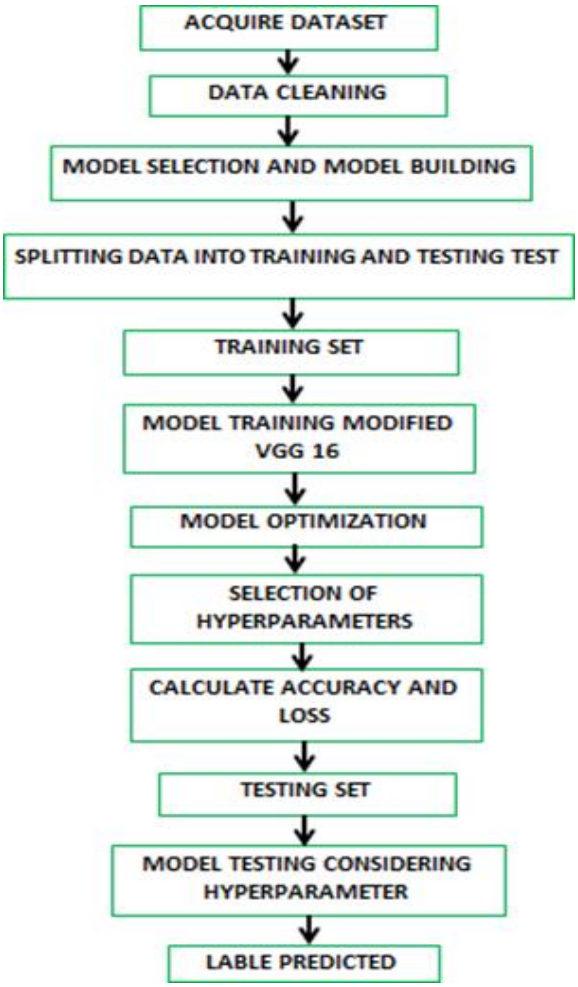


Figure 1. Flow Diagram of the Proposed Model for Chest Disease Detection and Classification

Dataset

For our research, we used the publicly available NIH Chest X-ray dataset on Kaggle. This dataset consists of thousands of X-ray images of the frontal chest annotated with 14 distinct thoracic illness diagnoses. For this study, we concentrated on four distinct diseases: mass, nodule, cardiomegaly, and atelectasis.

A few samples of chest X-ray pictures are shown in Figure 2. Pixels in each image in the collection are 1024 by 1024.

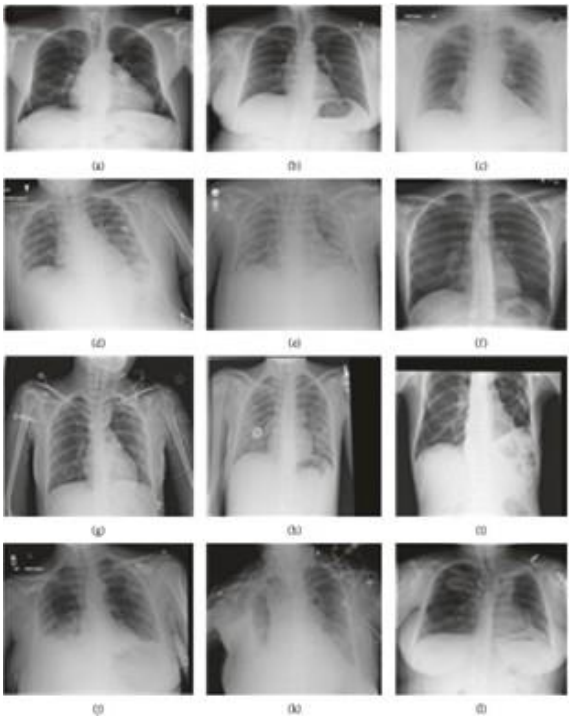


Figure 2. Samples of chest x-ray images.

Implementation of the Modified Vgg16 Model

The VGG16 model and a number of specially designed fully connected layers are included in the suggested model architecture for chest disease detection in order to accomplish multi-class classification as shown in figure 3. A 100x100 RGB picture is fed into the model, and deep hierarchical features are extracted using the pre-trained VGG16 model.

After that, a 4608-dimensional vector is created by flattening the 3x3x512 feature map that was produced using VGG16. Before arriving at the final output layer, this vector is routed via a series of four fully linked layers that gradually reduce the dimensionality from 4608 to 32 neurons. The output layer utilizes a softmax activation function to classify data, with four neurons rep- resenting the four target classes.

For testing, 30 percent of the dataset is utilized, while seventy percent is used to train the proposed model. For effective data handling, the suggested model is trained using a generator and built using the RMSProp optimizer with categorical crossentropy loss. The model's performance across 30 epochs was monitored using ac- curacy and loss curves from training and testing. The training results showed a steady increase in accuracy with a corresponding decrease in loss, indicating effective learning from the training data.

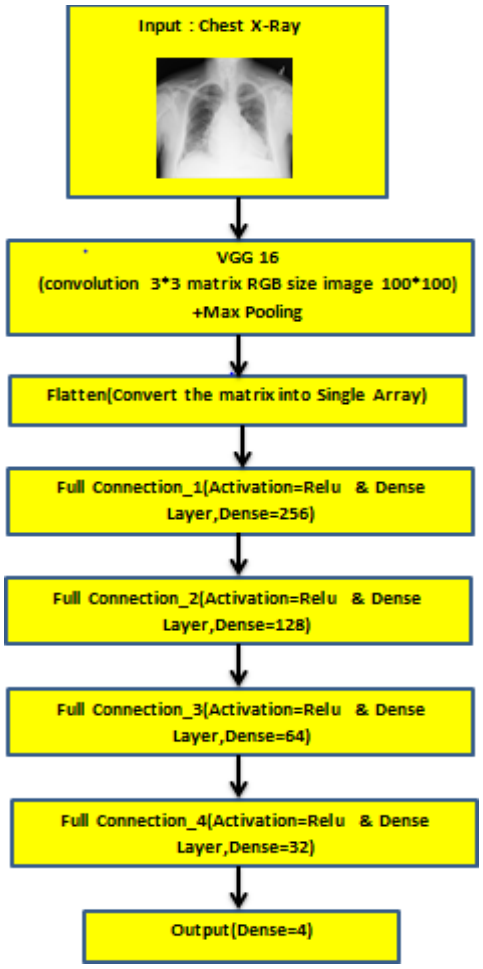


Figure 3. Architecture of the Modified VGG16 Model for Chest Disease Detection and Classification.

4. Result

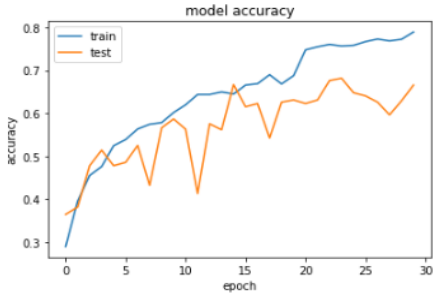
A sequence of fully connected (dense) layers that progressively reduces the dimensionality from 4608 features to 4 output classes (as shown in figure 4) is incorporated into the suggested model architecture after a feature extraction process based on VGG16.Accuracy and loss from training and testing over 30 epochs are used to assess this model's performance, as shown in Figure 5: Accuracy and Loss Curve of Modified VGG16 Model. While the training accuracy steadily rises to almost 78 percent by the 30th epoch, the test accuracy fluctuates and peaks at roughly 62 percent, as seen in Table 1. The test accuracy does, however, vary noticeably, suggesting that the model is struggling to extrapolate to the unknown data. The model may be overfitting if it fits training data well but performs badly on test data, as indicated by this oscillation. By the 30th epoch, the test accuracy trails the training accuracy, which may indicate overfitting.

Likewise, the training loss continuously drops, suggesting that the model is picking up knowledge from

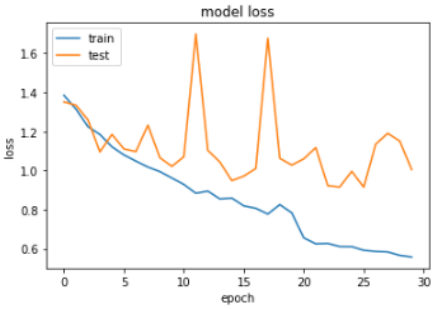
the training set. The test loss is still erratic and greater than the training loss, though, which further points to overfitting.

```
Model: "sequential_5"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
vgg16 (Model)                (None, 3, 3, 512)         14714688
_________________________________________________________________
flatten_5 (Flatten)          (None, 4608)              0
_________________________________________________________________
FC1 (Dense)                  (None, 256)               1179904
_________________________________________________________________
FC2 (Dense)                  (None, 128)               32896
_________________________________________________________________
FC3 (Dense)                  (None, 64)                8256
_________________________________________________________________
FC4 (Dense)                  (None, 32)                2080
_________________________________________________________________
Output (Dense)               (None, 4)                 132
=================================================================
Total params: 15,937,956
Trainable params: 1,223,268
Non-trainable params: 14,714,688
```

Figure 4. Architecture Summary of the Modified VGG16 Model for Chest Disease Detection and Classification.



a) Accuracy



b) Loss

Figure 5. Modified VGG16 Model Accuracy and Loss Curve

Table 1: Result Analysis Modified Vgg16 Model

Model	Train Accuracy (%)	Test Accuracy (%)	Accuracy Difference (%)	Train Loss (%)	Test loss%	Model Performance
VGG16 Model	**78.9**	**62.7**	**16.2**	**0.55**	**1.6**	**Overfitting**

5. Comparison with Other Models

We have compared our model with the other existing models that we have covered during over literature reviewing and have listed the accuracy in Table 2. Bar charts of the accuracy of the models are also shown in Figure 6.

Table 2: Comparison with Other Models

Model	Accuracy
VGG16[12]	**56%**
AlexNet[12]	**60.00%**
Our Model	**78.98%**

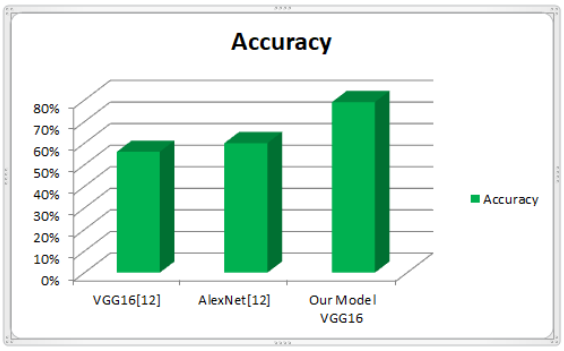


Figure 6. Accuracy of previous models versus our model using a bar chart

6. Conclusion and Future Works

This proposed model provides an accuracy of 78.9 percent for 30 epochs. The proposed architecture, though effective in learning from the training data, demonstrates overfitting, as shown by the difference between metrics used for testing and training. This shows that although the model has mastered the

training set, it is unable to generalize adequately to the test data.

Future research should think about using strategies like regularization and dropout layers to lessen overfitting or data augmentation to boost the variety of the training data in order to solve this problem and improve the model's generalization skills. These improvements might increase the model's resilience and result in improved performance on data that hasn't been seen before. In order to guide future developments for more accurate chest illness diagnosis, this research offers a thorough grasp of the model's design and existing limitations.

Additionally, exploring multimodal data inputs, such as combining X-ray images with clinical data, could further boost diagnostic performance. Finally, real world validation using datasets from various hospitals would be essential to assess the model's practical applicability.

References

[1] WenZe Fan, Xingchen Guo, Lei Teng, YuX- uan Wu et al., Research on Abnormal Tar- get Detection Method in Chest Radiograph Based on YOLO v5 Algorithm," IEEE International Conference on Computer Science, Electronic Information Engineering and Intelligent Control Technology (CEI) 2021, IEEE. DOI: 10.1109/CEI52496.2021. 9574450.

[2] Mostofa Kamal Sagor, Shakib Mahmud Dipto, Ishrat Jahan, Susmita Chowdhury, Md Tanzim Reza, and Md Ashraful Alam et al., "An Efficient Deep Learning Approach for Detecting Lung Disease from Chest X-Ray Images Using Transfer Learning and Ensemble Modeling," Asia-Pacific Conference on Computer Science and Data Engineering (CSDE) 2021 IEEE. DOI: 10.1109/ CSDE53843.2021.9718454.

[3] Siddhika Arunachalam, Prasenjit Bhavathankar et al., "Deep Learning Approach for Diagnosis of Thoracic Diseases from Chest X-Ray Images," International Conference on Communication Information and Computing Technology (ICCICT) 2021, IEEE. DOI: 10.1109/IC- CICT50803.2021. 951013.

[4] Sreena V G, Narain Ponraj, and Deepa P L et al., "Study on Public Chest X-ray Data sets for Lung Disease Classification", 2021 3rd International Conference on Signal Processing and Communication (ICPSC) 2021, IEEE. DOI: 10.1109/ ICSPC51351.2021.9451726.

[5] Yassamine Lala Bouali, Isra Boucetta, Imad Eddine Ibrahim Bekkouch, Mourad Bouache, Smaine Mazouzi et al., "An Image Dataset for Lung Disease Detection and Classification," International Conference on Theoretical and Applicative Aspects of Computer Science (ICTAACS) 2021, IEEE. DOI: 10.1109/IC- TAACS53298.2021. 9715227.

[6] Md Rakibul Haque and Md. Al Mamun et al., "A Lightweight CNN Architecture for Chest X-ray Images Analysis to Facilitate Early Stage Detection of Lung Diseases," 2022 25th International Conference on Computer and Information Tech- nology (ICCIT) 17-19 December 2022, IEEE. DOI:10.1109/ICCIT57492.2022.10054663.

[7] Chathurika K.B.A.B., Gamage A. et al.," Deep Learning Approach for Designing and Development of Risk Level Indicator for Patients with Lung Diseases," 2nd International Conference on Advanced Research in Computing (ICARC) 2022, IEEE. DOI: 10.1109/ICARC54489. 2022.975397.

[8] Ryunosuke Maeda, Daisuke Fujita, Kosuke Tanaka, Jyunichi Ozawa, Mitsuhiro Haga, Haoyuki Miyahara, Fumihiko Nanba, Syoji Kobashi et al., "Predicting the severity of Neonatal Chronic Lung Disease from chest X-ray images using deep learning," International Conference on Systems, Man, and Cybernetics (SMC) 2022, IEEE. DOI: 10.1109/SMC53654.2022.9945489.

[9] Syed Krar Haider Bukhari, Labiba Fahad et al.," Lung Disease Detection using Deep Learning," 2022 17th International Conference on Emerging Technologies (ICET) 2022, IEEE. DOI: 10.1109/ ICET56601.2022.10004651.

[10] Swati Patil, Snehal Rathi, Vaibhav Mankar et al., "A Novel Approach to Chest Disease Detection from Chest X-Ray Images," 2nd Asian Conference on Innovation in Technology (ASIANCON) 2022, IEEE. DOI: 10.1109/ASIANCON55314.2022.9909156.

[11] P.V. Naresh, R. Visalakshi, B. Satyanarayana et al., "Analysis on Classification of Coronavirus Disease 19 From Radiography Medical Images (Computed Tomography and X-Rays) With Deep Learning," IEEE Renewable Energy and Sustain- able E-Mobility Conference 2023, IEEE. DOI: 10.1109/ RESEM57584.2023.10236205.

[12] Ryunosuke Maeda, Daisuke Fujita, Kosuke Tanaka, Jyunichi Ozawa, Mitsuhiro Haga, Naoyuki Miyahara, Fumihiko Nanba, Syoji Kobashi et al., "Predicting the Development of Chronic Lung Disease in Neonates from Chest X-ray Images Using Deep Learning," IEEE 53rd International Symposium on Multiple-Valued Logic (ISMVL) 2023, IEEE. DOI: 10.1109/IS- MVL57333.2023. 00020.

[13] Saba Siddiqua Sadique Ahemed Siddiqui, Rimsha Taskeen Siddi Habib Hyder, Arati Manjaramkar, Megha Jonnalagedda et al., "Automatic De- tection of Lung Diseases Using CNN and SVM," 3rd International Conference on Intelligent Technologies (CONIT) 2023, IEEE. DOI: 10.1109/CONIT59222.2023.10205788.

[14] Fatma A. Mostafa, Lamiaa A. Elrefaei, Mostafa M. Fouda, Aya Hossam et al., "Diagnosis of Lung Diseases from Chest X-Ray Images Using Different Fusion Techniques," 11th International Conference on Information and Communication Technology (ICoICT) 2023, IEEE. DOI: 10.1109/ ICoICT58202.2023.10262761.

[15] Mehedi Hasan Imran, Pintu Chandra Shill et al., "Automatic Classification and Localization of Lung Diseases from Chest X-Ray Images using Deep Learning," International Conference on Recent Advances in Science and Engineering Technology (ICRASET) 2023, IEEE. DOI: 10.1109/ ICRASET59632.2023.10420300.

[16] Lekh Kumar Shisodiya, Anek Chauhan, Vishnu Kallil, R. K. Nadesh et al., "Predicting Diseases Using Chest X-Ray Medical Images," Innovations in Power and Advanced Computing Tech- nologies (i-PACT) 2023, IEEE. DOI: 10.1109/I- PACT58649. 2023.10434700.

[17] Archana D, Naveen R S, Mithilesh Ravi Shankaran, Janarthanan K, Ragavendran R M et al., "Automated Classification of Chest Im- age Using Deep Learning," International Con- ference on Intelligent Technologies for Sustain- able Electric and Communications Systems (iTech SECOM) 2023, IEEE. DOI: 10.1109/iTech- SECOM59882. 2023.10435016.

[18] Zahraa Ch. Oleiwe, Ebtesam N. AlShemmary, Salam Al-augby, "Classification Technique of Chest X Rays Image Based Cardiomegaly Disease Prediction," International Conference on Information Technology, Applied Mathematics and Statistics (ICITAMS) 2023, IEEE. DOI: 10.1109/ICI- TAMS57610.2023.10525488.

[19] Jannie Fleur V. Oran˜o, Elmer A. Maravillas, Jonah Flor V. Oran˜o et al., "Lung Disease Classification Utilizing Convolutional Neural Net- work with CXR Imaging," 2023 3rd International Conference on Mobile Networks and Wireless Communications (ICMNWC) 2023, IEEE. DOI: 10.1109/ ICMNWC60182.2023.10435917.

[20] Samuel Vasamsetti, Vaibhav Chemboli, G.S.S. Shreyas, Dr. Srikanth Thota et al., "Comparative Performance Analysis of Deep Learning Models for Lung Disease Prediction using Chest X-Ray Images," International Conference on Inventive Computation Technologies (ICICT) 2023, IEEE. DOI: 10.1109/ICICT57646.2023.10134132.

[21] Kosaraju Chaitanya, D. Bhargavi, K. Sri Sowmya, G. Bhargavi et al., "Predicting the Spread of Covid Disease Based on Chest X-Ray Images Using Convolutional Neural Network with Improved Accuracy," 6th Inter- national Conference on Advances in Science and Technology (ICAST) 2023, IEEE. DOI: 10.1109/ICAST59062.2023.10455061.

[22] Salma Sultana, Anik Pramanik, Md. Sadekur Rahman et al., "Lung Disease Classification Using Deep Learning Models from Chest X-ray Images," 3rd International Conference on Intelligent Communication and Computational Techniques (ICCT) 2023, IEEE. DOI: 10.1109/ICCT56969. 2023.10075968.

[23] Amina Djoudi, Ahmed Amine Zaid, Younes Guel- louma, Hadda Cherroun et al., "Genetic Convolutional Neural Networks Approach for Disease Detection from Chest X-Ray Images," 5th International Conference on Pattern Analysis and Intelligent Systems (PAIS) 2023, IEEE. DOI: 10.1109/PAIS60821.2023.10322027.

[24] T Jemima Jebaseeli, D Jasmine David, S Suriya et al., "Classification of Influenza from Chest Radiography using Deep Neural Architecture," 2023 International Conference on Computer Communication and Informatics (ICCC) 2023, IEEE. DOI: 10.1109/ICCCI56745.2023.10128639.

[25] Ashhadul Islam, Farida Mohsen, Zubair Shah, Samir Brahim Belhaouari et al., "Introducing Novel Radon-Based Transform for Disease Detection from Chest X-Ray Images," 2024 6th International Conference on Pattern Analysis and Intelligent Systems (PAIS) 2024, IEEE. DOI: 10.1109/ PAIS62114.2024.10541204.