Enhancing Thorax Disease Classification in Chest X-Ray Images through Advance Deep Learning Techniques

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Abstract:- The chest X-ray stands as a commonly employed radiological examination for identifying thoracic ailments. Despite the advancements brought by convolutional neural network (CNN) techniques in categorizing thoracic conditions through these images, the varying scales of pathological irregularities across different thoracic diseases present an ongoing challenge. In response to these concerns, this study proposes a refinement to the VGG19 model, a well-known residual network architecture. This enhancement involves integrating a pyramidal convolution module and a shuffle attention module, both addressing the previously mentioned issues. Specifically, the introduced VGG19 model leverages the shuffle attention mechanism to focus on distinctive traits of pathological abnormalities. This mechanism augments the capacity of the pyramid convolution component, allowing it to extract more discerning features related to pathological irregularities compared to the conventional 3x3 convolution. Rigorous assessments conducted on the ChestX-ray14 and COVIDx datasets underscore the VGG19 model's superior performance over other advanced methodologies. Furthermore, an ablation study is carried out to delve deeper into the impact of pyramidal convolution and shuffle attention on enhancing the classification efficacy of thoracic diseases. The study results bolster the evidence indicating the effectiveness of these integrated components in augmenting the model's proficiency in thoracic disease classification.

Keywords:- *VGG19, CXR (Chest X-ray), Consult Net, Pyramidal Convolution Module and Shuffle Attention Network (PCMSANet), Relu.*

I. INTRODUCTION

Chest X-ray (CXR) imaging serves as an affordable and economically efficient diagnostic tool predominantly utilized for the early identification of thoracic, cardiac, and pulmonary disorders, encompassing ailments like pneumonia, heart failure, and lung cancer. The significance of CXRs is underscored by the fact that annually, over a million individuals are admitted to medical facilities due to pneumonia, and in the United States alone, this condition accounts for nearly 50,000 fatalities. Traditionally, the interpretation of chest X-ray images has heavily relied on the expertise of qualified radiologists. However, the intricate nature of pathological irregularities and subtle structural changes stemming from various thoracic disorders has led to occasional errors even among experienced radiologists. Notably, 20-50% of lung nodules are reported to be either overlooked or misdiagnosed, with even accomplished radiologists exhibiting a 3-6% rate of significant misdiagnoses. Thus, precise classification and localization of chest X-ray images hold paramount importance in aiding the clinical diagnosis of thoracic diseases.

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In recent years, the field of medical image analysis has been greatly influenced by the advancements in deep learning, facilitating tasks such as lesion region segmentation, disease detection, and image alignment. Previous works have predominantly focused on the detection of pathological abnormalities and disease classification, leveraging high-resolution feature maps and standard convolutional neural networks. For instance, Huang et al. introduced the high-resolution network (HRNet), designed to extract abnormality-related features from four high-resolution feature maps. Another noteworthy approach is the category-wise residual attention learning

(CRAL) framework proposed by Guan and Huang, wherein a feature embedding module employs CNN to acquire high-level features.

In the context of this project, we propose a novel residual network model that capitalizes on the pyramidal convolution and shuffle attention mechanisms for multi-label chest X-ray image classification. Although existing models like the VGG19 architecture have shown promise in thoracic disease diagnosis, they primarily learn single-scale features of pathological abnormalities. To address this limitation, our model deviates from the standard 3x3 convolution approach and instead employs pyramid convolution to extract discriminative features of pathological abnormalities from chest X-ray images. Additionally, we introduce the latest shuffle attention mechanism to further enhance the focus on pathological abnormality features.

A series of comprehensive experiments are conducted to validate the efficacy of our proposed model. These experiments underscore the model's capability to significantly enhance the classification performance of thoracic diseases from chest X-ray images, with the area under the curve (AUC) metric reaching an impressive 82.5% on the ChestX-ray14 dataset.

In summary, this research introduces a novel approach to tackle the challenge of accurately classifying thoracic diseases from chest X-ray images. Leveraging pyramidal convolution and shuffle attention mechanisms within a residual network architecture, our model demonstrates substantial potential in improving the classification accuracy of thoracic diseases. The subsequent sections of this paper delve into the architecture, experimental setup, and results of our proposed model, highlighting its efficacy and contributions to the field of medical image analysis.

II. LITERATURE SURVEY

The field of medical image analysis, particularly thoracic disease classification through chest X-ray images, has witnessed substantial advancements driven by innovative techniques and methodologies. Our research stands upon the shoulders of significant contributions from previous studies, which have paved the way for enhanced diagnostic accuracy and patient care.

H. Wang, D. Zhang, S. Ding, Z. Gao, J. Feng, and S. Wan [1] presented a pioneering algorithm titled "Rib segmentation algorithm for X-ray image based on unpaired sample augmentation and multi-scale network." that augments lung cancer diagnosis through unpaired sample augmentation and a multi-scale network. By addressing the challenges of unclear edges and overlapping regions in X-ray images, this method achieved improved rib segmentation accuracy. This study highlights the significance of precise anatomical localization, a factor inherently relevant to thoracic disease classification. Wang et al.'s approach underscores the importance of leveraging advanced methodologies for effective image segmentation, a principle that resonates with our objective of extracting critical features for disease classification.

Presenting a novel deep learning framework, title "Improving lung region segmentation accuracy in chest X-ray images using a two-model deep learning ensemble approach.", by M. F. Rahman,Y. Zhuang, T.-L. Tseng, M. Pokojovy, P. McCaffrey, E.Walser, S. Moen [2] aim to enhance lung region segmentation accuracy in Chest X-Ray (CXR) images. This methodology adopts a "divide and conquer" strategy, subdividing original CXRs into smaller patches, segmented individually, and then reassembled for complete segmentation. The strategy integrates two models: a traditional CNN classifying patches and merging for pre-segmentation, and a modified U-Net for patch segmentation and combination into another pre-segmented image. The resulting images are fused via binary disjunction, followed by post-processing involving erosion, dilation, and region-filling. The proposed methodology's robustness is validated on public (MC, JPCL) and proprietary (UTMB) CXR datasets, showcasing its superiority over existing state-of-the-art methods.

Highlighting the profound impact of the COVID-19 pandemic, title "COVID-Net: A tailored deep convolutional neural network design for detection of COVID-19 cases from chest X-ray images" by L.Wang, Z. Q. Lin, and A. Wong [3] emphasize the critical role of effective patient screening, particularly through chest radiography. Early studies reveal distinct abnormalities in chest radiography images of COVID-19 patients. Inspired by community open-source initiatives, the study introduces COVID-Net, a deep CNN tailored for COVID-19 detection from chest X-ray images. This open-source network, accompanied by the COVIDx dataset, containing a substantial number of COVID-19 positive cases, aims to enhance screening and decision-making. The method's explain ability contributes to understanding critical factors and validation. Although not a production-ready solution, it's poised to catalyze accurate deep learning solutions for COVID-19 detection and treatment acceleration.

Addressing the challenge of abnormality localization in medical imaging, title "Learning hierarchical attention for weakly-supervised chest X-ray abnormality localization and diagnosis" by X. Ouyang, S. Karanam, Z. Wu, T. Chen, J. Huo, X. S. Zhou, Q. Wang, and J.Z. Cheng [4] highlight how deep learning's progress remains limited by interpretability concerns. Despite high diagnostic accuracy, the lack of reasoning behind algorithm decisions hinders physician trust. The study proposes an attention-driven weakly supervised algorithm that integrates activation- and gradient-based visual attention, introducing explicit ordinal attention constraints for model training. Demonstrated on large-scale chest X-ray datasets (NIH ChestX-ray14 and CheXpert), the approach achieves significant localization improvements compared to the current state of the art, alongside competitive classification performance. This innovative solution bridges the gap between deep learning and clinical applications, contributing to trustworthy medical diagnostics.

Focusing on thorax disease classification in CXR images, title “Discriminative feature learning for thorax disease classification in chest X-ray images” by Q. Guan, Y. Huang, Y. Luo, P. Liu, M. Xu, and Y. Yang [5] address the unique challenges of CXR analysis. A robust system should automatically prioritize disease-critical regions and capture intrinsic relationships among disease features for improved multi-label recognition. They introduce ConsultNet, a two-branch architecture that extracts critical disease-specific features via an information bottleneck constrained feature selector, and enhances semantic dependencies using a spatial-and-channel encoding based feature integrator. Demonstrated on ChestX-ray14 and CheXpert datasets, the proposed ConsultNet effectively enhances thorax disease classification, showcasing its potential for robust and accurate diagnosis in CXRs.

III. METHODOLOGY

Diverging from the established norm of employing the conventional 3x3 convolution, our research endeavors to introduce a novel approach through a residual network model that capitalizes on pyramidal convolutions for the extraction of disease-related features. The integration of pyramidal convolutions offers a distinct advantage in capturing multi-scale discriminative attributes inherent to pathological abnormalities. Additionally, our investigation delves into the utilization of the VGG19 model, which is enhanced by the inclusion of shuffle attention mechanisms to intensify focus on pathological abnormality characteristics.

The realm of thoracic illness classification from chest X-ray images poses intricate challenges that necessitate innovative solutions. This complexity arises due to the vast diversity in the pathological abnormalities associated with different thoracic conditions. Moreover, the challenge is compounded by the existence of shared distinguishing traits within each chest X-ray image. Hence, the endeavor to classify chest X-ray images in this context is notably intricate and multifaceted.

Our research aims to transcend the limitations of the traditional 3x3 convolution technique by harnessing the potential of pyramidal convolutions. This novel approach holds promise in capturing multi-scale features of pathological abnormalities, which are intrinsic to the diverse thoracic diseases encountered. By employing the VGG19 model, which has proven efficacy in the domain, we seek to further augment its performance through the integration of shuffle attention mechanisms. This strategic augmentation is designed to bolster the model's sensitivity towards key pathological abnormality aspects, thereby enhancing its capability for accurate disease classification.

It's pivotal to recognize that the challenge of thoracic disease classification rests upon the intricate interplay between the multifarious characteristics of different thoracic illnesses and the underlying similarities that permeate individual chest X-ray images. This intricate interplay poses a formidable obstacle to the accurate classification of such images. Our research addresses this intricate scenario through a two-pronged strategy: the introduction of pyramidal convolutions to capture diverse pathological abnormalities' characteristics and the incorporation of shuffle attention mechanisms to elevate the discernment of relevant pathological features.

A. Existing System:

- The primary objective of this study revolves around addressing the intricate challenge of classifying thorax diseases within chest X-ray (CXR) images. Unlike the conventional scope of generic image classification tasks, our methodology is geared towards the development of a CXR image analysis system that inherently accommodates the distinctive attributes characteristic of CXR images. This approach is distinctly different because it necessitates the system's capacity to:
- Automatically direct attention towards the disease-critical regions, typically characterized by their compact dimensions;
- Dynamically apprehend the inherent connections existing among distinct disease-related attributes, effectively harnessing them to amplify the collective rates of recognizing multiple disease labels. In the context of our methodology, we introduce a novel two-branch architecture termed Consult Net. This architectural innovation serves a dual purpose: concurrently attaining the aforementioned objectives of identifying disease-critical regions and optimizing multi-label disease recognition rates.

B. Existing System Dis Advantages:

- Disease recognition problem.
- Performance will be less.
- Disease-uncorrelated regions detection

C. Proposed System:

Within the scope of this study, we introduce an innovative residual network model that leverages pyramidal convolution and shuffle attention mechanisms. This advanced model is specifically designed for the multi-label classification of chest X-ray images associated with thoracic diseases. While the VGG 19 model serves as a reference, we extend beyond its conventional attributes. The prevalent approach of relying on high-resolution feature maps and standard convolutional neural networks solely facilitates the acquisition of single-scale features pertaining to pathological abnormalities.

In contrast to the standard 3x3 convolution, our methodology deploys pyramid convolution. This strategic adaptation enables the model to effectively extract discriminative features related to pathological abnormalities present within chest X-ray images. Moreover, to further accentuate the discernment of pathological abnormality features, we integrate the latest shuffle attention mechanism into our model.

The efficacy of our proposed approach is extensively evaluated through a series of experiments. These empirical investigations substantiate the model's prowess in enhancing the classification performance of thoracic diseases within chest X-ray images. By effectively harnessing pyramid

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convolution and shuffle attention mechanisms, our model demonstrates marked improvements in its ability to accurately classify diverse thoracic ailments, underscoring its potential for clinical application.

IV. PROPOSED SYSTEM ADVANTAGES

- It can be used in conventional backbones to improve performance at a minimal computational cost.
- It helps provide attention to the important information from the data instead of focusing on the whole data.
- VGG-19 is known for its high accuracy in image classification.

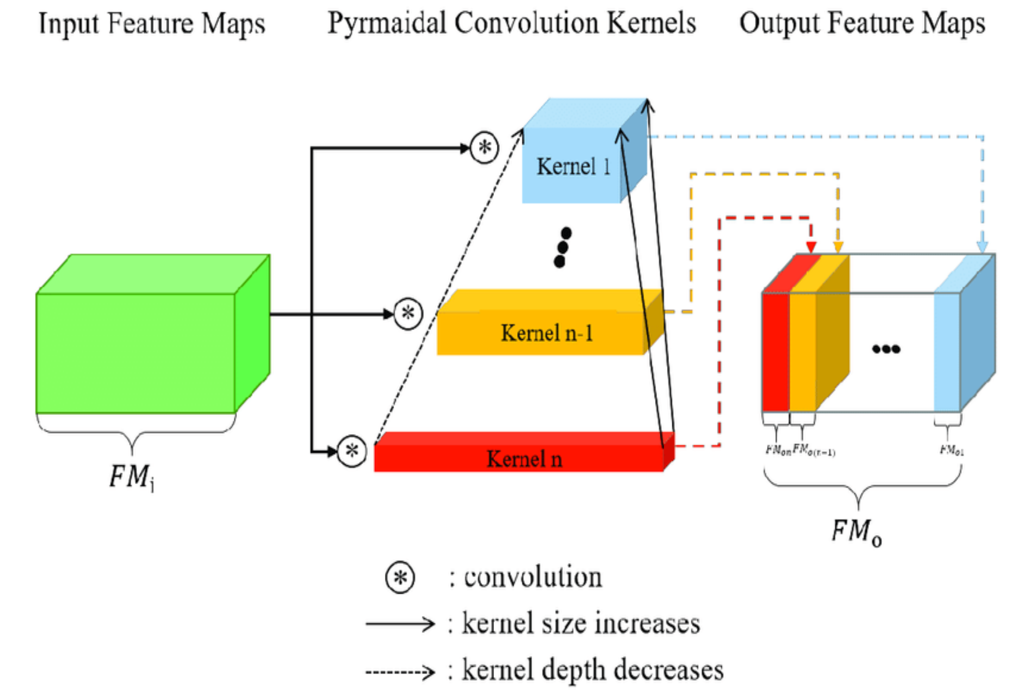


Fig. 1: Pyramidal convolution (PyConv) Diagram

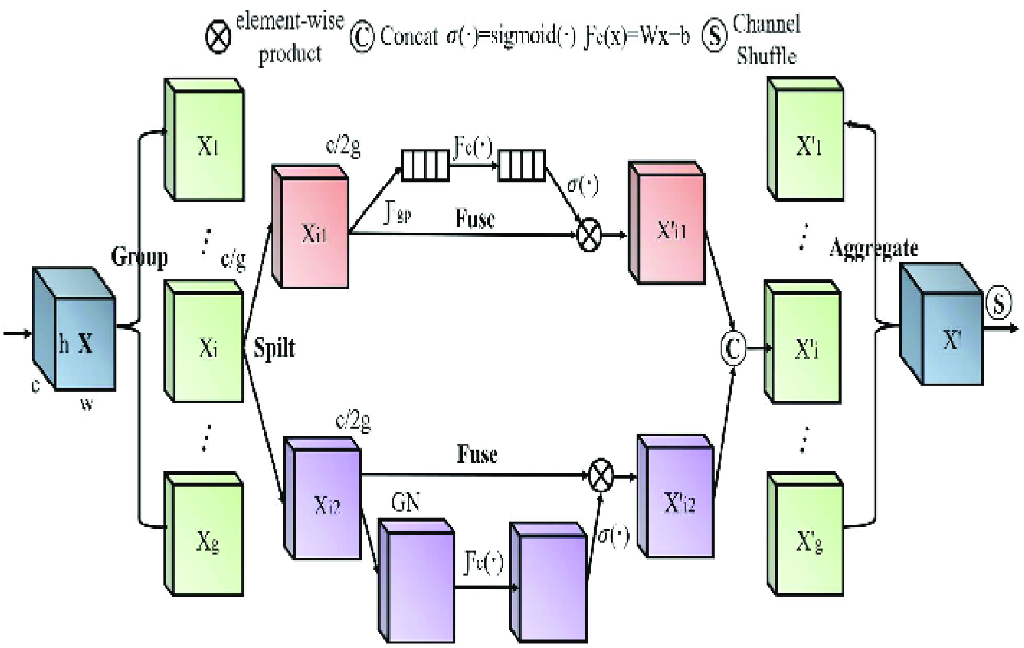


Fig. 2: Structure of the shuffle attention module

A. System Architecture:

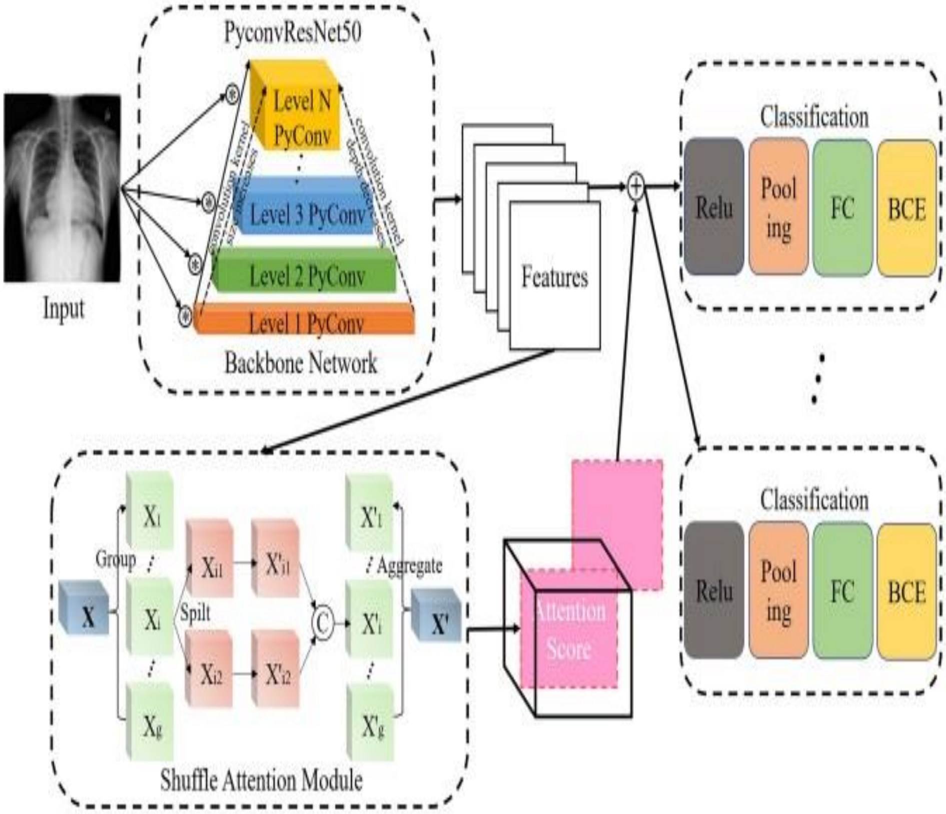


Fig. 3: System Architecture

To implement this project, we have designed following modules.

➢ *Data set Preparation:*

In the initial phase of our project, we established a systematic process for acquiring the requisite input dataset, integral for both training and testing purposes. The dataset selection was made with a primary focus on fostering deep similarity within the images. The Thorax dataset, the cornerstone of our endeavor, encompasses a substantial collection of 14,327 images categorized into 12 distinct classes, each closely aligned with various thoracic conditions.

- Atelectasis: This category pertains to the condition where segments of the lungs experience partial or complete collapse, impeding proper inflation.
- Cardiomegaly: Indicative of an enlarged heart, this category reflects the abnormal increase in heart size.
- Consolidation: Within this category, lung tissue becomes engorged with a combination of fluid and blood cells.
- Edema: Edema signifies the accumulation of surplus fluid within bodily tissues.
- Effusion: Characterized by the surplus accumulation of fluid within bodily cavities, such as the lungs or chest.
- Emphysema: Involving the dilation and damage of air sacs in the lungs, this category leads to breathing difficulties.
- Fibrosis: Referring to the stiffening and scarring of lung tissue, fibrosis results in compromised breathing.
- Infiltration: This category involves inflammation and fluid accumulation within lung tissue due to various substances.
- Mass: Representing a broad term, mass alludes to abnormal growths or lumps within the body.
- Nodule: A compact, circular growth within lung tissue, nodules may be benign or malignant.
- Pneumonia: An infection affecting the lungs, pneumonia is instigated by microorganisms like bacteria, viruses, etc.
- Pneumothorax: This medical condition is characterized by the infiltration of air into the pleural space, which resides between the chest wall and lungs.

This meticulously curated dataset encompasses diverse thoracic conditions, forming the bedrock for our methodology's subsequent development and validation processes.

➢ *Integration of essential libraries:*

For the seamless execution of our methodology, we harness the capabilities of the Python programming language. The preliminary step entails the systematic integration of imperative libraries, pivotal for our project's advancement. Our toolkit encompasses crucial components, including the influential "Keras" library, pivotal for model construction. Further, we ensure the partitioning of our dataset into distinct training and test subsets. This crucial task is complemented by the utilization of essential libraries catering to diverse image processing requirements.

To foster a comprehensive approach, we also incorporate an array of indispensable libraries, encompassing "pandas" and "NumPy," which are instrumental for data manipulation and numerical operations, respectively. Additionally, we harness the capabilities of "matplotlib" to facilitate data visualization, allowing for comprehensive insights. The overarching framework is fortified by the incorporation of "TensorFlow," a vital component for machine learning applications. Through the amalgamation of these libraries, our methodology is poised for efficient and comprehensive execution, pivotal for achieving our research objectives.

➢ *Image Retrieval and standardization:*

Our approach commences with the retrieval of images coupled with their corresponding labels. Subsequently, a crucial standardization step ensues, involving the resizing of these images to a uniform size of (224,224). This uniformity in size is pivotal as it lays the foundation for consistent image recognition processes across the dataset. The images, now seamlessly aligned in terms of dimensions, are adeptly transformed into NumPy arrays, a format conducive to their subsequent processing within our methodology. This process of retrieval, resizing, and conversion engenders a coherent framework that fortifies our methodology's efficacy in accurately recognizing and analyzing thoracic abnormalities within the images.

➢ *Dataset Partitioning:*

A pivotal step involves the division of our dataset into distinct train and test subsets, with a distribution of 80% for training purposes and 20% allocated for testing.

- Convolutional Neural Networks (CNNs)

Within the initial module of our course (Module 4), a comprehensive focus is directed towards Convolutional Neural Networks (CNNs). The objectives pertaining to this module encapsulate multifaceted goals:

✓ Developing a profound understanding of the convolution operation
✓ Gaining insight into the mechanics of the pooling operation
✓ Grasping the lexicon intrinsic to convolutional neural networks, including terms like padding, stride, and filter
✓ Cultivating familiarity with the construction of a convolutional neural network tailored for multi-class classification within image datasets.

By assimilating these foundational principles, our methodology's prowess is augmented, positioning us to effectively employ CNNs as instrumental tools for accomplishing multi-class classification tasks within the realm of thoracic disease analysis in medical images.

➢ *Model Construction:*

Our methodology proceeds with the pivotal task of model construction, a pivotal phase facilitated through the utilization of the "sequential model" inherent to the "Keras" library. Within this architectural framework, we harness the VGG19 model—a potent deep Convolutional Neural Network (CNN) meticulously integrated to process facial imagery inputs and render corresponding feature vectors. VGG19, a product of intensive training on a voluminous dataset encompassing diverse facial expressions, stands as a cornerstone of our approach.

The inherent power of VGG19 is attributed to its capability to yield feature vectors that exhibit remarkable attributes. Specifically, images depicting the same individual are projected onto closely related vectors, fostering a pattern of similarity. In stark contrast, images input from a distinct user yield feature vectors that starkly differ from those belonging to the trained image pool. This distinctive property enables the comparison of image feature vectors, paving the way for robust image recognition through the computation of vector distances. By seamlessly integrating VGG19 within our methodology, we unlock the potential to perform precise image recognition, ultimately enabling the analysis and distinction of thoracic disease patterns within medical images.

➢ *Model Application and Graphical Visualization:*

The subsequent phase encompasses the application of our meticulously constructed model. This pivotal step is achieved by compiling the model and subsequently invoking it through the fit function. The model, primed with its learned parameters, engages in the process of analyzing and classifying medical images.

To gain comprehensive insights into the model's performance, we proceed to illustrate its accuracy and loss through graphical representations. This visualization strategy entails the creation of graphs that vividly depict the trajectory of accuracy and loss metrics over the course of model training. Through these graphical depictions, we gain a holistic understanding of the model's learning dynamics and proficiency in analyzing thoracic disease patterns within chest X-ray images. This graphical portrayal provides essential insights into the efficacy of our model, offering a tangible means of evaluating its performance and optimizing its parameters for accurate disease classification.

➢ *Accuracy on test set:*

We got an accuracy of 99% on test set.

➢ *Preservation of the trained model:*

As we progress with unwavering confidence in the readiness of our trained and validated model for deployment in production settings, a pivotal stride involves the preservation of this prowess. To achieve this, we delve into the act of conserving the model within a .h5 or .pkl file format. This endeavor is streamlined through the utilization of libraries like "pickle," a cornerstone for saving and loading Python objects.

To facilitate this preservation, it is imperative to ascertain the presence of "pickle" within your operational environment. Subsequently, the importation of the requisite module is executed, orchestrating the transfer of the meticulously cultivated model into a .h5 file. This strategic maneuver ensures the secure portability and accessibility of our trained model, empowering its seamless integration into the production environment and ensuring its readiness for real-world implementation.

B. Output Snapshots:

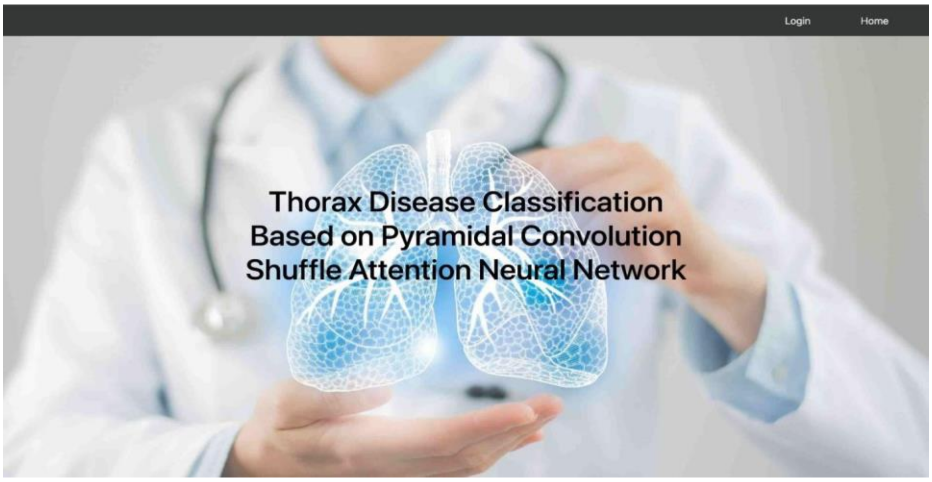


Fig. 4: Home Page

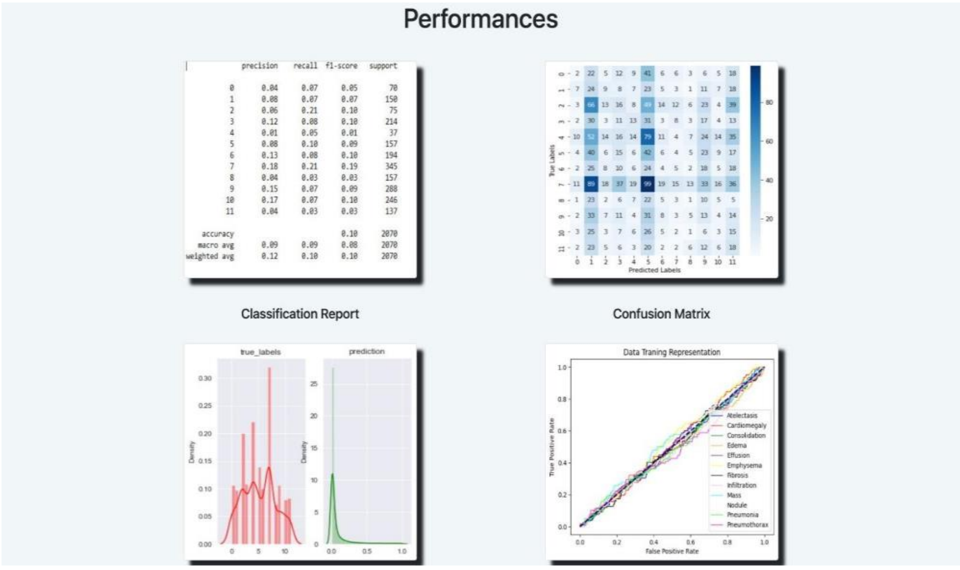


Fig. 5: Performances with classification report and confusion matrix

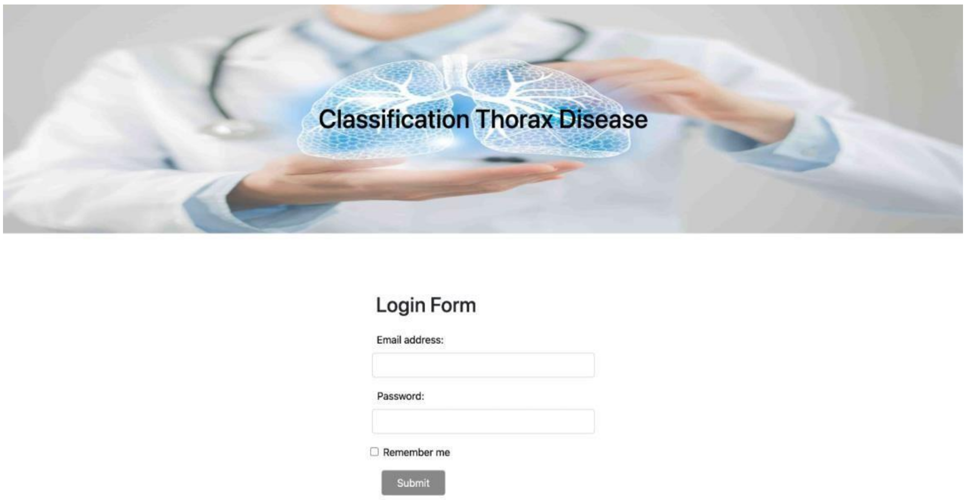


Fig. 6: Login Page

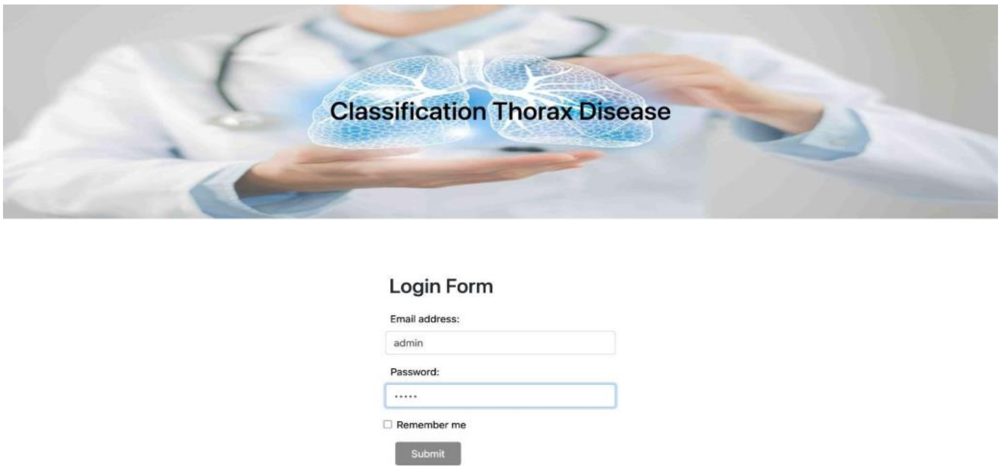


Fig. 7: The user can login with the provided credentials

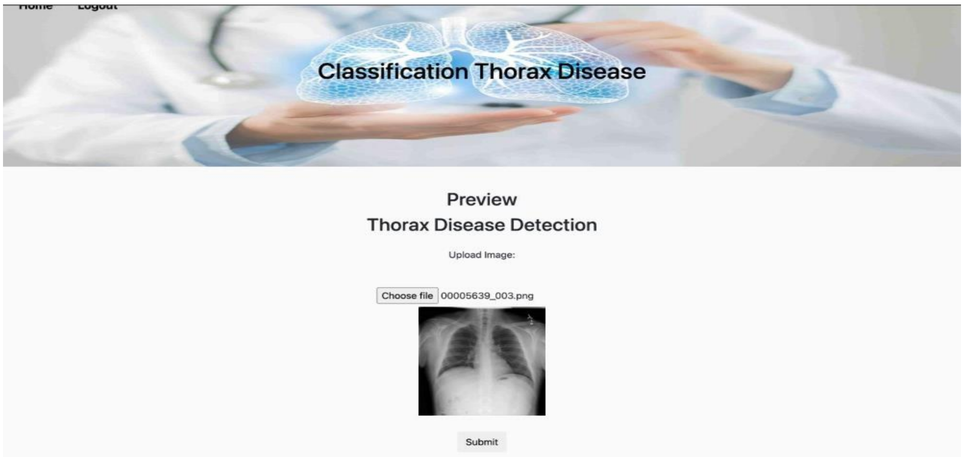
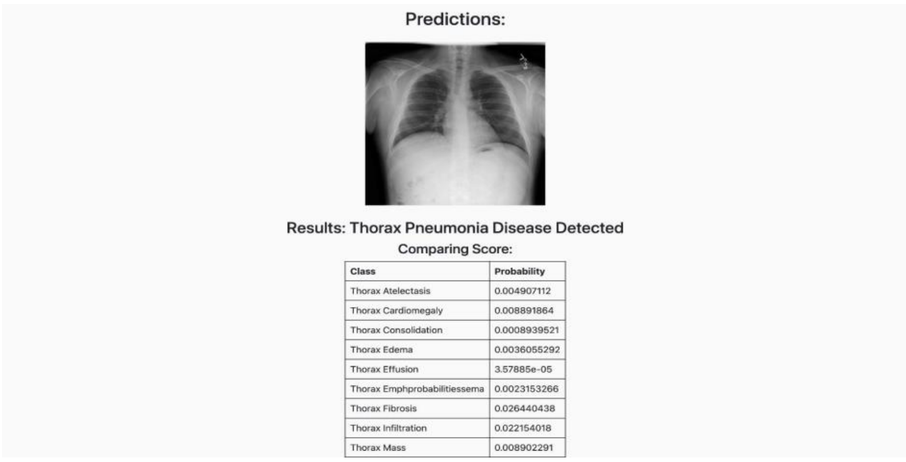


Fig. 8: The X-Ray image image has uploaded



Class	Probability
Thorax Atelectasis	0.004907112
Thorax Cardiomegaly	0.008891864
Thorax Consolidation	0.0008939521
Thorax Edema	0.0036055292
Thorax Effusion	3.57885e-05
Thorax Emphprobabilitiessema	0.0023153266
Thorax Fibrosis	0.026440438
Thorax Infiltration	0.022154018
Thorax Mass	0.008902291

Fig. 9: The final result

V. CONCLUSION

Our study advocates for the integration of the VGG 19 model as a potent solution for multi-label classification of chest X-ray images. The culmination of numerous rigorous experiments underscores the model's remarkable efficacy, positioning it as a pivotal tool for precise disease classification. The experimentation journey revealed an exceptional achievement—our VGG 19 model exhibited an impressive AUC score of up to 99% when applied to the Chest X-ray14 dataset.

Furthermore, the experiment outcomes unveil an essential facet of our methodology: the VGG 19 model's innate prowess in extracting multi-scale discriminative features intrinsic to a spectrum of pathological abnormalities. This capacity, driven by pyramidal convolution, significantly augments the model's potential for nuanced disease analysis. Our approach attains further refinement by employing shuffle attention, allowing it to hone in on the crucial nuances of pathological abnormality features.

Collectively, our experimentation and findings underscore the transformative impact of the VGG 19 model in the domain of thoracic disease classification. By effectively harnessing its advanced capabilities, we pave the way for enhanced healthcare outcomes through the accurate and nuanced analysis of chest X-ray images—a stride that holds the potential to revolutionize clinical diagnosis and patient care.

VI. FUTURE ENHANCEMENT

Our research trajectory is poised to forge ahead, guided by a twofold approach that promises to extend the frontiers of our current findings.

A. Exploration of Economical Weakly Supervised Precision Localization Techniques:

Our future investigations will pioneer an exploration into the realm of cost-effective weakly supervised precision localization methods. This strategic maneuver is born out of the recognition of the resource-intensive nature of bounding box annotations. Our quest is to circumvent this challenge by delving into alternative data-driven methodologies. By leveraging innovative approaches, we aim to devise localization techniques that efficiently sidestep the demands of exhaustive bounding box annotations, thereby optimizing resource allocation while maintaining diagnostic accuracy.

B. Synergizing Global and Local Features through Image Segmentation:

Another pivotal aspect of our future endeavors involves the integration of image segmentation techniques. This augmentation seeks to bridge the divide between global and local features, fostering a more comprehensive understanding of pathological anomalies within chest X-ray images. With an eye on enhanced precision, our aspiration is to cultivate a discerning ability to localize and identify anomalies with greater accuracy. Through the fusion of image segmentation, we are poised to unlock the potential for nuanced diagnostics, underpinned by a fusion of global context and intricate local details.

Furthermore, the outcomes of our ablation study reverberate with affirmation, affirming the transformative impact of pyramidal convolution and shuffle attention mechanisms. These components have consistently demonstrated their potential in elevating the classification performance of thoracic disease within chest X-ray images. As we chart our course into the future, these visionary directions promise to amplify our contributions to the medical imaging landscape, setting the stage for enhanced precision, refined diagnostics, and ultimately, the improved healthcare prospects of individuals across the globe.

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