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LungCare AI : Pioneering Advancements in Respiratory Care using Deep Learning

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ABSTRACT
The LungCare AI system, tailored for X-ray and CT scan image processing, employs diverse enhancement techniques to mitigate noise and enhance contrast. Following the pre- processing phase, a pre-trained Convolutional Neural Network (CNN) model is employed to analyze features like nodule shape, size, and distribution pattern. Cross-referencing with a comprehensive knowledge base ensures accurate identification, subject to verification by medical professionals, enabling prompt interventions to potentially avert disease progression. The proposed architecture streamlines appointment booking and image uploading, ensuring a secure workflow overseen by authorized personnel with a focus on prioritizing medical data confidentiality. Leveraging advanced technology for precise disease assessment contributes to enhanced patient care.
In tandem, traditional lung disease detection methods include skin tests, blood tests, and imaging techniques like chest X- rays and CT scans [8]. Recent advances in deep learning have transformed medical image analysis, particularly in diagnosing lung diseases. Inspired by the brain's structure, this sub-field of machine learning [13] excels in identifying patterns without hand-designed features, significantly improving performance in medical applications for efficient detection and classification of conditions. The transformative impact of the "LungCare AI" application, harmonizing innovative technology and user-centric design, signifies a positive shift towards improved respiratory health outcomes. This convergence underscores the transformative role of artificial intelligence in healthcare diagnostics.
Keywords: CNN, Deep Learning, Chest X-Ray, CT scan

I. INTRODUCTION

In the contemporary healthcare environment, the urgency to address respiratory challenges has reached unprecedented levels, necessitating a profound examination of transformative technologies. This survey meticulously explores the escalating need for advancements, with a specific focus on the early detection and management of diseases affecting lungs. Leading this technological revolution are advanced Deep Learning (DL) models, distinguished for their proficiency in deciphering subtle patterns indicative of respiratory conditions.

The survey endeavours to illuminate the pivotal role played by these advancements in reshaping the entire landscape of respiratory healthcare.

Beyond the realms of diagnostics, the survey recognizes that comprehensive care demands a holistic approach. To this end, it underscores the imperative integration of features such as appointment booking and direct chat communication with healthcare professionals. In an era where patient engagement and proactive management stand as paramount objectives, the incorporation of these user-centric elements becomes crucial. By shedding light on the symbiotic relationship between advanced DL technology and patient-oriented functionalities, the survey envisions not only improved healthcare outcomes but also a heightened quality of life for individuals navigating the intricate challenges posed by respiratory health issues. This holistic perspective lays the groundwork for a transformative paradigm, fostering collaborative and informed relationships between patients and healthcare providers, ultimately contributing to an elevated standard of care and well-being.

II. LITERATURE SURVEY

A. ECHO STATE NETWORK MODEL

In the past few years, notable advancements have been achieved in the realm of Artificial Intelligence (AI), particularly in the domain of biomedical diagnostics, such as the detection of cancer. This study

[1] introduces an innovative model by Harnessing the power of Deep Learning. The study employs Gabor filtering for image preprocessing and utilizes GhostNet for feature extraction. Hyperparameter adjustments through AFAO and cancer detection via TSA [6] with echo state network (ESN) contribute to the model's effectiveness. Extensive experimental results showcase the superior performance of BICLCD-TSADL, achieving a remarkable accuracy of 99.33%, signifying a noteworthy advancement in cancer detection efficiency.

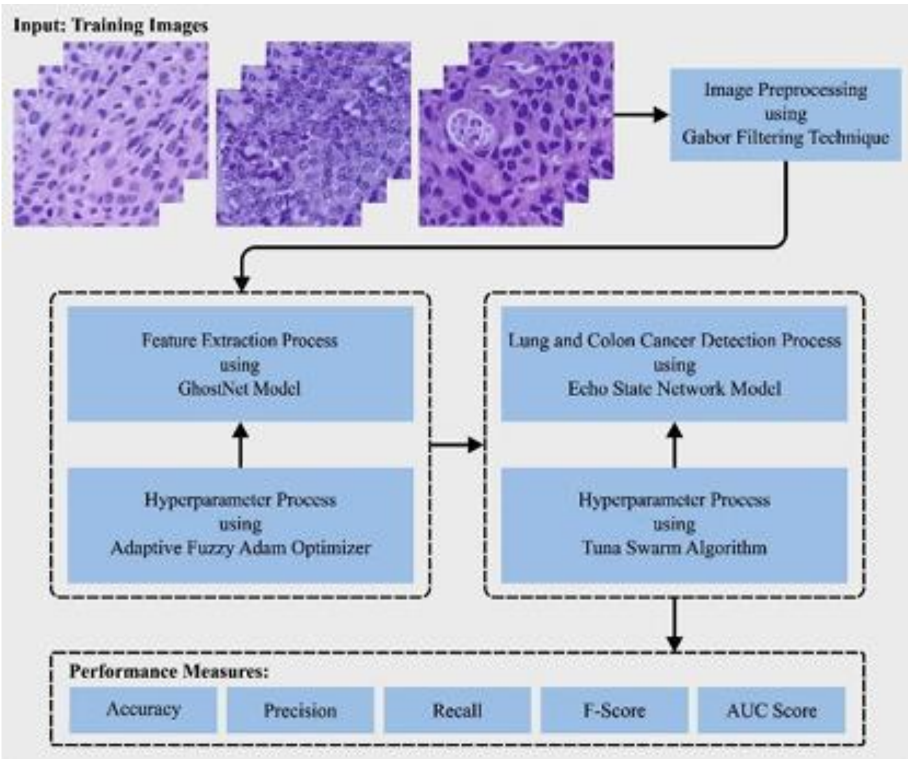

Fig. 1: Architecture Diagram

1) *Feature Extraction:* The GhostNet model is incorporated for efficient feature extraction. This innovative approach reduces computations and inputs, enhancing the overall effectiveness of the GhostNet model [1]. Central to GhostNet is the Ghost bottle- neck, a pivotal component that employs two ghost models to create mapping features. The process involves downsizing input mapping features through a typical convolution, followed by a linear operation on the downscaled features, generating a substantial quantity of ghost features. These outcomes are then amalgamated to produce an output mapping feature. To optimize the GhostNet model's performance, the Adaptive Firefly Algorithm Optimization (AFAO) is employed. The Adaptive Firefly Algorithm Optimization, modified iteration of stochastic gradient descent (SGD), enhances efficacy and expedites the learning process by iteratively evaluating biased and bias- corrected first and second moments, adjusting the model's parameters. The prediction accuracy of GhostNet with AFAO is subsequently evaluated using the testing set. This optimized GhostNet feature extractor, coupled with AFAO, improves the precise representation of colon and lung cancer image data, contributing to the improved overall performance of the biomedical image analysis system.
2) *Classification:* In the process of cancer detection and classification, the Echo State Network (ESN) model is utilized due to its effectiveness in training Recurrent Neural Networks (RNNs). This ensures streamlined training procedures and reduced time consumption compared to conventional statistical and machine learning methods. The ESN model computes reservoir layer updates using specific equations, and its output is determined through a weighted connection matrix. The optimal solution for the weighted matrix is obtained through the least squares or Mean Squared Error (MSE) method, contributing to an effective and time-efficient cancer detection system.

To achieve optimal parameter tuning in the ESN model, the study employs the Tuna Swarm Algorithm (TSA). TSA utilizes a spiral foraging strategy inspired by tuna schools, adapting its approach based on probability allocation and incorporating a fitness function derived from cancer detection outcomes. This approach enhances global exploration abilities and contributes to the overall effectiveness of the cancer detection system. Fig 1 shows the architecture diagram.

3) *Experiment Analysis:* The experimental validation of the proposed model in the study was conducted using Python 3.6.5 on a PC equipped with an i5- 8600k processor, GeForce 1050Ti 4GB GPU, 16GB RAM, 250GB SSD, and 1TB HDD. The model was simulated with specific parameter settings, including a learning rate of 0.01, dropout of 0.5, batch size of 5, 50 epochs, and ReLU activation.

The validation was performed on the dataset LC25000, comprising five classes, each consisting of 5000 samples. The approach demonstrated accurate identification and classification of all five class labels, as illustrated in confusion matrices, precision-recall analysis, and ROC investigation.

Detailed results on 70% of training (TRP) and 30% of testing (TSP) data demonstrated elevated accuracy, precision, F-score, recall, and AUC scores for each class.

Comparisons with other models revealed the superior performance of BICLCD-TSADL, emphasizing its effectiveness in medical image analysis. The BICLCD-TSADL model exhibited performance of 99.17% accuracy, 97.38% precision, 98.64% recall, 98.01% F-score, and an AUC score of 98.98%. The incorporation of IAFO and TSA algorithms for hyperparameter optimization further enhanced the model's overall outcomes, confirming its improved performance compared to existing techniques.

B. MULTI VIEW - KNOWLEDGE BASED COLLABORATIVE MODEL

The research [2], classifies lung nodules as benign or malignant on chest CT scans [7]. The model decomposes the three-dimensional image of each lung nodule into 9 fixed plane views and uses a knowledge-based collaborative approach. It employs three ResNet-50 neural networks to understand three basic properties of a nodule - Appearance, Shape and Voxel heterogeneity and with help from a penalty loss function controls the balance between false negative and false positive rates.

The methodology of the said algorithm comprises of four major steps: extraction of two dimensional nodule slices from the nine view planes, extracting patches representing overall appearance of the lung condition, heterogeneity in voxel values, and shapes on two dimensional nodule slices, constructing nine submodels and training each of them using the patches extracted on each view of planes, and con- struction and training of the model for classification. The model's performance is evaluated using the database termed LIDC-IDRI, and it achieved superior accuracy in comparison to state-of-the-art approaches. The study also compared the model's performance with other deep learning methods and traditional CADs (Computer-Aided Diagnostic systems), demonstrating the effectiveness of the multi- view learning approach.

In summary, the MV-KBC model uses a multi-view approach and a penalty loss function to accurately seggregate lung nodules as non-cancerous or cancerous, showcasing the potential of deep learning for medical imaging and contributing to the detection of lung cancer before its obvious onset.

1) *Multi-View Slice Extraction:* The multi-view slice extraction method used in the research involves decomposing three-dimensional lung nodules into nine fixed view planes, namely coronal, axial, sagittal, and six diagonal planes. From these views, two-dimensional nodule slices are extracted, and overall appearance (OA), heterogeneity in voxel values (HVV), and shapes (HS) patches are further extracted. These patches are used to train a submodel for each view, where three pre-trained ResNet-50 neural networks are fine-tuned to describe the OA, HVV, and HS of the lung nodules. The submodels are then combined to construct and train the complete model for lung nodule classification. This multi-view approach aims to leverage complementary information from different perspectives to improve the accuracy of lung nodule classification. The method is illustrated in Fig. 2. The approach aims to capture the 3D characteristics of the nodules from multiple perspectives, enhancing the model's ability to accurately classify lung nodules as non-cancerous or cancerous.

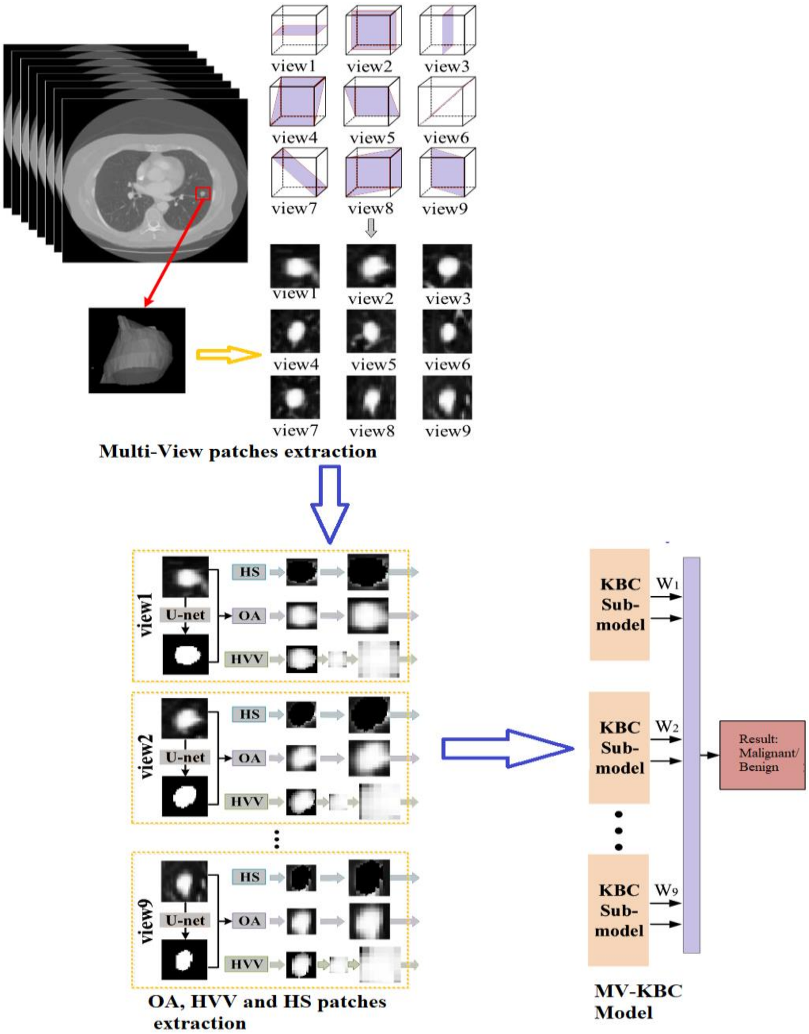

Fig 2: Framework of the proposed algorithm

2) *OA, HVV and HS Patches Extraction:* The method of Extracting OA, HVV, and HS Patch involves decomposing 3D lung nodules into nine fixed view planes and extracting 2D nodule slices from each view. The U-Net network is employed for nodule segmentation, and the extracted patches are used to train a submodel. Each submodel contains three pre- trained ResNet-50 neural networks, which are finetuned to characterize the overall appearance (OA), heterogeneity in voxel values (HVV), and heterogeneity in shapes (HS) of the lung nodules. The extracted patches are used to train the submodel, and the complete model is constructed and trained for lung nodule classification. Data augmentation is applied to alleviate overfitting, and the model's performance is evaluated using various metrics like sensitivity, accuracy, etc. The method aims to lever- age the complementary information from different perspectives to improve the accuracy of lung nodule classification.

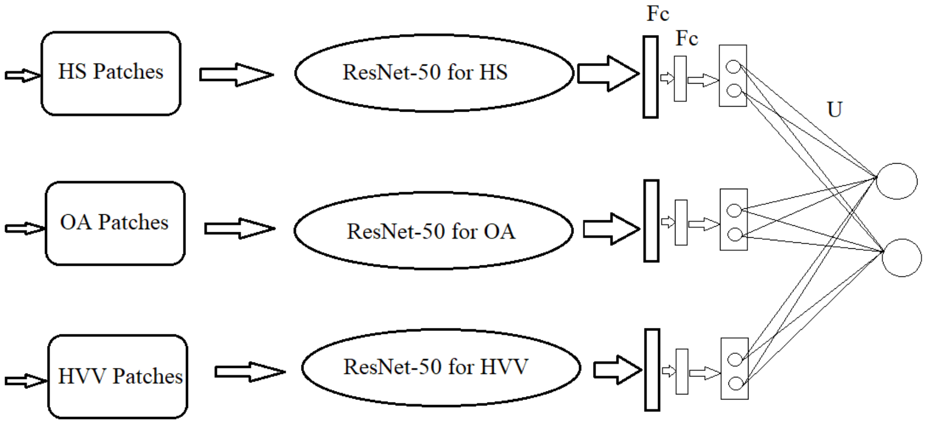

Fig 3: Architecture of a submodel for a specific view

3) *KBC Submodel:* The proposed submodel is designed to describe lung nodules from different perspectives, namely overall appearance (OA), heterogeneity of voxel values (HVV), and heterogeneity in shapes (HS). The submodel consists of three pre- trained ResNet-50 networks, each fine-tuned to capture specific nodule characteristics. The architecture of a submodel involves extracting OA patches, HVV patches, and HS patches from two- dimensional nodule slices on each of the nine fixed views of planes. These patches are used to train each of the submodels, and the outputs of the three ResNet-50 networks are combined to form the prediction made by the complete model. The KBC sub-model aims to leverage the complementary features captured by the ResNet-50 networks from different perspectives, enhancing the model's ability to accurately classify lung nodules as benign or malignant. The submodel's architecture is illustrated in Fig 3 of the paper.

Fig.3 illustrates the architecture of the Knowledge- Based Collaborative (KBC) sub-model for lung nodule classification. It shows three sets of patches representing different nodule characteristics: heterogeneity in shapes (HS), overall appearance (OA), and heterogeneity in voxel values (HVV). Each set of patches is processed by a dedicated ResNet-50 network, designed to extract relevant features for that characteristic. After feature extraction, the outputs from the three networks are passed through fully connected (Fc) layers and then integrated in a collaborative unit (U), which combines the features to make a final classification decision. The figure visually represents the parallel processing of different nodule features and the subsequent integration for diagnosis.

4) *MV-KBC Model:* The model, or the complete model comprises of nine KBC sub-models, employs a unique architecture. Each submodel features a double neuron output layer linked to a common single neuron in the classification layer, followed by the sigmoid function. The overall model prediction is derived from the output of this classification layer.

To address the potential cost imbalance of misclassifications in medical contexts, where misidentifying a malignant nodule as 'benign' or non-cancerous may have graver consequences than the reverse, the authors propose a penalty cross-entropy loss. Unlike traditional cross-entropy loss, this variant allows for differential penalization of false negative and false positive errors. In medical scenarios, such as lung tumor detection, this approach aims to mitigate the risk of overlooking early-stage tumors by discouraging the false reassurance of benign classifications.

5) *Performance Analysis:* The MV-KBC algorithm proposed here has achieved 91.60% Accuracy, 86.52% Sensitivity, and 87.75% Precision in classifying lung nodules. It also received an F1 score of 87.13% and thus has proved to be a viable tool in the domain.

The emphasis lies on the enhanced performance in distinguishing nodules within each Median Malignancy Level (MML) subgroup, achieved through the utilization of a multi-view architecture and penalty loss that regulates the balance between false negative and false positive rates. However, it is crucial to acknowledge the potential risk of overfitting in the deep model employed, stemming from insufficient training data.

C. U-NET AND CUSTOM IRV2 INTEGRATION MODEL

A novel Computer-Aided Diagnostic (CAD) system is proposed in [3] to empower radiologists with enhanced accuracy and efficiency in diagnosing pulmonary diseases from chest X-rays [7] (CXRs). The system leverages a fine-tuned Convolutional Neural Network (CNN) architecture, analyzing CXR images [5] in two stages: initial healthy/infected classification followed by in-depth disease type identification for confirmed infections. Lung region segmentation ensures focus on relevant information, boosting processing efficiency and noise reduction. This approach surpasses existing methods in both segmentation and classification, as validated on the standard NIH chest X-ray dataset (detailed architecture visualization omitted).

1) *Segmentation:* This study [3] highlights the crucial role of lung segmentation in enhancing the ac- curacy of pulmonary disease classification in chest X-rays. Segmenting the lung region offers several advantages: it reduces computational demands by focusing on relevant areas, concentrates analysis on features directly associated with lung diseases, and minimizes interference from irrelevant background information. To achieve this segmentation, the re- searchers utilized a U-Net architecture, characterized by its distinctive encoder-decoder structure. The contraction path of the proposed model entails a series of iterative 3x3 convolution operations, succeeded by Rectified Linear Unit (ReLU) Activation, and 2x2 max pooling to achieve down sampling. At each operation in this path, there is a twofold increase in feature channels, contributing to the overall efficiency and representational capacity of the model. The expansion phase of the model relies on up-convolution layers, combined with skip connections that retrieve lost detail from earlier stages. Training is driven by manually segmented lung masks extracted from the NIH Chest X-ray dataset.

Training spans a maximum of 200 epochs, with hyperparameters fine-tuned for optimal performance. Dropout (50%) is introduced for regularization in the expanding path, and batch normalization enhances efficiency and stability. Hyperparameters are adjusted considering computational constraints, with specific values such as a batch size of 32, a U- Net depth of 5, and two convolutional operations per depth. The model attains optimal performance following these adjustments.

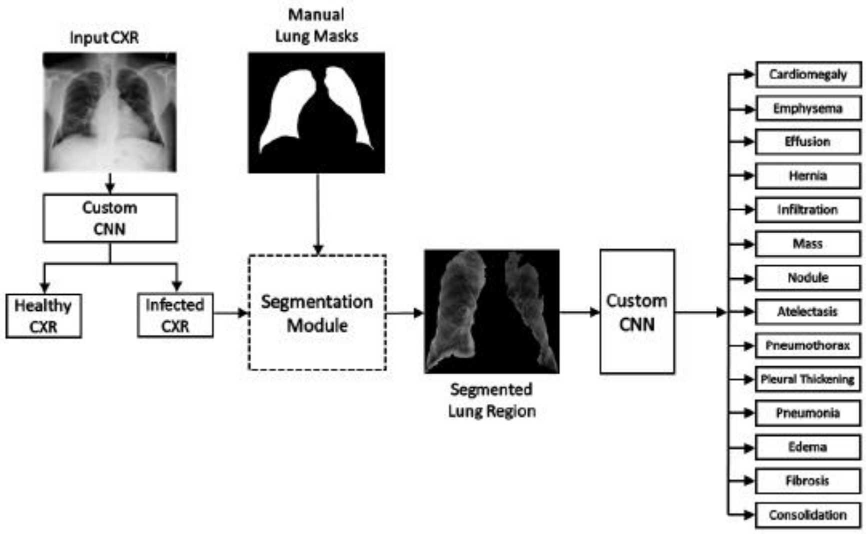

Fig 4: Architecture Diagram

2) *Classification:* This study tackles the issue of low accuracy in classifying specific pulmonary dis- eases by proposing a custom CNN architecture that extends Inception-ResNet. The model first distinguishes CXR images as healthy or infected, followed by a segmentation module for isolating the lung region in infected images. The segmented region undergoes a secondary evaluation to ex- amine disease-specific texture and shape features at a micro-level for a multi-class classification. In this process, the custom Convolutional Neural Network (CNN) incorporates four supplementary convolutional layers before reaching the Inception- ResNet, ensuring the preservation of image resolution to facilitate micro-level feature extraction. Hyperparameters, including learning rate, optimizer, and activation function, are fine-tuned for optimal performance.

The optimizer algorithm used is Adam. Inception- ResNet extracts meaningful features, and the output traverses additional fully connected layers for weight determination through backpropagation. The classification layer initially handles binary classification and is later adapted for multi-class classification of 14 pulmonary diseases, resulting in enhanced overall accuracy and individual class accuracies. Fig 4 shows the architecture diagram.

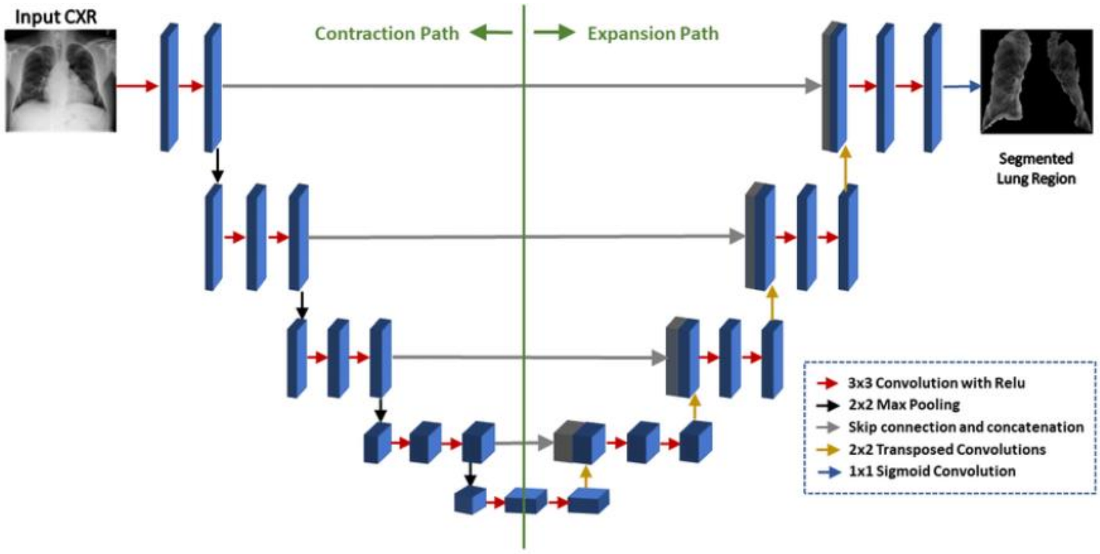

Fig 5: U-Net Architecture

3) *Experimentation and Results:* To streamline the computationally demanding task of training a CNN, a GTX 1080ti GPU with 8 GB memory is combined with a standard system featuring a core i7 8th Gen CPU and 16 GB system memory. Code implementation is carried out in Python using Keras with TensorFlow as the backend engine. The training process involved 200 epochs for both segmentation and classification tasks. Data was carefully split: 70% for training, 10% for validation, and 20% for testing, ensuring no patient data overlapped between sets. The dataset utilized comprised 112,120 images, with 78,484 specifically used for classification training. A batch size of 64 images resulted in 1,227 steps per epoch across the 200 training epochs.

Building upon a modified U-Net architecture, researchers pushed the boundaries of lung segmentation and disease classification in chest X-rays [11]. Leveraging pre-trained weights and the vast NIH dataset, their model achieved state-of-the-art performance, boasting a remarkable mean Dice score of 0.9734 and IoU of 0.9646 for lung segmentation. While specific details of the architecture and training regimen are restricted, the results indicate significant promise for this approach in advancing medical image analysis. Strikingly, it distinguishes healthy and infected CXR images with 91% accuracy and exhibits exceptional class-wise accuracies between 0.975 and 0.984 for 14 distinct pulmonary diseases. Notably, the entire CXR image is used for healthy vs. infected classification, while for infected cases, the model focuses on the segmented lung region for deeper analysis. These remarkable findings suggest the proposed U-Net architecture's potential to significantly improve medical professionals' capabilities in lung analysis and diagnosis. This process, involving the collection and utilization of manual lung masks, stands as a notable contribution of this research study.

D. CNN MODEL-BASED LUNG DISEASE IDENTIFICATION

Lung diseases such as Lung Cancer, Pneumonia and COVID-19[10] are the most found diseases in human beings. Lung diseases [9] need to be diagnosed timely. To serve this purpose many machine learning models have been developed. Vanilla network, capsule network, and VGG net algorithms serve this purpose. In the study [4] Convolutional Neural Network is used for predicting lung diseases from Chest X-Ray [11] images sourced from the Kaggle repository dataset. Spyder, Keras and TensorFlow are the tools used for implementation. 93% of mean accuracy is yielded by model. Diseases which include lung cancer, Pneumonia, covid or none are predicted by this model.

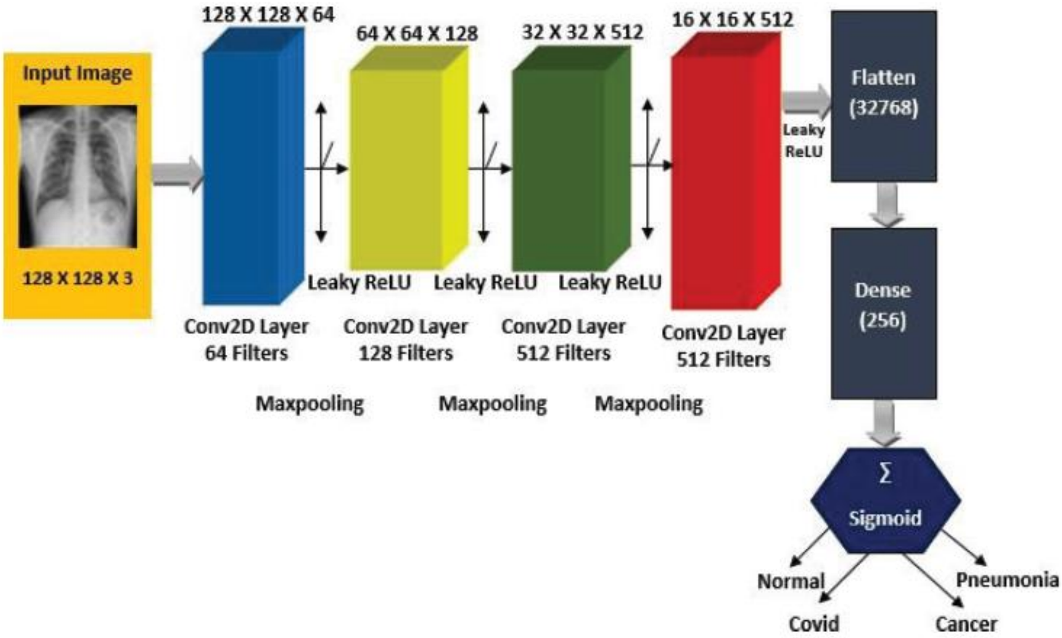

Fig 6: Architecture Diagram

1) *Proposed Model:* Convolutional Neural Network: The primary task of CNN [12] is classification, offering a scalable approach not only for classification but also for recognition of objects. CNN is further divided into three layers.
2) *Convolutional Layer:* The Convolution layer is the cornerstone of CNN, where most of the computation takes place. It plays a crucial role in determining complex data representations that can be visualized through extensive datasets. The fundamental inspiration for convolutional neural networks is drawn from the organization of visual cortex in animals, the regions responsive to different parts of the visible field.

In this context, neuronal cells exhibit responses to the presence of edges in defined orientations. For instance, some cells activate when exposed to horizontal edges, while others respond to vertical edges or diagonal edges. The convolution operation involves using an input image with a filter of M×M size in this layer. This filter moves across the input image, and dot product is performed with the specified size of M×M. The resulting output called feature maps provides information on edges and corners.

3) *Pooling Layer:* Pooling layer is after the Convolution Layer. The size of the feature map that gets convolved is reduced, this decreases the computational costs. To operate independently on each of the feature map, the connections in layers are reduced, serving as a bridge between the Convolution layer and the Fully Connected Layer. Various operations of pooling exist according to the method employed. Max Pooling selects the largest element from each section of the feature map. Average Pooling calculates the average of the elements within a predefined-sized image section and Sum Pooling determines the sum of the elements in that section.
4) *Fully Connected Layer:* This layer contains the weights and biases essential for connecting neurons between the two layers. The input from the previous layer is flattened and transmitted to the Fully Connected layer. Within this layer, the flattened vector undergoes various mathematical operations. The classification process takes place in this process. Fig 6 Shows the Architecture diagram.

5) *Activation Function:* Network Model. This method identifies all types of relationships between the variables in the network. This method introduces nonlinearity to the network. Various activation functions such as Leaky ReLU and Sigmoid are employed for this purpose, each serving different roles within the model. The Sigmoid function is employed in the Binary Classification CNN model and SoftMax is employed for the Multiclass Classification.

A Comparative study of the advantages and disadvantages of the methodologies proposed in the various reference papers are provided in Table 1.

III. PROPOSED SYSTEM

The devised LungCare AI system is engineered to process CT scan and X-Ray images of the lungs. Employing diverse enhancement techniques during preprocessing mitigates noise and enhances contrast. Subsequently, these refined images undergo analysis by a pre-trained Convolutional Neural Network (CNN) [12] model. Specific features are scrutinized by the CNN model, such as nodule shape, size, and distribution pattern, cross-referencing its findings with a comprehensive Knowledge base. Upon identifying relevant features, the model generates an output, subject to verification by a medical professional before communicating results to the patient. This expeditious diagnostic approach facilitates prompt initiation of remedial actions, potentially averting disease progression. The system's efficiency lies in its ability to swiftly and accurately deliver probable results, contributing to timely intervention and improved patient outcomes. Fig. 7 shows the proposed system architecture.

Patients can conveniently book appointments within the doctor's schedule, during which the doc- tor can upload medical images for preprocessing before model input. The system generates prediction results and a diagnostic report. Exclusively, the doctor forwards images to the admin for result generation, incorporating prediction details. This meticulous process ensures a secure and efficient workflow, prioritizing medical data confidentiality. Advanced technology facilitates precise disease assessment, contributing to enhanced patient care. The stream- lined process, overseen by authorized personnel, ensures confidentiality, while advanced technology enhances diagnosis of diseases, promoting accurate and timely medical interventions for improved patient care.

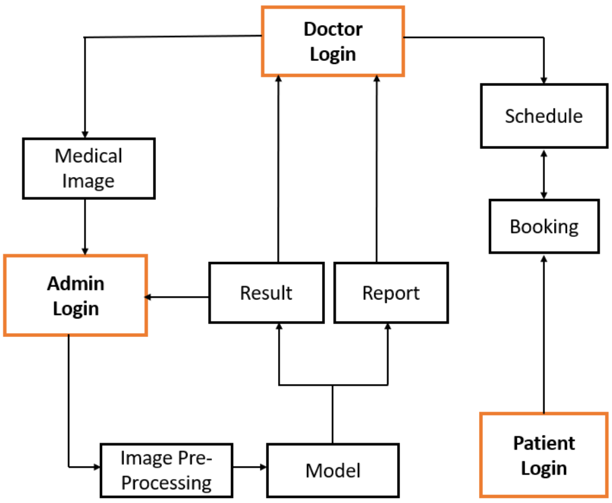

Fig 7: Proposed Architecture

IV. COMPARATIVE STUDY

Based on the reviewing of the papers, a thorough comparison analysis was conducted. This study attempted to identify and evaluate the different benefits and drawbacks that are present in every technology that was discussed in the literature. Table 1, which methodically provides a comprehensive summary of the observed contrasts and captures the complex subtleties of the technologies covered in the corresponding papers, is essential to this analysis. After a methodical examination and evaluation, the table provides significant value as a tool for comprehending the technologies under investigation and provides information about their individual advantages and disadvantages.

Title	Technique Used	Advantages	Disadvantages
Biomedical Image Analysis for Colon and Lung Cancer Detection Using Tuna Swarm Algorithm With Deep Learning Model	GhostNet and Ecostatic network	High Accuracy	Higher Complexity
Knowledge-based Collaborative Deep Learning for Benign-Malignant Lung Nodule Classification on Chest CT	MV-KBC approach	Multi-view learning, Collaborative Sub models	Nodule segmentation accuracy affect classification
Lung Segmentation-Based Pulmonary Disease Classification Using Deep Neural Networks	Image segmentation based approach	Focused feature extraction without loss of information	Manual annotation requirement and high computer resources
Lungs Diseases Prediction based on Convolutional Neural Network	CNN algorithm	Early Detection	Data limitations and overfitting

Table 1: Comparative study of the reference papers

V. CONCLUSION

In conclusion, we examine the" LungCareAI" application, highlighting its pivotal role in revolutionizing respiratory healthcare. Through the strategic fusion of innovative technology and user-centric design, the mobile health solution utilizes deep learning algorithms to swiftly and accurately predict lung diseases. The integration of features like appointment booking and direct communication with healthcare professionals enhances the user's experience. With robust report generation capabilities, the application becomes a valuable tool for users and healthcare providers. As a beacon of progress in mobile health," LungCareAI" signifies a positive shift towards improved respiratory health outcomes, showcasing the transformative impact of artificial intelligence in healthcare diagnostics.

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