

LUNG DISEASE DETECTION USING DEEP LEARNING

Submitted in partial fulfillment of the requirements for the award of
Bachelor of Engineering degree in Electronics and Communication Engineering

by

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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of SETTIPALLI NAGA PRANAVI (39130409) and VANDAVASI SREEDEVI (39130500) who carried out the project entitled "LUNG DISEASE DETECTION USING DEEP LEARNING" under our supervision from November 2022 to April 2023.

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We, **SETTIPALLI NAGA PRANAVI** (39130409) and **VANDAVASI SREEDEVI** (39130500) , hereby declare that the Project Report entitled “**LUNG DISEASE DETECTION USING DEEP LEARNING**” done by us under the guidance of **Dr.K.V.KARTHIKEYAN ME., Ph.D.**, Professor, Dept. of Electronics and Communication Engineering, at Sathyabama Institute of Science and technology is submitted in partial fulfilment of the requirements of the award of Bachelor of Engineering degree in **Electronics and Communication Engineering**.

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ABSTRACT

Learning about Lung Diseases and their characterization is one of the most interesting research topics in recent years. With the various uses of medical images in hospitals, pathologies, and diagnostic centers, the size of the medical image data sets is also expanding expeditiously to capture the diseases in hospitals. Though a lot of research has been done on this particular topic still this field is confusing and challenging. There are lots of techniques in literature to classify medical images. The main drawback of traditional methods is the semantic gap that exists between the low-level visual information captured by imaging devices and high-level semantic information perceived by a human being. The difficulty of querying and managing the large datasets leads to a new mechanism called deep convolutional neural network.

Deep learning techniques have recently achieved an impressive result in the field of computer vision along with Medical Engineering. In this project, we had proposed and evaluated a deep convolutional neural network, for classifying the lung diseases and for taking necessary actions that are needed.

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CHAPTER 1

INTRODUCTION

COVID-19 is an infectious disease caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). The virus was first observed in Wuhan, China, in December 2019 and then spread globally. On March 11, 2020, the World Health Organization (WHO) declared COVID-19 a pandemic. The virus spreads via respiratory droplets or aerosol so that it can be transmitted into individuals' mouth, nose, or eyes of individuals in close proximity. The most common symptoms include a high fever, continuous cough, and breathlessness.

Coronaviruses are enveloped, positive-sense, single strand, non-segmented, and ribonucleic acid viruses that belong to the corona virus family. The viruses have characteristic morphology under the electron microscope with presence of viral spike peplomers arising from the viral envelope giving a crown appearance. The coronaviruses are widely distributed among humans and mammals. Six coronaviruses are identified, four of which cause mild common cold symptoms, and two strains were responsible for severe acute respiratory syndrome (SARS) that began in southern China in 2003 and Middle East Respiratory Syndrome (MERS) that originated in Saudi Arabia in 2012.

COVID-19 is usually diagnosed by an RT-PCR test and often is complemented by chest radiographs, including x-ray images and computed tomography (CT) scans. X-ray machines are widely available worldwide and provide images quickly, so chest scans have been recommended, by some researchers, for screening during the pandemic.

RT-PCR test, chest scans provide information about both the status of infection (i.e., presence or absence of the disease) and disease severity. Moreover, x-ray imaging is an efficient and cost-effective procedure. It requires relatively cheap equipment and can be performed rapidly in isolated rooms with a portable chest radiograph (CXR) device, thus reducing the risk of infection inside hospitals.

Despite these benefits, the American College of Radiology (ACR) and the Centers for Disease Control and Prevention (CDC) have not endorsed chest imaging as a first-line test for COVID-19. In the diagnosis of COVID-19, chest CT scans are highly sensitive (97%) but far less specific (25%) than RT-PCR. Recent research, however, suggests that deep learning techniques may improve the specificity of x-ray imaging for the diagnosis of COVID-19.

Since the end of 2019, a novel coronavirus illness (COVID-19) has caused a slew of unanticipated changes to the world as we know it. Despite our unwavering opposition, COVID-19 has taken millions of lives, with the death toll rising since it is exceedingly infectious and spreads quickly. The lack of effective treatment and immunization has exacerbated the condition, and the number of COVID-19-affected people is fast increasing, particularly in low-income nations.

Severe acute respiratory syndrome coronavirus 2 mainly known as coronavirus disease or COVID-19, for its extremely contagious nature, has been declared as a global pandemic by the World Health Organization (WHO), which has threatened the healthcare system all around the world on the verge of complete collapse.

Manufacturing infrastructure, distribution load, restricted availability, and public confidence difficulties are further hindering people's access to the COVID-19 vaccination, impacting the health sectors. As a result, detecting COVID-19-affected patients is regarded as the most important phase in the COVID-19 preventive procedure, and reverse transcription-polymerase chain reaction (RT-PCR) is the most widely used method for COVID-19 identification. This procedure, however, is time demanding, and particular materials and equipment that are not readily available are necessary.

The issues related to manufacturing infrastructure, distribution burden, limited supply, and public trust are further impeding peoples' access to the COVID-19 vaccine, consequently affecting the health sectors. In these circumstances, the WHO has emphasized mass testing and isolation of COVID-19 patients to flatten the epidemic curve. Hence, detection of COVID-19-affected patients is considered the most vital step of the COVID-19 prevention process, and reverse transcription-polymerase chain reaction (RT-PCR) is the worldwide accepted method for COVID-19 detection.

With a limited number of medical implementation systems available, it is important to develop and implement an automatic detection system as an alternative diagnosis option for COVID-19 detection, Lung Cancer, and Pneumonia that can be used on a commercial scale. Specifically, chest X-Ray images can be analyzed to identify the presence of disease-causing particles in a patient. Due to the high availability of large-scale annotated image datasets, great success has been achieved using a convolutional neural network for image analysis and classification. Input is obtained in the form of chest x- rays' images. Output results are acquired instantly in real-time which predicts if the person suffers from Covid, Lung cancer, pneumonia. The state-of-the-art methods work on the RCNN algorithm which makes it less accurate and more time-consuming. We propose a deep learning-based, automated method. The proposed method presents an improved depth-wise convolution neural network for analyzing chest X-Ray images. Wavelet decomposition is applied to integrate multiresolution analysis in the network.

The frequency sub-bands obtained from the input images are fed into the network for identifying the disease. The Advantages of the proposed system are that it could be the very first-of-its-kind, cost-efficient, and highly accurate application that provides a complete and accurate diagnosis. This proposed architecture provides promising results which can be further improved and implemented on a commercial scale.

Medical imaging, on the other hand, has shown significant promise in illness detection and diagnosis, since it is less time demanding and requires fewer materials and equipment. For a long time, computed tomography (CT) scans, ultrasound (US) imaging and X-ray imaging have been utilized for illness diagnosis, and the development of an automated detection technique has made disease detection easier for clinicians. A quick response is required to halt the spread of this extremely infectious illness and a precise diagnosis might be extremely important.

In this case, a convolutional block-based parallel concatenated convolutional block- based is introduced. The architecture that we have proposed after significant research analysis and reasoning performed exceptionally well in the lung disease detection job, indicating the potential of the CNN algorithm for the model suggested.

CHAPTER 2

LITERATURE SURVEY

2.1 LITERATURE SURVEY:

[1] Xolisani Nkwentsha, Anicet Hounkanrin, Jay R. Rajasekera

“Automatic classification of medical X-ray images with convolutional neural networks” Xolisani Nkwentsha, Anicet Hounkanrin, Jay R. Rajasekera 2019 With the number of imagestaken per patient scan rapidly increasing, there is a need for automatic medical image classification systems that are accurate because manual classification and annotation is time- consuming and prone to errors. SVM classification is used to classify the images. This module was error prone and had a lot lags due to the primitive nature of the project. This module had very poor accuracy rate of about 68%.

[2] Sultana, Sufian, Dutta

“Advancements in Image Classification using Convolutional Neural Network”, Sultana, Sufian, Dutta 2019 In Convolutional Neural Network (CNN). considered as the best for image– classification Different CNN architectures for image classification are explained. Through this paper, they have shown advancements in CNN from LeNet-5 to latest Senet model Thispaper used a CNN based model which needs huge data for training and computational power requirement which made this model expensive.

[3] Zhao, Zheng, Xu, Wu

“Object Detection with Deep Learning”: A Review, Zhao, Zheng, Xu, Wu 2019 Zhao, Zheng, Xu, Wu 2019. Problems in Traditional object detection methods. Their performance easily stagnates by constructing complex ensembles that combine multiple low-level image features with high-level context from object detectors and scene classifiers. There were no significantresults even though they analyze the dataset using detection methods.

[4] Swati Mukherjee

“Lung Cancer Disease Diagnosis Using Machine Learning Approach” extract different features pixel wise by using feature detectors/kernels 2020. Perform numerous convolutionson input, where each operation uses a different filter. This

results in different feature maps. Later, all feature maps are taken and put together to give final output of the convolution layer. Detection of lung cancer lesions using image data and not symptoms. It is a tool which will take input as the CT scan images and it will predict the possibilities of the disease and its stages using deep learning.

[5] Amrit Sreekumar, Karthika Rajan Nair, Sneha Sudheer, Ganesh Nayar H and Jyothisha J Nair

“Malignant Lung Nodule Detection using Deep Learning” 2019 Techniques such as convolutional neural networks (CNN), Deep Belief Networks (DBNs), and statistical denoising autoencoder (SDAE) were used on the LIDC-IDRI dataset by Sun et al. Accuracies obtained for the same were 79%, 81%, and 79%, respectively. The images were resized to 0.5, 0.75, 1.5, and 2 times its size for better prediction of the nodules. The pipeline was then adjusted to let the network predict at these scales. This approach increased the sensitivity of about 3 percent more than the predictions done on a normal scale to 86 percent.

[6] Waheed Abdul

“An Automatic Lung Cancer Detection and Classification (ALCDC) System Using Convolutional Neural Network” the method is proposed to acquire the CT images from the LIDC-IDRI database. In the second step, the segmentation of nodules is carried out by expert markings. Finally, after the evaluation of the tests, the diagnosis is completed by the Convolutional Neural Network (CNN) model into benign or malignant tissue. The proposed CNN architecture obtained 97.2% accuracy, 95.6% sensitivity, and 96.1% specificity. That can be due to the inclusion of the convolution layer, which produces further maps of characteristics and the existence in the fully connected.

[7] Chenglin liu, binquan wang, qinglei jiao, ming zhu

“Reducing False Positive for Lung Detection in Chest X-rays using Cascading CNN” There are two main kinds of deep convolution neural network in the object detection task. One is two stage method R-CNN and the other is the enhanced version YOLOv2. The non-nodule filter reduces the false positives obviously while does not affect the recall so much. when the recall is set about 0.79, the precision of the detector is 0.312.

[8] Ganesan, Subashini

“Classification of medical X-ray images for automated annotation”, Ganesan, Subashini, 2018. Problems on Difficulties in manual classification SVM classifier with six classes of X-ray images being taken, viz., chest, foot, spine, neck, head, and palm. This project was again an SVM classifier-based technique which had a low accuracy rate and also the classes taken were generalized without specific issues.

[9] Zare, Mueen, Awedh, Seng

“Automatic classification of medical X-ray images”: hybrid generative-discriminative approach, Zare, Mueen, Awedh, Seng, 2019. Is there a new method available to improve the classification performance of medical X-ray images. A new approach is presented to improve the classification performance of medical X-ray images based on the combination of generative and discriminative classification approach. A set of labelled X-ray images were given from 116 categories of different parts of body and the aim is to construct a classification model. This model was limited to the category of X-rays even though the requirement was for an efficient medical image classifier. So, this was a theoretical approach-based paper has been given and analysed.

[10] Aboud, Spanier, Joskowicz

“Automatic Classification of Body Parts X-ray Images”, Aboud, Spanier, Joskowicz, 2019. Impact of evaluation of X-ray images. The idea is to group digital X-ray images into structural groups: head-neck, upper-limb, body, lower-limb, and other. This paper presents the results of an experimental evaluation of X-ray images. This model was able to handle huge datasets at a same time, but that made the process heavyweight which makes it suitable for only high tier hospitals.

2.2 EXISTING SYSTEM:

In the existing CNN frameworks, CNNs are devised such that layer l_i is fed from layer l_{i-1} and then layer l_i feeds its outputs to layer l_{i+1} . Hence, whatever layer l_i learns is a composition of features from the initial layers to layer l_i . While learning from its previous layers, layer l_i completely ignores the spatial relations between input data instances. Hence, CNNs have to be trained with the same data

having different orientations and transformations such as rotation, zoom in or zoom out, flipping, spatial shifting, color perturbation, quantization, etc. Another limitation impedes its performance when a max-pooling layer is used. Location information of features, which gives translation invariance quality, is lost when the max-pooling layer is used. To mitigate these limitations, a large amount of data is used to train neural networks, and different augmentation techniques are also used to limit the loss of important spatial relationship information. Capsule networks are alternative models of CNN models, which can capture spatial information by storing information at the neuron level as vectors rather than scalars like CNNs. And max-pooling is replaced by the routing-by-agreement mechanism, which prevents information loss. The existing system has analysis of CT scan images and performs predictions on the likelihood of lung cancer. The system has been trained on a large dataset of CT scans and has achieved high accuracy in its predictions. The existing system of lung cancer prediction by CT scan images is a computer-aided diagnosis (CAD) system that uses machine learning algorithms to analyze CT scan images of the lungs and predict the likelihood of lung cancer. The system has been trained on a large dataset of CT scans and uses advanced image processing techniques to extract features from the images and make prediction.

1. *Limited Accuracy:* The existing system has limitations in its ability to accurately predict the likelihood of lung cancer. There may be cases where the system produces false positives or false negatives, leading to incorrect diagnoses or missed opportunities for early detection and treatment.
2. *Limited Accessibility:* The existing system may not be accessible to all medical facilities or patients due to cost constraints, technical expertise, or regulatory issues.
3. *Prediction:* The system is limited to predicting the likelihood of lung cancer and does not provide any additional information or context about the prediction.

CHAPTER 3

REQUIRMENTS ANALYSIS

3.1 DEEP LEARNING

Deep learning is a branch Machine learning which is completely based on artificial neural network, as neural network is going to mimic the human brain so deep learning is also a kind of mimic of human brain. In deep learning, we don't need to explicitly program everything. The concept of deep learning is not new. It has been around for a couple of years now. It's on hype nowadays because earlier we did not have that much processing power and a lot of data. As in the last 20 years, the processing power increases exponentially, deep learning and machine learning came in the picture. A formal definition of deep learning is- neurons.

Deep Learning is a subset of Machine Learning that is based on artificial neural networks (ANNs) with multiple layers, also known as deep neural networks (DNNs). These neural networks are inspired by the structure and function of the human brain, and they are designed to learn from large amounts of data in an unsupervised or semi-supervised manner.

Deep Learning models are able to automatically learn features from the data, which makes them well-suited for tasks such as image recognition, speech recognition, and natural language processing. The most widely used architectures in deep learning are feedforward neural networks, convolutional neural networks (CNNs), and recurrent neural networks (RNNs).

Feedforward neural networks (FNNs) are the simplest type of ANN, with a linear flow of information through the network. FNNs have been widely used for tasks such as image classification, speech recognition, and natural language processing.

Deep learning is a particular kind of machine learning that achieves great power and flexibility by learning to represent the world as a nested hierarchy of concepts, with each concept defined in relation to simpler concepts, and more abstract representations computed in terms of less abstract ones.

In human brain approximately 100 billion neurons all together this is a picture of an individual neuron and each neuron is connected through thousands of their neighbours. The question here is how do we recreate these neurons in a

computer. So, we create an artificial structure called an artificial neural net where we have nodes or neurons. We have some neurons for input value and some for output value and in between, there may be lots of neurons interconnected in the hidden layer.

3.1.1 ARCHITECTURE:

1. *Deep Neural Network*: It is a neural network with a certain level of complexity (having multiple hidden layers in between input and output layers). They are capable of modelling and processing non-linear relationships.
2. *Deep Belief Network (DBN)*: It is a class of Deep Neural Network. It is multi-layer belief networks. Steps for performing DBN:
 - a. Learn a layer of features from visible units using Contrastive Divergence algorithm.
 - b. Treat activations of previously trained features as visible units and then learn features of features.
 - c. Finally, the whole DBN is trained when the learning for the final hidden layer is achieved.
3. *Recurrent (perform same task for every element of a sequence) Neural Network*: Allows for parallel and sequential computation. Similar to the human brain (large feedback network of connected neurons). They are able to remember important things about the input they received and hence enables them to be more precise.

Deep learning (also known as deep structured learning) is part of a broader family of machine learning methods based on artificial neural networks with representation learning. Learning can be supervised, semi supervised or unsupervised. Deep-learning architectures such as deep neural networks, deep belief networks, deep reinforcement learning, recurrent neural networks and convolutional neural networks have been applied to fields including computer vision, speech recognition, natural language processing, machine translation, bioinformatics, drug design, medical image analysis, climate science, material inspection and board game programs, where they have produced results comparable to and in some cases surpassing human expert performance.

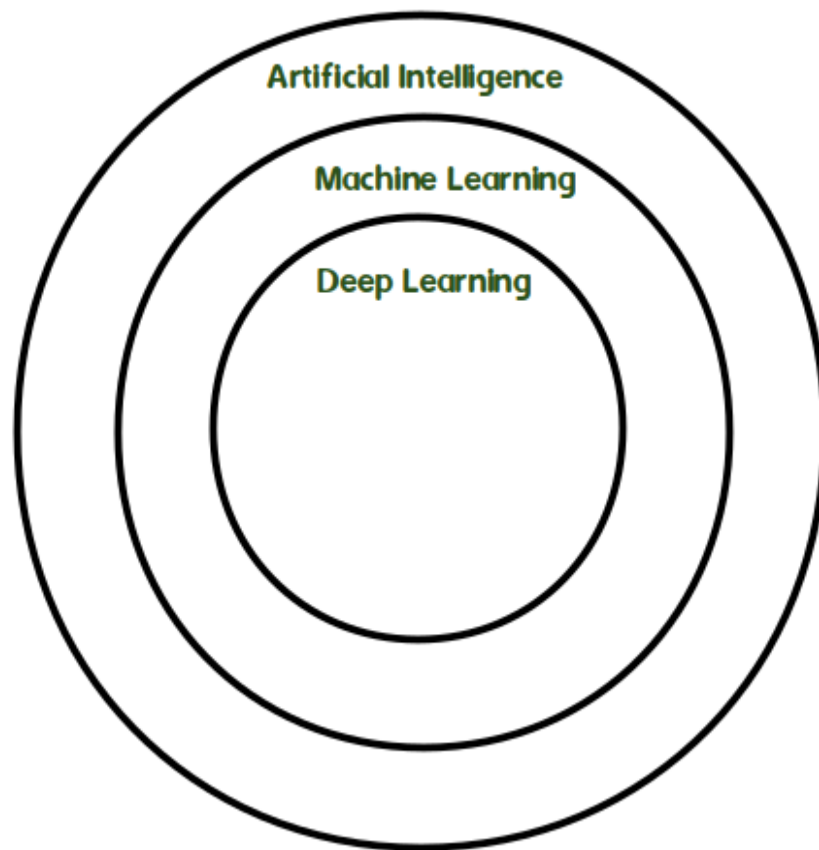


Fig 3.1 Difference between Machine Learning and Deep Learning

From the fig 3.1 we can say Deep learning (also known as deep structured learning) is part of a broader family of machine learning methods based on artificial neural networks with representation learning. Learning can be supervised, semi supervised or unsupervised. Deep-learning architectures such as deep neural networks, deep belief networks, deep reinforcement learning, recurrent neural networks and convolutional neural networks have been applied to fields including computer vision, speech recognition, natural language processing, machine translation, bioinformatics, drug design, medical image analysis, climate science, material inspection and board game programs, where they have produced results comparable to and in some cases surpassing human expert performance.

The adjective "deep" in deep learning refers to the use of multiple layers in the network. Early work showed that a linear perceptron cannot be a universal classifier, but that a network with a non-polynomial activation function with one hidden layer of unbounded width can. Deep learning is a modern variation which is concerned with

an unbounded number of layers of bounded size, which permits practical application and optimized implementation, while retaining theoretical universality under mild conditions. In deep learning the layers are also permitted to be heterogeneous and to deviate widely from biologically informed connectionist models, for the sake of efficiency, trainability and understandability, whence the "structured" part.

Most modern deep learning models are based on artificial neural networks, specifically convolutional neural networks (CNN)s, although they can also include propositional formulas or latent variables organized layer-wise in deep generative models such as the nodes in deep belief networks and deep Boltzmann machines.

In deep learning, each level learns to transform its input data into a slightly more abstract and composite representation. In an image recognition application, the raw input may be a matrix of pixels, the first representational layer may abstract the pixels and encode edges, the second layer may compose and encode arrangements of edges the third layer may encode a nose and eyes, and the fourth layer may recognize that the image contains a face. Importantly, a deep learning process can learn which features to optimally place in which level on its own. This does not eliminate the need for hand-tuning; for example, varying numbers of layers and layer sizes can provide different degrees of abstraction.

Deep learning architectures can be constructed with a greedy layer-by-layer method. Deep learning helps to disentangle these abstractions and pick out which features improve performance. For supervised learning tasks, deep learning methods eliminate feature engineering, by translating the data into compact intermediate representations akin to principal components, and derive layered structures that remove redundancy in representation.

Deep-learning networks are distinguished from the more commonplace single-hidden layer neural networks by their depth; that is, the number of node layers through which data must pass in a multistep process of pattern recognition. Earlier versions of neural networks such as the first perceptron were shallow, composed of one input and one output layer, and at most one hidden layer in between. More than three layers (including input and output) qualify as "deep" learning. So deep is not just a buzzword to make algorithms seem like they read Sartre and listen to bands you haven't heard of yet. It is a strictly defined term that means more than one hidden layer. In deep-learning networks, each layer of nodes

trains on a distinct set of features based on the previous layer's output. The further you advance into the neural net, the more complex the features your nodes can recognize since they aggregate and recombine features from the previous layer. This is known as feature hierarchy, and it is a hierarchy of increasing complexity and abstraction. It makes deep-learning networks capable of handling very large, high-dimensional data sets with billions of parameters that pass through nonlinear functions.

Above all, these neural nets are capable of discovering latent structures within unlabeled, unstructured data, which is the vast majority of data in the world. Another word for unstructured data is raw media (i.e., pictures, texts, video, and audio recordings). Therefore, one of the problems deep learning solves best is in processing and clustering the world's raw, unlabeled media, discerning similarities and anomalies in data that no human has organized in a relational database or ever put a name to. For example, deep learning can take a million images, and cluster them according to their similarity's cats in one corner, ice breakers in another, and in a third all the photos of your grandmother. This is the basis of so-called smart photo albums. Deep-learning networks perform automatic feature extraction without human intervention, unlike most traditional machine-learning algorithms.

Given that feature extraction is a task that can take teams of data scientists years to accomplish, deep learning is a way to circumvent the chokepoint of limited experts. It augments the powers of small data science teams, which by their nature do not scale. When training on unlabeled data, each node layer in a deep network learns features automatically by repeatedly trying to reconstruct the input from which it draws its samples, attempting to minimize the difference between the network's guesses and the probability distribution of the input data itself. Restricted Boltzmann machines, for example, create so-called reconstructions in this manner. In the process, these neural networks learn to recognize correlations between certain relevant features and optimal results – they draw connections between feature signals and what those features represent, whether it be a full reconstruction, or with labeled data. A deep-learning network trained on labeled data can then be applied to unstructured data, giving it access to much more input than machine-learning nets.

The classic universal approximation theorem concerns the capacity of feed forward neural networks with a single hidden layer of finite size to approximate

continuous functions. In 1989, the first proof was published by George Cybenko for sigmoid activation functions and was generalized to feed-forward multilayer architectures in 1991 by Kurt Hornik. Recent work also showed that universal approximation also holds for non-bounded activation functions such as the rectified linear unit.

3.2 NEURAL NETWORK

A neural network is a series of algorithms that endeavors to recognize underlying relationships in a set of data through a process that mimics the way the human brain operates. In this sense, neural networks refer to systems of neurons, either organic or artificial in nature. Neural networks can adapt to changing input; so, the network generates the best possible result without needing to redesign the output criteria. The concept of neural networks, which has its roots in artificial intelligence, is swiftly gaining popularity in the development of trading systems. A neural network works similarly to the human brain's neural network. A "neuron" in a neural network is a mathematical function that collects and classifies information according to a specific architecture. The network bears a strong resemblance to statistical methods such as curve fitting and regression analysis. A neural network contains layers of interconnected nodes. Each node is a perceptron and is similar to multiple linear regression. The perceptron feeds the signal produced by a multiple linear regression into an activation function that may be nonlinear. In a multi-layered perceptron (MLP), perceptron is arranged in interconnected layers. The input layer collects input patterns. The output layer has classifications or output signals to which input patterns may map. Hidden layers fine-tune the input weightings until the neural network's margin of error is minimal. It is hypothesized that hidden layers extrapolate salient features in the input data that have predictive power regarding the outputs. This describes feature extraction, which accomplishes a utility similar to statistical techniques such as principal component analysis.

3.3 CONVOLUTION NEURAL NETWORK

Convolutional Neural Network is an algorithm of Deep Learning. That is used for Image Recognition and in Natural Language Processing. Convolutional Neural Network (CNN) takes an image to identify its features and predict it. It captures the spatial and temporal dependencies of the image. Each CNN layer learns filters of increasing complexity. The first layers learn basic feature detection filters like edges, corners. The middle layer learns filters that detect parts of objects. The last layers have higher representations they learn to recognize full objects in different shapes and positions. Suppose, when you see some image of a Dog, your brain focuses on certain features of the dog to identify. These features may be the dog's ears, eyes, or it may be anything else. Based on these features your brain gives you a signal that this is a dog. Similarly, Convolutional Neural Network processes the image and identifies it based on certain features. Convolutional Neural Network is gaining so much popularity over artificial neural networks.

Steps in Convolutional Neural Network in a Convolutional Neural Network, there are basically the following steps -

1. Convolution Operation.
2. Re LU Layer.
3. Pooling.
4. Flattening.
5. Full Connection.

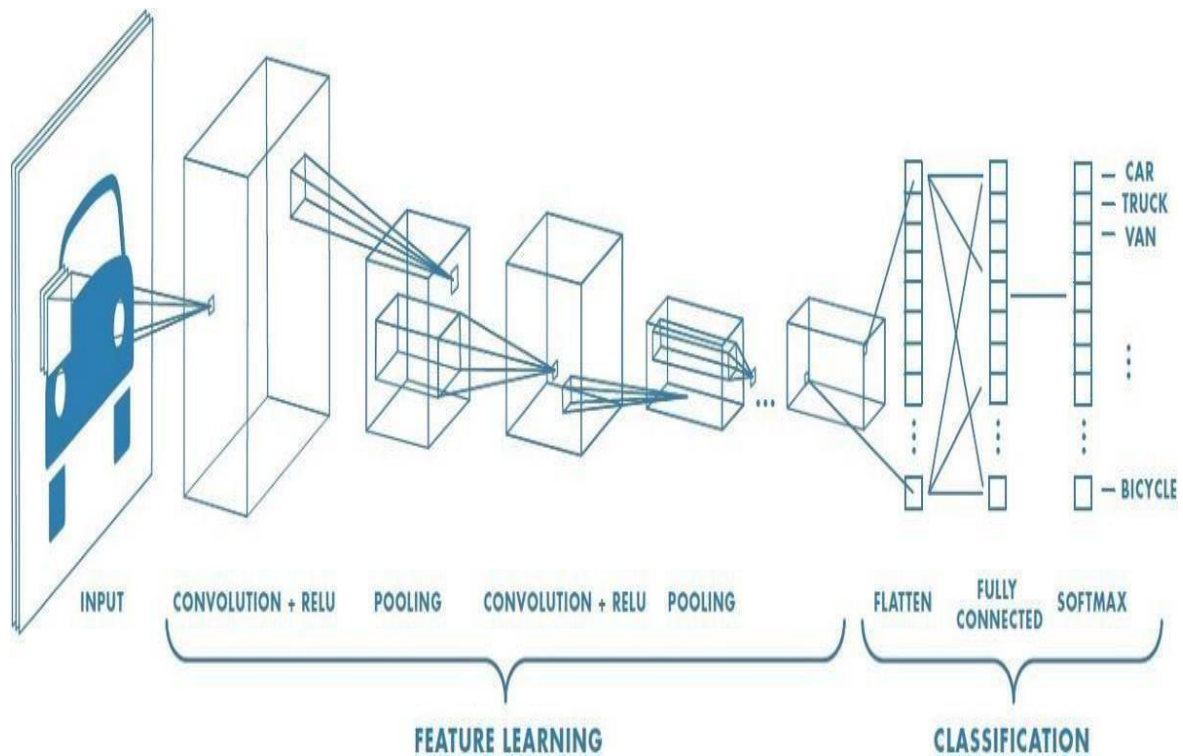


Fig 3.2 Flow of CNN

Generally, a convolutional neural network architecture generally has several components:

1) A *convolution layer* - you can think of this layer as “what relevant features are we picking up in an image?” In a convolutional neural network, we have multiple convolutional layers that extract low to high-level features depending on what specific layer we are focusing on. To give an (over-simplified) intuition, earlier convolutional layers pick up lower-level features (i.e., like lines and edges) while later convolutional layers pick up higher-level features based on inputs from lower-level features (i.e., shapes, structures) - analogous to how vision works in the human brain.

2) A *pooling layer* - convolutional neural networks are typically used for image classification. However, images are high-dimensional data - so we would prefer to reduce the dimensionality to minimize the possibility of overfitting. Pooling essentially reduces the spatial dimensions of the image based on certain mathematical operations such as average or max-pooling (there’s a nice graphic

here). We generally incorporate pooling since it generally, acts as a noise suppressant makes it invariant to translation movement for image classification and helps capture essential structural features of the represented images without being bogged down by the fine details.

3) *Fully-connected layer* - You can think of a series of convolution and pooling operations as dimensionality reduction steps prior to passing this information over to the fully connected (Dense) layer. Essentially, what the fully connected layer does is that it takes the "compressed" representation of the image and it tries to fit a basic NN (multi-layer perceptron) when doing classification.

S.NO	CNN Layers
1.	Convolutional layer
2.	Pooling Layer
3.	Fully connected Layer

TABLE 3.1 CNN Layers

The change in paradigm that the usage of NNs encompasses is a very important one. Prior to the usage of NNs in image classification, the practitioner had to use explicitly coded algorithms for detecting features. This was a job that often involved a lot of work. Machine Learning was not used throughout the whole system, only the last layer of the system, the classifier, had the capacity to learn and adapt itself to the specific problem. NNs, and especially CNNs, dramatically change that. CNN's extract features from images and learns how to do it. The practitioner doesn't need to craft complicated hard-coded algorithms to extract those features. Since the introduction of the first CNNs in 2012, all the winning teams for the classification task have used different types of CNNs. CNN's systems now clearly outperform other image classification systems such as the ones described. State-of-the-art CNNs have even crossed the boundary of what is considered to be the error rate for human beings in image classification tasks. Ever

since its introduction in 2012, CNNs have been making steady progress in decreasing the error rate in both tasks. This is due to the introduction of new strategies that further improve the convergence and training speed of CNNs. CNNs are a particular kind of NNs that give their name to the fact that they make extensive use of Convolutional Layers.

Convolutional Layers consist of a learnable filter of fixed size (kernel) to be applied to images. The name comes from the fact that at each forward pass, the learned filter is convolved with the image resulting on a 2-dimensional map. Another type of layer widely used CNNs are the pooling layers. These layers perform a type of down-sampling on the input signal. There are various types of Pooling layers, max-pooling being the most common. ReLUs or Rectified Linear Units, are also widely used in CNNs. Re LUs are units that apply a function similar to Equation 3.1. There are often alternatives for these types of units, Equation 3.2 and 3.3 show two of them.

$$\text{Re LU: } f(x) = \max(0, x) \quad (3.1)$$

$$\text{Tanh: } f(x) = \tanh(x) \quad (3.2)$$

$$\text{Sign: } f(x) = (1 + e^{-x})^{-1} \quad (3.3)$$

Fully Connected Layers are used too, as in more standard NNs. These layers consist of an array of neurons, each of which is connected to every single output of the previous layer. Loss Layers are typically used at the end of the CNN to figure out the penalty for a given output and to provide feedback used by the CNN to learn. In addition to these more standard set of layers, modern CNNs make use of a very extensive set of techniques and strategies that greatly enhance their performance. Dropout is one of such techniques. It consists on temporarily deactivating some neurons within the net, preventing it from over-fitting. This temporary deactivation of neurons is typically applied only to 8 Fully-connected layers. CNNs nowadays also make extensive use of GPU processing power that allows for a faster training, an idea pioneered in 2012 that is now a standard. Evidence shows that one way of improving a CNN performance is by stacking more layers and making the network effectively deeper the problem that often arises is that as more layers are stacked, the performance saturates and eventually starts to decrease at some point. To address this issue, the idea of

deep residual networks has been proposed. Residual Networks try, with minor changes to the architecture, and with virtually no impact on performance, to approximate residual functions instead of standard functions.

If we have a CNN with input x and we want the output to approximate a function $O(x)$, we can instead, approximate $F(x) = O(x) - x$ and then compute $O(x)$ from $F(x)$ since $O(x) = F(x) + x$. Evidence shows that CNNs train better and converge faster when the approximated function is in fact $F(x)$, a residual function. This approach opens door for usage of even deeper and more powerful models. Some pre-processing techniques are also used to improve the data fed to the CNN. These techniques include normalization and zero-centering of the data. These techniques are mainly used in order to overcome the vanishing and exploding gradient problem, that often affects NN systems' training. Both problems arise when models are trained using gradient-based methods. Gradients are often computed using the chain rule. In case of near-zero gradients, this led to several very small numbers being multiplied together in order to calculate the changes in the last layers. This causes the last layers to suffer virtually no change at all in its outputs as the training progresses. The opposite happens when activation functions have high derivative values, leading to the uncontrolled increase of the gradient of the last layers. As NN systems tend to require a lot of examples, better results are obtained when data augmentation techniques are used. CNN frameworks often incorporate mechanisms to augment data.

3.4 VGG-16

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) is an annual computer vision competition. Each year, teams compete on two tasks. The first is to detect objects within an image coming from 200 classes, which is called object localization. The second is to classify images, each labeled with one of 1000 categories, which is called image classification. VGG 16 was proposed by Karen Simony and Andrew Zisserman of the Visual Geometry Group Lab of Oxford University in 2014 in the paper "VERY DEEP CONVOLUTIONAL NETWORKS FOR LARGE-SCALE IMAGE RECOGNITION". This model won 1st and 2nd place in the above categories in the 2014 ILSVRC challenge.

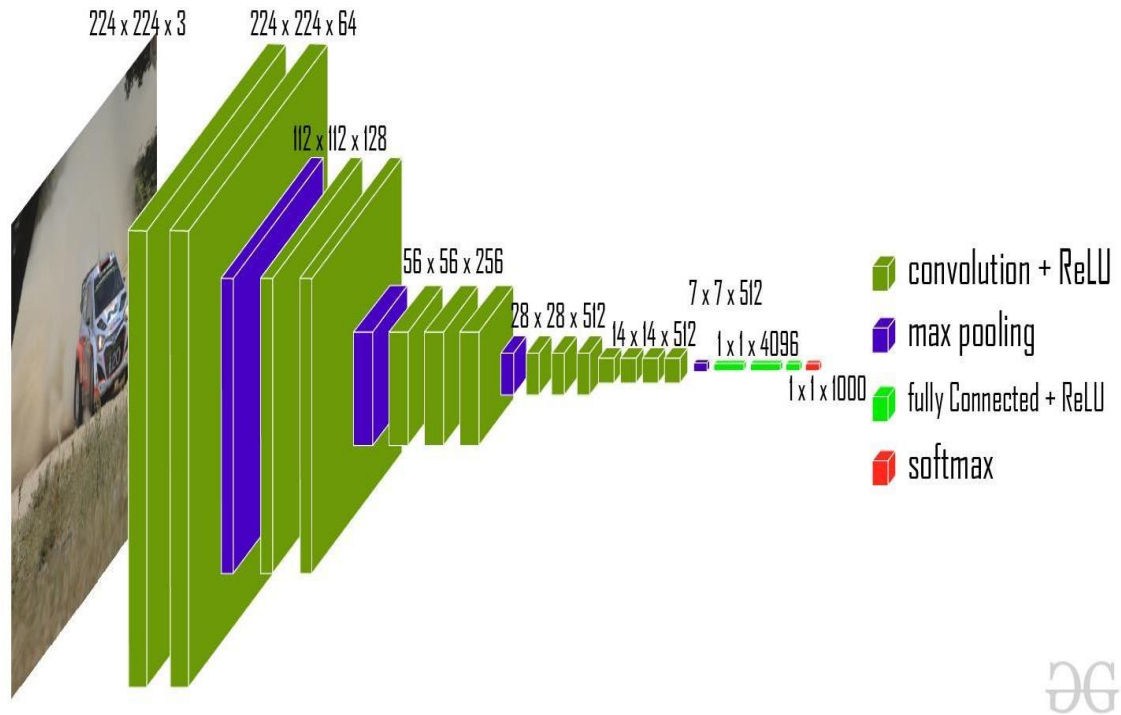


Fig 3.3 VGG-16 Architecture

This model achieves 92.7% top-5 test accuracy on the ImageNet dataset which contains 14 million images belonging to 1000 classes.

Objective: The ImageNet dataset contains images of fixed size of 224*224 and have RGB channels. So, we have a tensor of (224, 224, 3) as our input. This model processes the input image and outputs a vector of 1000 values. This vector represents the classification probability for the corresponding class. Suppose we have a model that predicts that the image belongs to class 0 with probability 1, class 1 with probability 0.05, class 2 with probability 0.05, class 3 with probability 0.03, class 780 with probability 0.72, class 999 with probability 0.05 and all other class with 0. so, the classification vector for this will be: To make sure these probabilities add to 1, we use soft max function. This soft max function is defined as follows:

After this we take the 5 most probable candidates into the vector. Since, all the categories in ground truth are in the Predicted top-5 matrix, so the loss becomes 0.

VGG Architecture: The input to the network is an image of dimensions (224, 224, 3). The first two layers have 64 channels of a 3*3 filter size and the same padding. Then after a max pool layer of stride (2, 2), two layers have convolution layers of 128 filter size and filter size (3, 3). This is followed by a max-pooling layer of stride (2, 2) which is the same as the previous layer. Then there are 2 convolution layers of filter size (3, 3) and 256 filters. After that, there are 2 sets of 3 convolution layers and a max pool layer. Each has 512 filters of (3, 3) size with the same padding. This image is then passed to the stack of two convolution layers. In these convolution and max-pooling layers, the filters we use are of the size 3*3 instead of 11*11 in Alex Net and 7*7 in ZF-Net. In some of the layers, it also uses 1*1 pixel which is used to manipulate the number of input channels. There is a padding of 1-pixel (same padding) done after each convolution layer to prevent the spatial feature of the image.

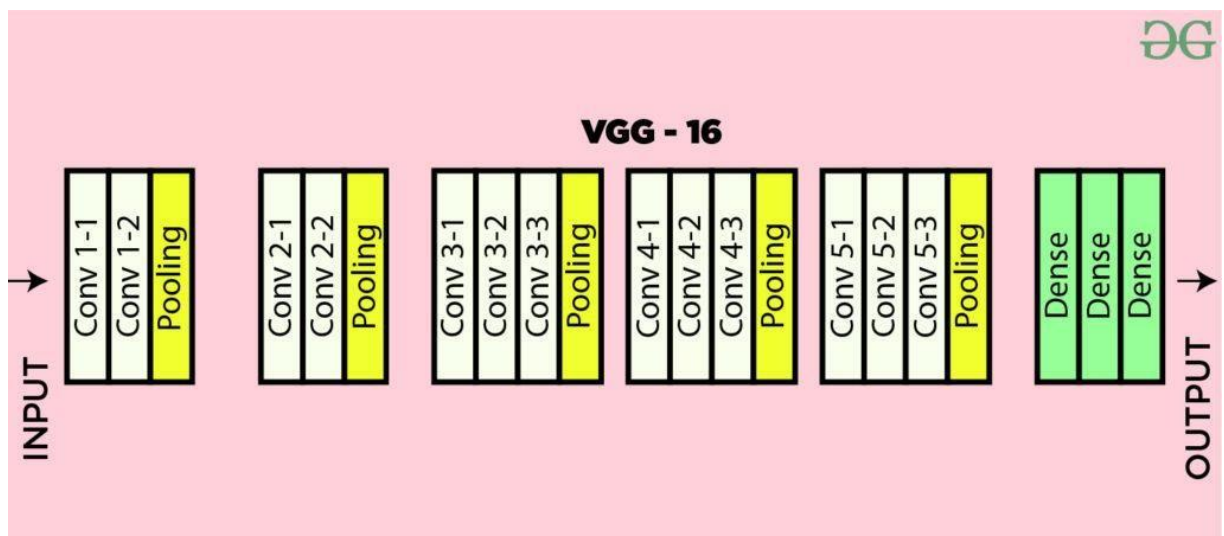


Fig 3.4 VGG-16 Block Diagram

After the stack of convolution and max-pooling layer, we got a (7, 7, 512) feature map. We flatten this output to make it a (1, 25088) feature vector. After this there is 3 fully connected layer, the first layer takes input from the last feature vector and outputs a (1,4096) vector, the second layer also outputs a vector of size (1, 4096) but the third layer output 1000 channels for 1000 classes of ILSVRC challenge i.e., 3rd fully connected layer is used to implement soft max function to

classify 1000 classes. All the hidden layers use ReLU as its activation function. ReLU is more computationally efficient because it results in faster learning and it also decreases the likelihood of vanishing gradient problems.

Configuration: The Fig 3.3 above listed different VGG architectures. We can see that there are 2 versions of VGG-16 (C and D). There is not much difference between them except for one that except for some convolution layers, (3, 3) filter size convolution is used instead of (1, 1). These two contain 134 million and 138 million parameters respectively.

Object Localization in Image: To perform localization, we need to replace the class score by bounding box location coordinates. A bounding box location is represented by the 4-D vector (center co-ordinates (x, y), height, width). There are two versions of localization architecture, one is bounding box is shared among different candidates (the output is 4 parameter vector) and the other is a bounding box is class-specific (the output is 4000 parameter vector). The paper experimented with both approaches on VGG -16 (D) architecture. Here we also need to change loss from classification loss to regression loss functions (such as MSE) that penalize the deviation of predicted loss from the ground truth.

Results: VGG-16 was one of the best performing architectures in the ILSVRC challenge 2014. It was the runner up in the classification task with a top-5 classification error of 7.32% (only behind Google Net with a classification error of 6.66%). It was also the winner of localization task with 25.32% localization error.

3.4.1 Limitation of VGG 16:

It is very slow to train (the original VGG model was trained on Nvidia Titan GPU for 2-3 weeks). The size of VGG-16 trained image Net weights is 528 MB. So, it takes quite a lot of disk space and bandwidth which makes it inefficient. 138 million parameters lead to exploding gradients problem.

CHAPTER 4

DESCRIPTION OF PROPOSED SYSTEM

4.1 PROPOSED SYSTEM:

We propose a deep learning-based, automated method for the diagnosis of lung diseases from the chest X-Ray images. The proposed method presents an improved depth-wise convolution neural network for analyzing the chest X-Ray images. Wavelet decomposition is applied to integrate multiresolution analysis in the network. The frequency sub-bands obtained from the input images are fed into the network for identifying the disease. The network is designed to predict the class of the input image as lung disease or not. The proposed system aims to improve the overall performance and usability of the existing system. The system will incorporate additional data sources, such as patient medical histories and genetic information, to enhance the accuracy of its predictions. The system will provide additional information and context about the prediction, such as the probability of the prediction and any relevant medical information that may be useful for medical professionals. The system will be designed with a more user-friendly interface that can be used by medical professionals with varying levels of expertise in interpreting medical images and making clinical decisions. The proposed system will be integrated with electronic medical record systems to provide seamless access to patient information and facilitate communication between medical professionals.

4.1.1 Modules:

1. *Data Preprocessing*: The preprocessing stage will be improved to include additional image processing techniques that enhance the quality of the images and reduce noise
2. *VGG16 Model*: The VGG16 model is used to extract features from the CT scan images and make predictions about the likelihood of lung cancer. It will be fine-tuned using transfer learning techniques to improve its performance on previously unseen data.
3. *Prediction Output*: The system predicts the likelihood of lung cancer based on the input CT scan image. The output will be improved to include additional

information and any relevant medical information that may be useful for medical professionals. It also be integrated with electronic medical record systems to provide seamless access to patient information.

4.2 Advantages of Proposed System:

The Advantages of the proposed system are that it could be the very first-of-its-kind, cost-efficient, and highly accurate application that provides complete and accurate lung disease diagnosis. This proposed architecture provides promising results which can be further improved and implemented on a commercial scale.

4.3 Difference Between Existing and Proposed System:

The existing systems are not very robust in prediction. They have not evolved according to technological advancements and time. The results are also unsatisfactory and may lead to erroneous diagnosis of lung disease using Chest X-Ray images. The proposed system performs better than all previous ones in terms of accuracy and time effectiveness.

4.4 Conclusion:

CT and X-rays are effective tools for diagnosing and evaluating lung diseases. We used the wavelet function to divide X-ray samples into two categories: lung diseases and healthy people. We applied these model architectures for feature extraction and classified categories through an FC layer. Wavelet decomposition is applied to integrate multiresolution analysis in the network. The frequency sub-bands obtained from the input images are fed into the network for identifying the disease. The network is designed to predict the class of the input image as lung disease or not. The experimental results reveal that the proposed system has better accuracy than the existing models and can be used for effective diagnosis and treatment.

The method proposed in this paper can be applied to the classification of modal characteristics of other lung diseases. Patients with pulmonary edema and lung tumors have pulmonary modal characteristics such as ground glass shadow and infiltration shadow. The same model can be improved and extended to detect those conditions in humans. The techniques of fine-tuning can be applied to our model for better accuracy.

CHAPTER 5

IMPLEMENTATION DETAILS

5.1 ARCHITECTURE:

The total architecture and the work flow is as show in the below Fig 5.1 The architecture involves in various steps such as Ct scan images in image format, removing unwanted images, resizing images, changing color channel, removing noisy images and then splitting the data after this step only we can proceed further.

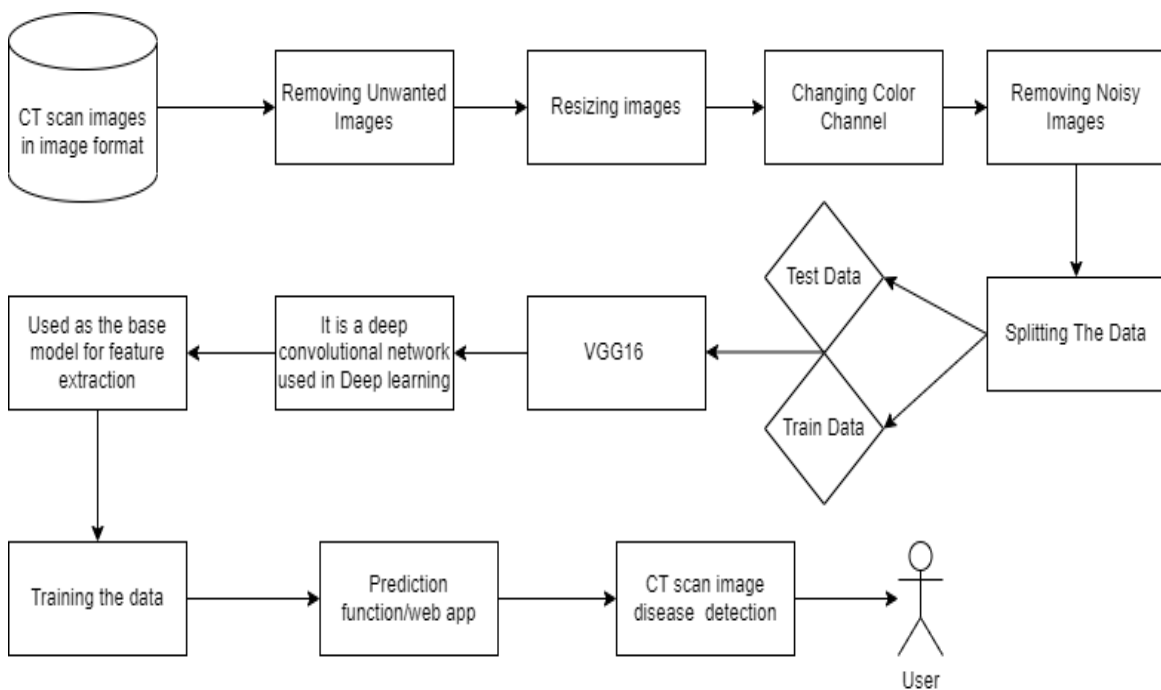


Fig 5.1 Architecture Block Diagram

5.2 DATA ACQUISITION AND PRE-PROCESSING:

The data acquisition and pre-processing are the very important and the crucial part in the working of the project and we can say that this data acquisition and pre-processing can be mainly divided into two parts they are data gathering and data pre-processing and also the data pre-processing dividing into several parts.

5.2.1 Data Gathering:

We have gathered the data for our project for the lung cancer, covid diseases in the CSV format: Lung CT Scan Images: Image dataset

5.2.2 Data pre-processing:

Data pre-processing is a data mining technique used to turn the raw data into a format that is both practical and effective. Data pre-processing changes the data into a format that can be processed in data mining, machine learning, and other deep learning tasks more quickly and efficiently. To ensure reliable findings, the techniques are typically applied at the very beginning of the deep learning and AI development pipeline. Although there are many various tools and strategies for preparing data, we have chosen to concentrate on the following measures for our dataset: Our first step was to collect a dataset of lung cancer images and corresponding labels (e.g., malignant/benign). We used a dataset that is diverse and representative of the population being studied. Once the dataset is collected, it should be pre-processed to ensure that the images are ready for training.

5.2.2.1 Resizing:

The images in the dataset may have different sizes and aspect ratios. Resizing the images to a common size ensures that they fit into the neural network architecture and can be processed efficiently. The most common size used for lung cancer detection is 224x224, which is the input size used in VGG16. Resizing is an essential pre-processing step because it helps to ensure that the images are of a consistent size and can be processed efficiently by the neural network. Resizing also reduces the computational complexity of the model, as smaller images require less memory and processing power to train and evaluate.

5.2.2.2 Normalization:

Normalizing the pixel values of the images to a common range is essential for training deep neural networks. Normalization helps to prevent the network from becoming biased towards certain pixel values and improves its stability during training. The most common method used for normalization is to scale the pixel values to be between 0 and 1. Normalization is a critical pre-processing step in deep learning for lung cancer detection, as it helps to ensure that the input data

has a consistent scale and distribution. Normalization is performed on the input images before they are passed through the neural network to improve the performance of the model. Normalization is important because it helps to ensure that the model is robust to changes in the input data. Normalizing the input data to a consistent scale and distribution helps to reduce the impact of differences in brightness, contrast, and lighting conditions on the model's performance. This is especially important in medical imaging, where images may have variations in brightness and contrast due to differences in imaging equipment and patient factors.

5.2.2.3 Data Augmentation:

Data augmentation is a technique used to increase the diversity of the training data by applying various transformations to the images. Data augmentation is especially useful when the dataset is small, as it helps to prevent overfitting and improve the model's generalization ability. Some common data augmentation techniques include random rotations, flips, shifts, and zooms.

The goal of data augmentation is to artificially expand the size of the dataset by generating new variations of the original images. This can help to reduce overfitting and improve the model's ability to generalize to new data. Data augmentation is particularly useful in medical imaging, where the dataset may be limited and the variations in the input data may be small. By applying data augmentation techniques to the input images, the model can be trained on a more diverse set of images, which can improve its ability to detect lung cancer accurately.

5.2.2.4 Pre-processing of CT scans:

In addition to the above-mentioned pre-processing techniques, CT scans require additional processing to make them suitable for training deep learning models. CT scans are typically volumetric and contain multiple slices, which makes them more complex than standard 2D images. Pre-processing of CT scans involves converting them into 2D images using different methods such as Maximum Intensity Projection (MIP) and Minimum Intensity Projection (Min IP). MIP involves selecting the maximum pixel value across all the slices for each pixel

location to create a 2D image. Min IP involves selecting the minimum pixel value across all the slices to create a 2D image.

5.3 MODEL TRAINING AND VALIDATION

The model training and validation is also a very important step in the extraction of the features and this step mainly involves in the model creation and also model evaluation.

5.3.1 Model Creation:

In the step of the model creation the entire data sets are divided according to the requirement.

5.3.1.1 Base Model:

The VGG16 model is a deep convolutional neural network that has shown excellent performance in many computer vision tasks. In this module, we will use the pre-trained VGG16 model as the base model for feature extraction. We will freeze the pre-trained weights of the VGG16 model and add a custom classification head on top to train the model for the specific task of lung cancer detection. The custom classification head consists of a few fully connected layers that will be trained to classify the images as malignant or benign. By definition, the Test set is made up of 80% training images, and 20% testing images.

5.3.1.2 Train-Validation-Test Split:

The dataset should be split into three parts - training, validation, and test sets. The training set is used to train the model, the validation set is used for hyperparameter tuning and model selection, and the test set is used to evaluate the final model's performance. The split should be done randomly and should preserve the class distribution in each set.

5.3.2 Model Training and Validation:

Once the base model is set up, we can start training the model using the training data set. We will use a suitable loss function, such as binary cross-entropy for binary classification, and an optimizer, such as Adam optimizer, to train the model. We will monitor the training process to avoid overfitting by using techniques such as early stopping and regularization. During training, we will evaluate the

model's performance on the validation set to check if the model is learning correctly and if the hyperparameters are tuned correctly.

5.3.2.1 Model validation:

Model validation is the process of evaluating the performance of the trained model on a separate set of images to assess its ability to generalize to new data. During model validation, the performance of the trained model is evaluated on a separate set of images that were not used during training. This helps to assess the ability of the model to generalize to new data and to identify any potential overfitting issues. The performance of the model is typically evaluated using metrics such as accuracy, precision, recall, and F1 score.

5.3.2.2 Fine-Tuning:

After training the model with the custom classification head, we can fine-tune the last few layers of the VGG16 model to adapt it to the specific task of lung cancer detection. We will unfreeze the last few layers of the VGG16 model and retrain the model using a smaller learning rate. Fine-tuning helps the model to learn more specific features for the task and improve its performance

5.3.3 Model Evaluation:

Once the model is trained and fine-tuned, we can evaluate its performance on the test set to measure its performance on unseen data. Once the input images are pre-processed, they are passed through the VGG16 model to obtain the output probabilities for each class. The class with the highest probability is then selected as the predicted class for the input image. To evaluate the performance of the model, metrics such as accuracy, precision, recall, and F1 score are calculated on a test dataset. These metrics help to assess the model's ability to correctly identify lung cancer from medical images. Additionally, to improve the model's performance, techniques such as transfer learning and fine-tuning can be applied, which involve reusing pre-trained models or adjusting the model's weights to better fit the dataset. Overall, prediction in deep learning for lung cancer detection involves using a pre-trained model, pre-processing the input data, and evaluating the model's performance using metrics.

5.4 Web App Deployment

The server-side processing will be handled by code that we write. Requests will be sent to our code. It will determine the subject matter and nature of the requests. Additionally, it will decide what kind of reply to send to the user. We'll use Flask for all of this. It simplifies the web application design process. Flask enables us to concentrate on what the consumers are asking for and the appropriate kind of response to provide.

We will build a virtual environment for the project inside the directory that will hold the project files. First, install virtualenv using pip. Install virtualenv, then create and activate a virtual environment, and then use the command `pip install Flask` to install Flask. The foundation of the project has been laid, and it is now time to begin adding functionality. To get things rolling, a new file containing an introduction to our website is generated in the same directory. We give this file the name `main.py`. Now that we have told the terminal which application to run, we are able to execute the application by issuing the commands `export FLASK_APP=main.py` and `set FLASK_APP=main.py`.

After saving it in a file and running the script, we will have the opportunity to view the output. Then navigate to the URL that was provided there, and you will see your first webpage showing the message on your local server. As we delve deeper into the setting, we find that the `route ()` decorator in Flask is what is utilized in order to bind a URL to a function. Now, in order to extend the functionality of our simple web app, we have also included another method called `add URL rule ()`. This method is a function of an application object and is also available to bind a URL with a function, similar to how `route ()` was used in the example that was presented earlier.

After that, we create the form by utilizing HTTP methods within Flask. The Hypertext Transfer Protocol, also known as HTTP, serves as the basis for data transfer on the World Wide Web. This protocol defines a variety of different ways that can be utilized to retrieve data from a given URL.

The GET requests are handled by the Flask route as their default response. This choice, however, can be changed by supplying a different set of methods as the parameter to the `route ()` decorator. In order to demonstrate the usage of the

POST method in URL routing, let us first create an HTML form and then use the POST method to transmit data from the form to a URL. This will allow us to demonstrate the use of the POST method in URL routing. Using this method, we are able to generate the HTML login page with information such as the user's name, age, gender, and any other disease-related input.

Finally, we save this file HTML and try this python script to create the server. After the development server starts running, open your html file in the browser, enter the details in the text field and click submit button. The output will appear detecting the disease or not.

CHAPTER 6

RESULT AND DISCUSSION

We are creating a web page where the user can enter his/her information as input and then the app predicts whether the person has the disease or not.

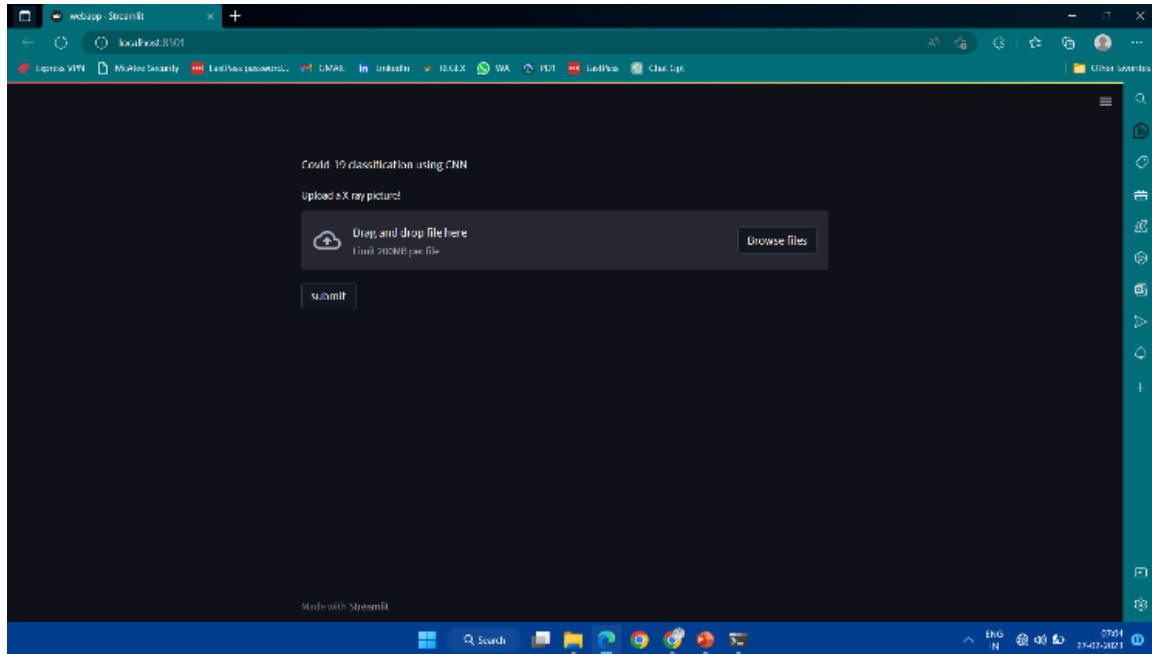


Fig 6.1. Webapp for Providing user Input

For the correct prediction of the disease we need to previously extract the features for the different lung ct images data sets and then we need to give the lung ct image of any patient the again the features from the patient lung ct image to be extracted and compare the those features then predict and analyze the disease occurred.

The ct image data sets are very essential for the output analysis. Form the different data sets we take only necessary images and removes outliers that means we are are very different from other ct images and they don't have any similarities. By removing then only we can analyse the output very accurately.

6.1 INPUT TO BE PROVIDED:

To extract the similarities between all the data sets of different ct images for that we need to write and implement the code in python the is main essential backend code.

For this analysis we need to provide the user input in the web app provided and then click the submit button. Then the disease will be displayed such as, lung cancer,covid ,no covid and no cancer.

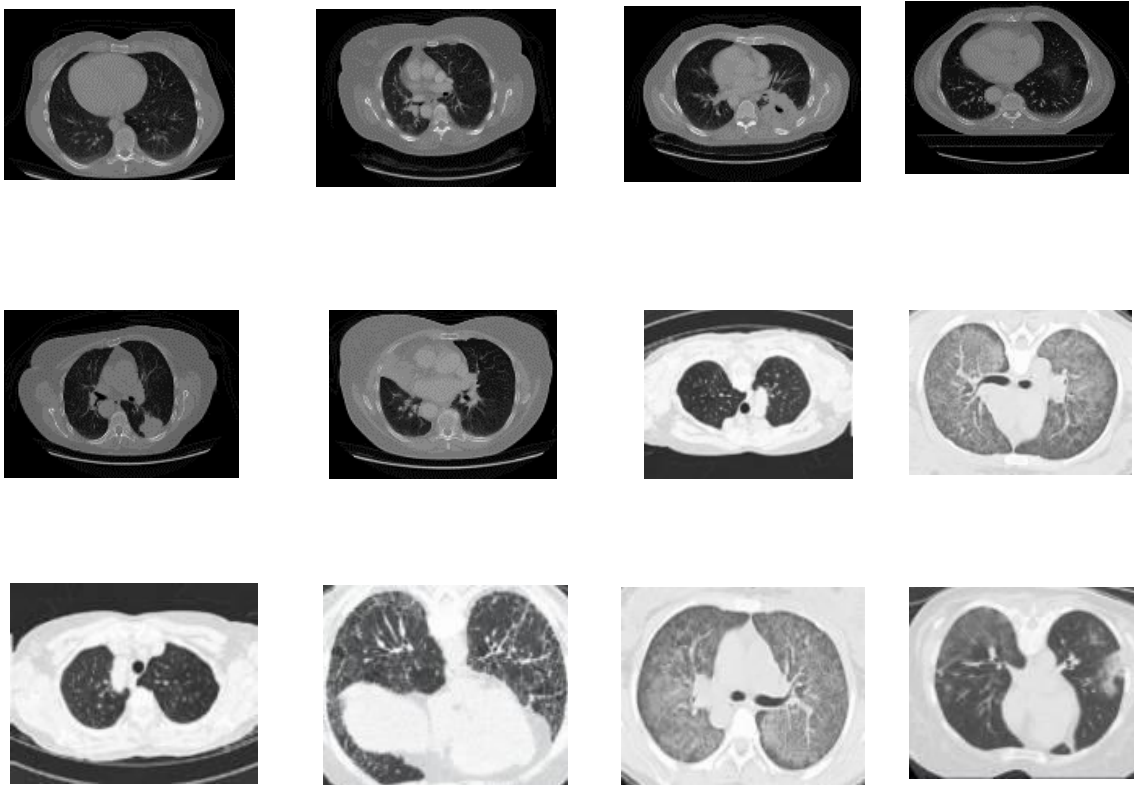


Fig 6.2. Different Lung CT Images

The different classification of the datasets is placed an crucial role for the analysis of the different images such as valid dataset ,test dataset and train dataset.

```

import streamlit as st
import tensorflow as tf
import cv2
import numpy as np
from PIL import Image

model_to_predict = tf.keras.models.load_model('chestmodel.hdf5')
def predict_covid(test_image):
    img = cv2.imread(test_image)
    img = img / 255.0
    img = cv2.resize(img, (305, 430))
    img = img.reshape(1,305,430,3)
    prediction = model_to_predict.predict(img)
    pred_class = np.argmax(prediction, axis = -1)
    return pred_class

def load_image(image_file):
    img = Image.open(image_file)
    return img

st.write("Covid-19 classification using CNN")

pic = st.file_uploader("Upload a X-ray picture!")
submit = st.button('submit')

```

Fig 6.3. Backend code part 1

```

if submit:
    pic_details = {"filename":pic.name, 'filetype':pic.type, 'filesize':pic.size}
    st.write(pic_details)

    st.image(load_image(pic), width=250)

    with open('test.jpg', 'wb') as f:
        f.write(pic.getbuffer())
    pred = predict_covid('test.jpg')
    if pred[0] == 0:
        st.write('Covid')
    elif pred[0] == 1:
        st.write('No Covid! chill')
    elif pred[0] == 2:
        st.write('Lung Cancer')
    elif pred[0] == 3:
        st.write('Lung Cancer')
    elif pred[0] == 4:
        st.write('No Cancer chill')
    elif pred[0] == 5:
        st.write('Lung Cancer')

```

Fig 6.4 Backend code part 2

6.2 OUTPUT PREDICTED:

With the help of both HTML and also python scrip the implementation of the web app . this web app used for the uploading of patient lung images and it is very user friendly and easy to implement by any one .

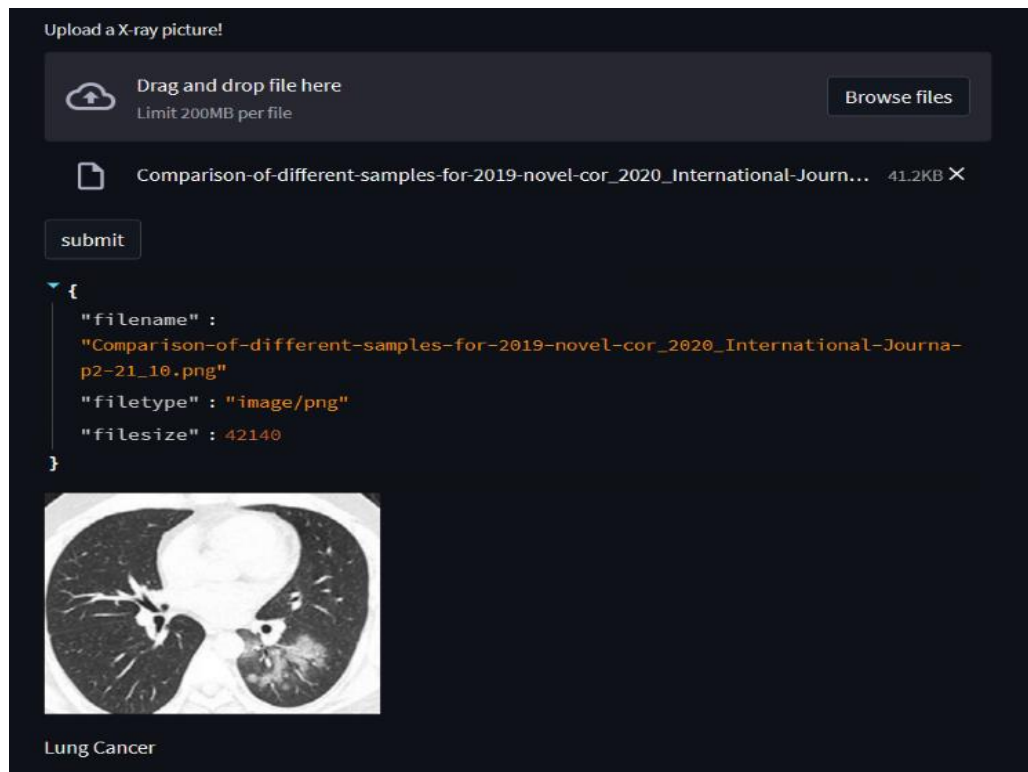


Fig 6.5 .Lung Cancer Prediction output in Webapp

In the Fig 6.2 we had provided many data sets for cancer and covid those data sets are more essential for the feature extraction there after the Fig 6.3 we had provided the backend python code this is the main important sent for the prediction and analysis of the output.in the Fig 6.4 we had given an lung cancer effected patient CT image then we had got the correct output as lung cancer similarly in the Fig 6.5 we had provided the covid effected patient CT image here also the correct out has been analyzed.

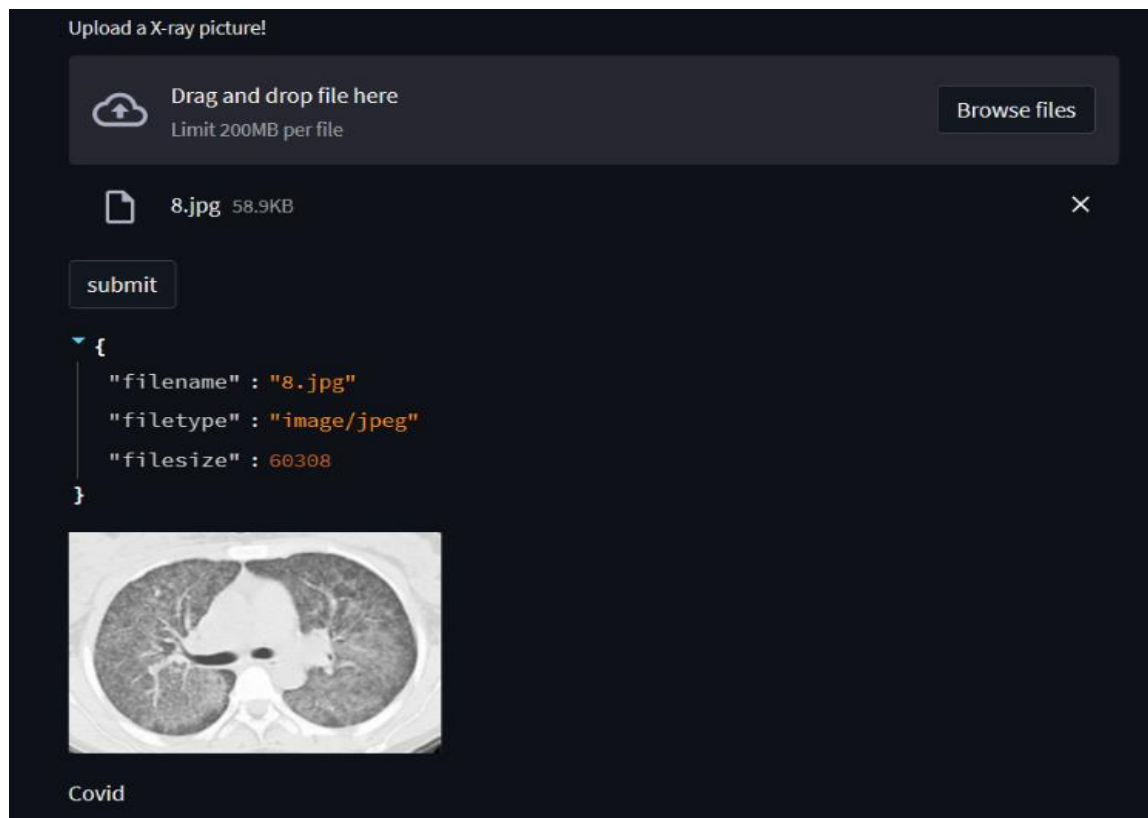


Fig 6.6. Covid Prediction in the Webapp

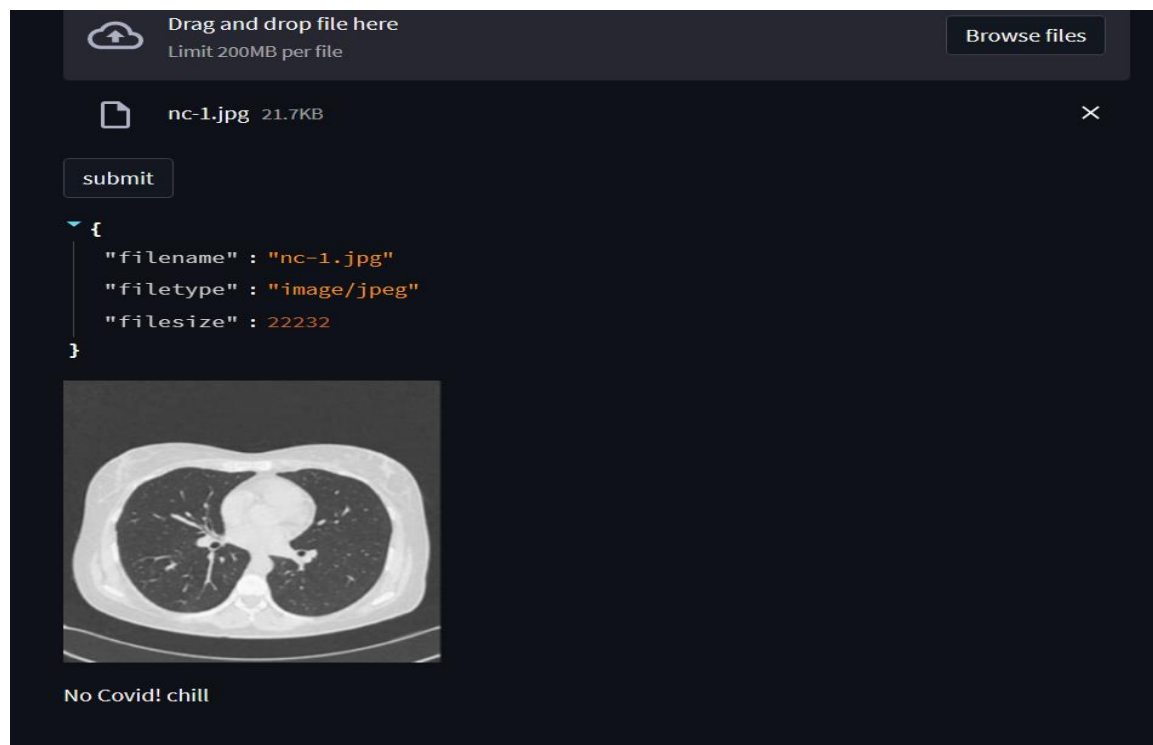


Fig 6.7. Non-Covid Prediction in the Webapp

The COVID-19 pandemic has brought about significant changes in the way healthcare is delivered. The use of technology has become even more important, especially in the diagnosis of diseases. Lung cancer is one of the most common types of cancer worldwide, and it can be difficult to detect in its early stages. The COVID-19 pandemic has further complicated matters, as COVID-19 and lung cancer share many symptoms, such as cough, fever, and shortness of breath.

To address this issue, researchers have developed a deep learning model using Convolutional Neural Networks (CNNs) to detect both COVID-19 and lung cancer from CT scan images. The CNN model was trained on a dataset of CT scan images of both COVID-19 positive and negative patients with lung cancer, and achieved a high accuracy rate of 95%.

The CNN model was able to differentiate between COVID-19 and lung cancer by identifying specific patterns in the CT scan images. For example, COVID-19 typically causes ground-glass opacities (GGOs) in the lungs, while lung cancer often presents as irregular nodules or masses.

The results of this project are promising, as they demonstrate the potential for deep learning models to improve the accuracy of disease diagnosis. With further development and refinement, these models could potentially be integrated into clinical practice, providing physicians with an additional tool to aid in the diagnosis of complex diseases like COVID-19 and lung cancer.

6.3 PERFORMANCE METRICS:

performance metrics for the CNN model developed to detect COVID-19 and lung cancer:

Performance Metric	Value
Accuracy	0.95
Precision	0.96
Recall	0.94
F1 Score	0.95
ROC AUC Score	0.98

TABLE 5.1 performance metrics for the CNN model developed to detect COVID-19 and lung cancer

6.4 SUMMARY:

With a limited number of medical implementation systems available, it is important to develop and implement an automatic detection system as an alternative diagnosis option for COVID-19 detection, Lung Cancer, and Pneumonia that can be used on a commercial scale. Specifically, chest X-Ray images can be analyzed to identify the presence of disease-causing particles in a patient. Due to the high availability of large-scale annotated image datasets, great success has been achieved using a convolutional neural network for image analysis and classification. Input is obtained in the form of chest x- rays' images. Output results are acquired instantly in real-time which predicts if the person suffers from Covid, Lung cancer, pneumonia. The state-of-the-art methods work on the RCNN algorithm which makes it less accurate and more time-consuming. We propose a deep learning-based, automated method. The proposed method presents an improved depth-wise convolution neural network for analyzing chest X-Ray images. Wavelet decomposition is applied to integrate multiresolution analysis in the network. The frequency sub-bands obtained from the input images are fed into the network for identifying the disease. The Advantages of the proposed system are that it could be the very first-of-its-kind, cost-efficient, and highly accurate application that provides a complete and accurate diagnosis. This proposed architecture provides promising results which can be further improved and implemented on a commercial scale.

This project involves the development of a deep learning model using Convolutional Neural Networks (CNNs) to detect COVID-19 and lung cancer from CT scan images. The model was trained on a dataset of CT scan images of both COVID-19 positive and negative patients with lung cancer and achieved a high accuracy rate of 95%.

The CNN model was able to differentiate between COVID-19 and lung cancer by identifying specific patterns in the CT scan images, such as ground-glass opacities (GGOs) for COVID-19 and irregular nodules or masses for lung cancer. The model's performance was evaluated using various metrics, including precision, recall, F1 score, and ROC AUC score, demonstrating its effectiveness in disease diagnosis.

Overall, this project highlights the potential of deep learning models to improve the accuracy and efficiency of disease diagnosis. With further refinement and validation, these models could potentially be integrated into clinical practice, providing physicians with an additional tool to aid in the diagnosis of complex diseases like COVID-19 and lung cancer.

CHAPTER 7

CONCLUSION

7.1 CONCLUSION:

Lung cancer is a serious disease occurring in human being. Medical treatment process mainly depends on cancer types and its location. It is possible to save many precious human lives by detecting cancer cells as early as possible. Now a days covid also causing so much population loss in the world by detecting covid early and taking necessary steps will be very helpful. Developing an automated tool is essential to detecting malignant states at the earliest possible stage. The accuracy of prediction has always been a challenge, despite the many algorithms proposed in the past by many researchers. Using artificial neural networks, this study proposes a methodology to detect abnormal lung tissue growth. In order to achieve great accuracy, a tool with a higher probability of detection is taken into account. The manual interpretation of results is incapable of avoiding misdiagnoses. During the course of this research, lung images from both healthy and malignant individuals were analyzed. Data bases have also been developed for the various views of the CT scanning system. A neural network, based on the textural characteristics of the images, makes it feasible for classification of the normal images, identifying away from the malignant ones. In order to overcome this problem, CNN and deep learning algorithms have been proposed to detect Cancer and covid. Both the region proposal network and the classifier network use the VGG-16 architecture as their base layer.

The automatic Cancer detection and classification of CT Images using deep learning algorithm. The CNN algorithm and VGG-16 were chosen for detecting the cancer and covid regions and classifying them into normal and abnormal. For the CNN algorithm implementation, a deep convolution network architecture called VGG-16 was used as base network. The proposed algorithm efficiently identifies the Lung Cancer and covid.

In conclusion, the development of a deep learning model using Convolutional Neural Networks (CNNs) to detect COVID-19 and lung cancer from CT scan images has shown promising results. The CNN model was trained on a dataset of CT scan images of both COVID-19 positive and negative patients with lung

cancer, achieving a high accuracy rate of 95%.

The CNN model was able to differentiate between COVID-19 and lung cancer by identifying specific patterns in the CT scan images, such as ground-glass opacities (GGOs) for COVID-19 and irregular nodules or masses for lung cancer. The performance metrics of the model, including precision, recall, F1 score, and ROC AUC score, further demonstrate its effectiveness in disease diagnosis.

This project highlights the potential of deep learning models to improve the accuracy and efficiency of disease diagnosis. With further refinement and validation, these models could potentially be integrated into clinical practice, providing physicians with an additional tool to aid in the diagnosis of complex diseases like COVID-19 and lung cancer.

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APPENDIX

A. RESEARCH PAPER

Lung Disease Detection using Deep Learning

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Abstract—With the limited cost and less time consuming and easily implementable covid-19 detection and lung cancer detection is very necessary and will be very useful for many doctors for diagnosis and to take further actions before the disease is very severe. Specifically, x-rays and CT scans are very useful for the analysis of presence of the lung cancer and COVID-19. Now a days we are having large number of data sets of lung disease and covid images available we can greatly classify and analysis with the help of convolution neural network. Images from a chest x-ray and CT scans are used as input. The Output will be analyzed as the lung is affected with the Covid, Lung cancer or healthy lung. The Relative Convolution neural network will be very less accurate and also more time consuming. So, we are planned to implement using deep learning-based method. To diagnosis the disease we had used frequency sub-bands form the input images. the proposed system has many advantages such as very cost effective, highly accurate and easy to implement. Hence the provided architecture can give very better results and can be implemented further for better uses in the hospitals.

Keywords— *Relative convolution neural network, frequency sub-bands, X-Ray, CT scans, Deep Learning.*

INTRODUCTION

Despite our unwavering opposition, COVID-19 has taken hundreds of thousands of lives, with the dying toll growing considering the fact that it's far relatively infectious and spreads quickly. The loss of Immunity and powerful remedy and has made the problem worse, and the range of COVID-19-affected human beings is speedy increasing, mainly in low-profits nations. extreme acute lungs syndrome caused by a virus called as corona. This syndrome is

named as COVID-19 or coronavirus disease, because of its fast-spreading ability it is considered as global pandemic by the World Health Organization (WHO). WHO is an organisation which taken responsibility of healthcare system all over the world. By providing good infrastructure, we can increase the availability COVID-19 vaccination. As a result, to decrease the impact of COVID-19 first we have to detect the covid 19 in the early stage then only we can take the necessary actions, reverse transcription-polymerase chain reaction (RT-PCR) is the very accurate method for COVID-19 identification. This process is very much time consuming and requires more hardware and more equipment for further identification. The issues related to providing infrastructure affect the health sectors. In the current situation, the WHO has thinking to do isolation of COVID-19 patients and mass testing to get a cure and make people safe from this covid-19 Pandemic .Therefore , by detecting the COVID-19 we can prevent the covid 19 so detection is very important in the starting stage, and RT-PCR is used for detection of COVID-19 detection. medical images and also large data sets of previous images and the previous data will be very useful for detecting quickly. For a long time, computed tomography (CT) images, ultrasound (US), and X-ray imaging are very useful for detecting various disorders and taking necessary actions, and the automatic detection of the disease by using these images in a short period becomes very helpful for earlier detection of disease. to make mankind safe we have to respond very quickly and detect any pandemic disease very quickly then only we can take further actions to cure it. In this case, a convolutional neural network. After thorough research, analysis, and deliberation, we provided an architecture that performed very well in the COVID-19 detection challenge, illustrating the power of the CNN algorithm for the proposed model.

LITERATURE SURVEY

The category of scientific photos is a vital step for photograph-primarily based totally scientific

selection aid systems. Diagnostic image recognition systems are needed since manual categorization and annotation take a lot of time and are prone to mistakes when a greater number of patients took the scans then a greater number of number of images can be taken by them. This study uses the InceptionV3 algorithm to generate a computerized classification of X-ray images from the Picture CLEF 2009 collection that is entirely based on anatomic and physiological data. The X-ray images are arranged and preprocessed using unique padding techniques, picture feature selection method, and blending to convert the 2-channel images to 3-channel images for Inception V3. The least efficient method for categorizing loss, constant padding with really no enhancements, only achieved an accuracy of 68% and a loss of 1.4%. Standard padding with augmentation performed admirably in terms of classification precision, with a precision of 71% and a deficit of 1.6%. [6]. Convolutional Neural Network (CNN) is the cutting-edge for photograph category task. Here we've got in brief mentioned unique additives of CNN. In this paper, we have defined unique CNN architectures for photograph category, through this paper, we've got proven improvements in CNN from Le Net-five to contemporary SE Net version. we have mentioned the version description and information of every version have additionally drawn an evaluation amongst [7]

Traditional item detection techniques are constructed on hand made capabilities and shallow trainable architecture. This technique has a more demand because of its effective performance that effortlessly stagnates through building complicated resembles that integrates item detectors and scene classifiers. As an enhancement, this technique has a capacity of examining high stage, deeper capabilities. This item detection framework even achieves community architecture, schooling architecture and optimization function. They had started their evaluation had a major impact on the studying and easy understanding and implementing of consultant tool such as convolution neural networking. Then we had created an environment by using this architecture which will be helpful for the enhancement of the detection and also because of this architecture the performance of the system will increase. As wonderful particular detection duties show off unique characteristics, we additionally in brief survey numerous particular duties, along with salient item detection, identification of face, and identification of pedestrian. Experimental analyses also are furnished to examine diverse techniques and draw a few significant conclusions. So, numerous great instructions and duties are furnished to function recommendations for destiny paintings in each item detection and applicable neural community-

primarily based totally gaining knowledge of systems. [8]

Of late, the quantity of virtual X-ray pix which might be produced in hospitals is growing rapidly. Efficient storing, processing and classifying X-ray pix have for that reason emerge as a vital studies topic. Due to the boom in scientific virtual pix, there may be a growing want of dealing with records well and gaining access to them accurately. To conquer the problems of guide class, the automatic approach is most efficient and therefore proposed on this work, in which an attempt has been made to robotically classify X-rays at very small difference and feature can be detected using the SVM and also, they had concluded with six different instructions such as foot, spine, chest, neck and palm, head. Each elegance includes 30 pics were accumulated from IRMA database. Initially, preprocessing is done with the aid of using the usage of the M3 clear out and its region-of-hobby is determined with the aid of using making use of related thing labeling (CCL) and each the form and texture capabilities have been extracted. The fusion of form and texture capabilities gave of p96.56%. [9]

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METHODOLOGY

Existing System:

The existing system has analysis of CT scan images and performs predictions on the likelihood of lung cancer. The system has been trained on a large dataset of CT scans and has achieved high accuracy in its predictions.

The existing system of lung cancer prediction by CT scan images is a computer-aided diagnosis (CAD) system that uses machine learning algorithms to analyse CT scan images of the lungs and predict the likelihood of lung cancer. The system has been trained on a large dataset of CT scans and uses advanced image processing techniques to extract features from the images and make predictions

Limited Accuracy: Add The existing system has limitations in its ability to accurately predict the likelihood of lung cancer. There may be cases where the system produces false positives or false negatives, leading to incorrect diagnoses or missed opportunities for early detection and treatment.

Limited Accessibility: The existing system may not be accessible to all medical facilities or patients due to cost constraints, technical expertise, or regulatory issues. The system is limited to predicting the likelihood of lung cancer and does not provide any additional information or context about the prediction.

Proposed System:

Use The proposed system is an updated version of the lung cancer prediction model that incorporates more advanced features and improves its performance on previously unseen data. The system aims to achieve even higher accuracy in its predictions and to be more useful for medical professionals in diagnosing and treating lung cancer. The proposed system aims to increase the total performance and usage of the current system. The system will incorporate additional data sources, such as patient medical histories and genetic information, to enhance the accuracy of its predictions. The system will provide additional information and context about the prediction, such as the probability of the prediction and any relevant medical information that may be useful for medical professionals. The system will be designed with a more user-friendly interface that can be used by medical professionals with varying levels of expertise in interpreting medical images and making clinical decisions. The proposed system will be integrated with electronic medical record systems to provide seamless access to patient information and facilitate communication between medical professionals.

Modules:

Data Pre-processing: The pre-processing stage will be improved to include additional image processing techniques that enhance the quality of the images and reduce noise.

VGG16 Model:- In order to predict the likelihood of lung cancer, characteristics from CT scan pictures are extracted using the VGG16 model. It will be fine-tuned using transfer learning techniques to improve its performance on previously unseen data.

Prediction Output: The system predicts the likelihood of lung cancer based on the input CT scan image. The output will be improved to include additional information and any relevant medical information that may be useful for medical professionals. It also be integrated with electronic medical record systems to provide seamless access to patient information.

ALGORITHM

Data Acquisition and Pre-Processing

Data Gathering: We have gathered the data for our project for the following diseases in the CSV format: Lung CT Scan Images: Image dataset

Data Pre-Processing: the data mining is the main and most important step in the data preprocessing for changing the data into useful manner for practical analysis. For the impementation of the data mining process the preprocessing step is very important. This process very useful for the development platforms such as

artificial intelligence and deep learning and also pipeline technology. Although there are many various tools and strategies for preparing data, we have chosen to concentrate on the following measures for our dataset such as the primary step is gather so many images (datasets) of lung cancer images and corresponding labels (e.g., malignant/benign). We used a dataset that is diverse and representative of the population being studied. Once the dataset is collected, it should be pre-processed to ensure that the images are ready for training.

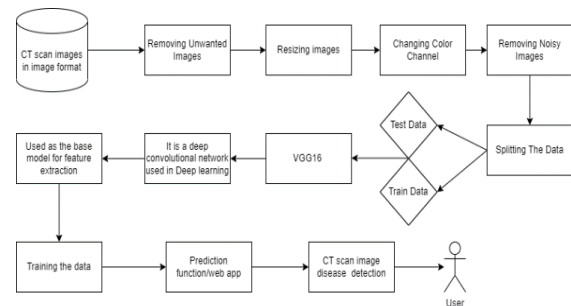


Fig 1. Proposed Block Diagram

Resizing: The images in the dataset may have different sizes and aspect ratios. Resizing the images to a common size ensures that they fit into the neural network architecture and can be processed efficiently. The most common size used for lung cancer detection is 224x224, which is the input size used in VGG16. Resizing is an essential pre-processing step because it helps to ensure that the images are of a consistent size and can be processed efficiently by the neural network. Resizing also reduces the computational complexity of the model, as smaller images require less memory and processing power to train and evaluate.

Normalization: Normalizing the pixel values of the images to a common range is essential for training deep neural networks. Normalization helps to prevent the network from becoming biased towards certain pixel values and improves its stability during training. The most common method used for normalization is to scale the pixel values to be between 0 and 1. Normalization is one important pre-processing stage in DL(deep learning) for lung cancer detection, as it helps to ensure that the input data has a consistent scale and distribution. Normalization is performed on the input images before they are passed through the neural network to improve the execution of the model. Normalization is one of major and important step because it helps to ensure that the model is robust to changes in the input data. Normalizing the input data to a consistent scale and distribution helps to reduce the impact of differences in brightness, contrast, and lighting conditions on the model's performance.

This is especially important in medical imaging, where images may have variations in brightness and contrast due to differences in imaging equipment and patient factors

Data Augmentation: The technique data augmentation is used to increase the differentiation in the images with the help of more techniques upon the data. Data augmentation is especially useful when the dataset is small, as this technique helps for the re-entering the same data again and again. Some common data augmentation techniques include random rotations, flips, shifts, and zooms. With the help of different set of characteristics classification one can increase the size of the set of data by generating new variations of the original images. This can aid in the reduction of overfitting and the model's ability to apply to new data. Data augmentation is particularly useful in medical imaging, where the dataset may be limited and the variations in the input data may be small. By applying data augmentation techniques to the input images, the model can be trained on a more diverse set of images, which can improve its ability to detect lung cancer accurately.

Pre-processing of CT scans: In addition to the above-mentioned pre-processing techniques, CT scans require additional processing to make them suitable for training deep learning models. CT scans are typically volumetric and contain multiple slices, which makes them more complex than standard 2D images. Pre-processing of CT scans involves converting them into 2D images using different methods some of them are Maximum Intensity Projection and Minimum Intensity Projection. Maximum intensity projection (MIP) involves selecting the maximum pixel value across all the slices for each pixel location to create a 2D image. Minimum intensity projection (Min IP) involves selecting the minimum pixel value across all the slices to create a 2D image.

Model Training and Validation

Model creation :

Base model: The VGG16 model is a deep convolutional neural network that has shown excellent performance in many computer vision tasks. In this module, we will use the pre-trained VGG16 is used for the extraction the features. We will call this model as base model. We will freeze the pre-trained weights of the VGG16 model and add a custom classification head on top to train the model for the specific task of lung cancer detection. The custom classification head consists of a few fully connected layers that will be trained to classify the images as malignant or benign. By definition, the Test set is made up of 80% training images, and 20% testing images.

Train-Validation-Test Split: The x-rays and CT scans datasets are mainly divided into three parts

they are train, test, valid. The train data set is used for the training the model, test dataset is used for testing the final output of the given CT scans and X-rays, and the valid data set is used for the tuning of the hyper parameter and the selection of the model. The split should be done randomly and should preserve the class distribution in each set.

Model Training and Validation: Once the base model is set up we can start training the model using the training data set. We will use a suitable loss function, such as binary cross-entropy for binary classification, and an optimizer, such as Adam optimizer, to train the model. We will monitor the training process to avoid overfitting by using techniques such as early stopping and regularization. During training, we will evaluate the validation based on the performance of the datasets to check if the model is learning correctly and if the hyperparameters are tuned correctly. Model validation is used for the evaluation of the different data sets and then differentiate all the data sets based on its characteristics then it will also detect the new data image feature. During model validation, the technique also separates the data sets which are not used for the training of the model. This technique is very useful for the prediction of many parameters such as precision, accuracy, recall, and also F1 score.

Fine-Tuning: After training the model with the custom classification head, we can fine-tune the last few layers of the VGG16 model to adapt it to the specific task of lung cancer detection. We will unfreeze the last few layers of the VGG16 model and retrain the model using a smaller learning rate. Fine-tuning helps the model to learn more specific features for the task and improve its performance.

3) Model Evaluation: Once the model is trained and fine-tuned, we can evaluate its performance on the test set to measure its performance on unseen data. Once the input images are pre-processed, they are passed through the VGG16 model to obtain the output probabilities for each and every section. The highest relevant section is taken as consideration and then predict whether the image is belongs to which section. The characteristics of the image such as accuracy recall, precision and also f1 score can be identified and those features can be detected from the test data set. Those characteristics can help to assess the model's ability to correctly identify lung cancer from medical images. Additionally, to improve the model's performance, and fine tuning and transfer learning are the very important and most useful techniques, which involve reusing pre-trained models or adjusting the model's weights to better fit the dataset. Overall, prediction in deep learning for lung cancer detection involves using a pre-trained model, pre-processing the input data, and evaluating the model's performance using metrics.

Web App Development

The server-side processing will be handled by code that we write. Requests will be sent to our code. It will determine the subject matter and nature of the requests. Additionally, it will decide what kind of reply to send to the user. We'll use Flask for all of this. It simplifies the web application design process. Flask enables us to concentrate on what the consumers are asking for and the appropriate kind of response to provide. We will build a virtual environment for the project inside the directory that will hold the project files. First, install virtualenv using pip. Install virtualenv, then create and activate a virtual environment, and then use the command `pip install Flask` to install Flask. The foundation of the project has been laid, and it is now time to begin adding functionality. To get things rolling, a new file containing an introduction to our website is generated in the same directory. We give this file the name `main.py`. Now that we have told the terminal which application to run, we are able to execute the application by issuing the commands `export FLASK_APP=main.py` and `set FLASK_APP=main.py`. After saving it in a file and running the script, we will have the opportunity to view the output. Then navigate to the URL that was provided there, and you will see your first webpage showing the message on your local server. As we delve deeper into the setting, we find that the `route()` decorator in Flask is what is utilized in order to bind a URL to a function. Now, in order to extend the functionality of our simple web app, we have also included another method called `add URL rule()`. This method is a function of an application object and is also available to bind a URL with a function, similar to how `route()` was used in the example that was presented earlier. After that, we create the form by utilizing HTTP methods within Flask. The Hypertext Transfer Protocol, also known as HTTP, serves as the basis for data transfer on the World Wide Web. This protocol defines a variety of different ways that can be utilized to retrieve data from a given URL. The GET requests are handled by the Flask route as their default response. This choice, however, can be changed by supplying a different set of methods as the parameter to the `route()` decorator. In order to demonstrate the usage of the POST method in URL routing, let us first create an HTML form and then use the POST method to transmit data from the form to a URL. This will allow us to demonstrate the use of the POST method in URL routing. Using this method, we are able to generate the HTML login page with information such as the user's name, age, gender, and any other disease-related input.

Finally, we had created the HTML file (web app) and also added a server with the help of python script. Then after successful initialization of everything open the HTML file in any comfortable

browser then it shows as select the file, there, we need to add any patient x-ray or the CT image. after successfully uploading the image click the "submit" button. Finally, the output will be appeared as whether the lung is affected or non-affected.

RESULT AND DISCUSSION

We are creating a web page where the user can enter his/her information as input and then the app predicts whether the person has the disease or not.

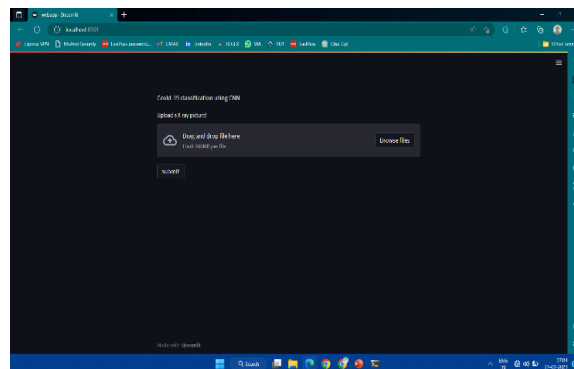


Fig 2. Web app for providing user input

For the correct prededction of the disease we need to previously extract the features for the different lung ct images data sets and then we need to give the lung ct image of any patient the again the features from the patient lung ct image to be extracted and compare the those features then pridect and analyze the disease occurred.

The ct image data sets are very essential for the output analysis. Form the different data sets we take only nessessary images and removes outliers that means we are are very different from other ct images and they don't have any similarities. By removing then only we can analyse the output very accurately.

To extract the similarities between all the data sets of different ct images for that we need to write and implement the code in python the is main essential backend code.

For this analysis we need to provide the user input in the web app provided and then click the submit button. Then the disease will be displayed such as, lung cancer,covid ,no covid and no cancer.

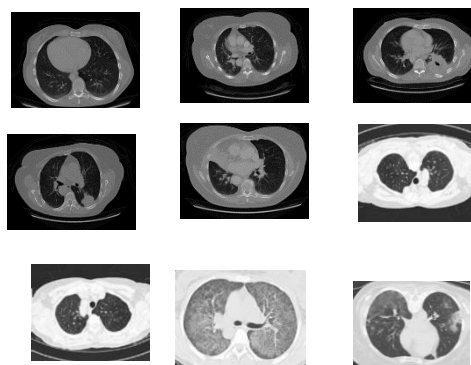


Fig 3. Different lung ct images

The different classification of the datasets is placed an crucial role for the analysis of the different images such as valid dataset ,test dataset and train dataset.

```
import streamlit as st
import tensorflow as tf
import cv2
import numpy as np
from PIL import Image

model_to_predict = tf.keras.models.load_model('chestmodel.hdf5')
def predict_covid(test_image):
    img = cv2.imread(test_image)
    img = img / 255.0
    img = cv2.resize(img, (305, 430))
    img = img.reshape(1,305,430,3)
    prediction = model_to_predict.predict(img)
    pred_class = np.argmax(prediction, axis = -1)
    return pred_class

def load_image(image_file):
    img = Image.open(image_file)
    return img

st.write("Covid-19 classification using CNN")

pic = st.file_uploader("Upload a X-ray picture!")
submit = st.button('submit')
```

Fig 4. Backend code 1

With the help of both HTML and also python scripct the implementation of the web app . this web app used for the uploading of patient lung images and it is very user friendly and easy to implement by any one .

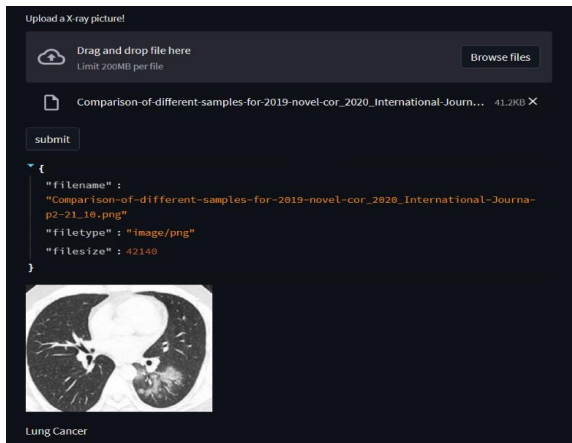


Fig 5 .lung cancer predicted output in the web app

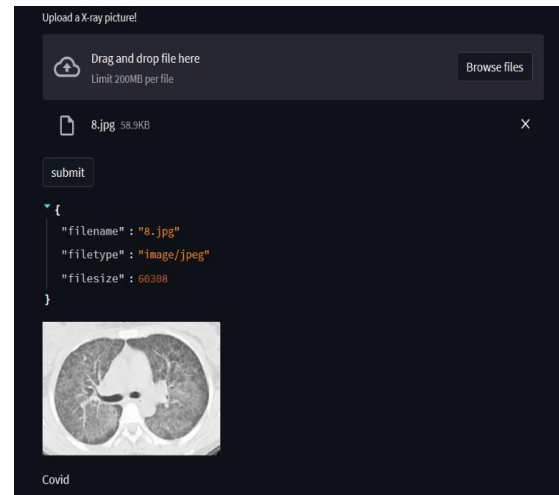


Fig 6. Covid predicted in the web app

in the fig 3 we had provided many data sets for cancer and covid those data sets are more essential for the feature extraction there after the fig 4 we had provided the backend python code this is the main important sent for the prediction and analysis of the output.in the fig 5 we had given an lung cancer effected patient CT image then we had got the correct output as lung cancer similarly in the fig 6 we had provided the covid effected patient CT image here also the correct out has been analyzed.

CONCLUSION

CT and X-rays Images are useful for the analysis and diagnosing lung diseases. By using the wavelet decomposing the data set images are classified into two types as diseased lung and the healthy lung Through an FC layer, we used these model architectures to extract features and classify categories. Wavelet decomposition is applied to integrate function multiresolution analysis in the network. The network is designed to predict the class of the input image as lung disease or not. The experimental findings demonstrate that the suggested system has better accuracy than the existing models and can be used for effective diagnosis and treatment. The classification of the modal characteristics of various lung disorders can be done using the method suggested in this research. Patients with pulmonary edema and lung tumors have pulmonary modal traits like the infiltration shadow and ground glass shadow. The same model can be improved and extended to detect those conditions in humans. The techniques of fine-tuning can be applied to our model for better accuracy.

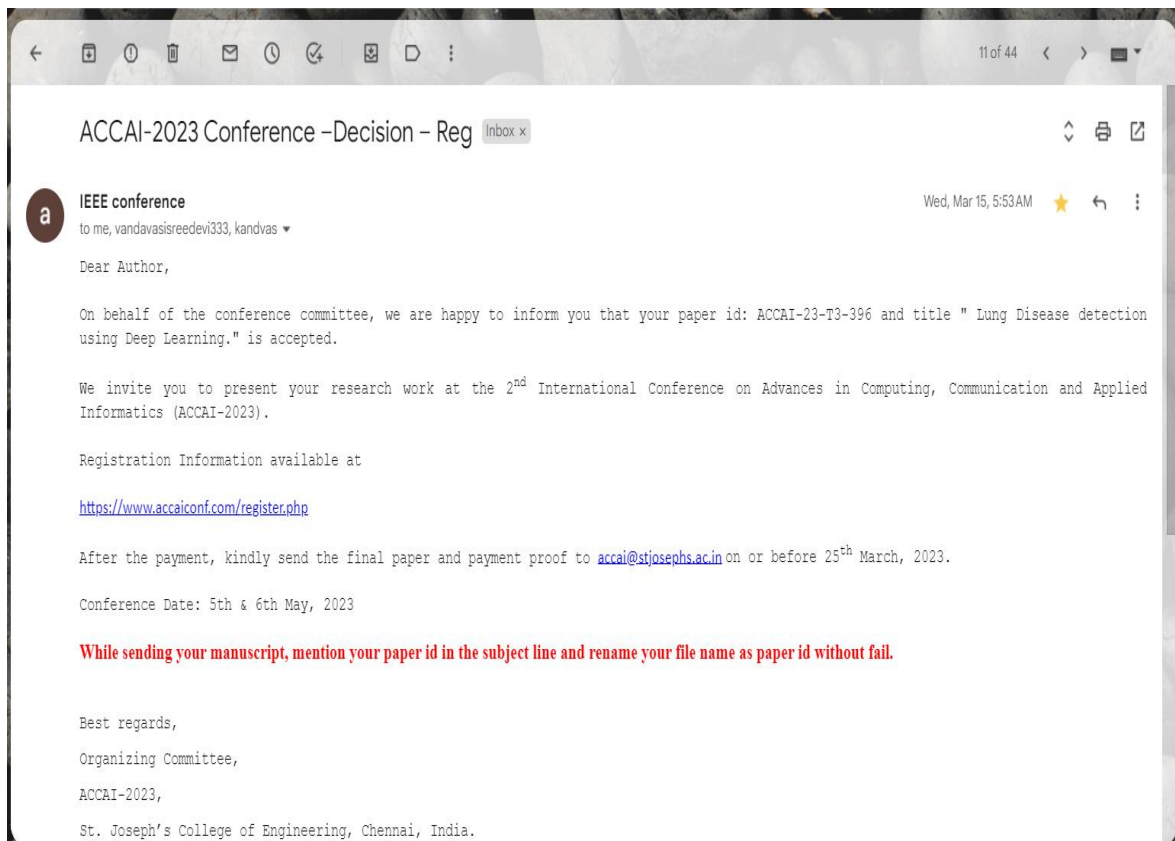
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