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ABSTRACT

Due to its extensive incidence and high death rate, pneumonia is a respiratory disease that is recognized on a global scale. The number of fatalities attributable to pneumonia must be decreased by prompt identification and treatment. Currently, diagnosing pneumonia using an X-ray is an effective procedure. Although it takes a qualified doctor 5 to 15 minutes to read a chest X-ray, when faced with a large number of cases, it can impose a major burden on clinical diagnosis.

Artificial intelligence is crucial in addressing this problem by increasing the precision and effectiveness of pneumonia diagnosis using chest X-rays. A quick and efficient solution is provided by convolutional neural networks (CNNs), which are renowned for their exceptional image identification skills. A dataset including 5216 training photos and 624 test images, labeled as "normal" and "pneumonia," was used to examine the efficacy of AI in detecting pneumonia. The study analyzed the outcomes of five frequently employed network algorithms for illness categorization.

The study found that the MobileNet network design performed better in terms of accuracy than the other methods. Beyond diagnosing pneumonia, the improved MobileNet network may be customized for use in a variety of other applications, demonstrating its potential for wider medical imaging applications.

Keywords—Deep learning techniques, CNN, X-Ray, CXR, Pneumonia diagnosis techniques.

CHAPTER 1: INTRODUCTION

12% of the world's population suffers from pneumonia, a common and serious respiratory illness. Its rising incidence can be attributed to a number of variables, such as population aging, reduced immune systems in some people, the advent of bacterial strains that are resistant to therapy, challenges in properly identifying the illness, and the evolution of disease-causing microorganisms. One popular method is chest radiograph analysis (CXR), which uses X-ray imaging to diagnose and distinguish between various types of pneumonia. Using this technique, healthcare workers may evaluate chest X-ray pictures to look for pneumonia symptoms. However, there is frequently a dearth of highly qualified radiologists who can swiftly and effectively interpret these X-rays in areas with poor access to healthcare services. The disturbingly high death rates linked to pneumonia may result from this lack of qualified radiologists, which might have catastrophic repercussions. The early detection and management of pneumonia cases can be hampered by the dearth of skilled healthcare personnel in some places, potentially leading to unfavorable patient outcomes. Timely and correct diagnosis is essential for effective treatment. As a solution to this problem, there is significant interest in using technology, such as artificial intelligence and deep learning, to increase the precision and effectiveness of pneumonia diagnosis, therefore saving lives, particularly in areas with a lack of access to healthcare.
Leveraging the potential of deep learning technology can help overcome the problems caused by pneumonia, such as the lack of qualified radiologists and the demand for precise and affordable detection. Recent years have witnessed impressive progress in deep learning, especially in areas like computer vision, voice analysis, and natural language processing that need considerable data analysis and pattern identification.

Regarding the issue of pneumonia detection, deep learning has numerous significant benefits:

- The capacity of deep learning algorithms to automatically extract complex and frequently subtle properties from raw, unprocessed data, such as pictures like X-rays, has given them a remarkable amount of appeal. Because it eliminates the necessity for explicitly selecting or designing characteristics within the data, this capability is highly notable. In many machine learning methodologies, professionals have historically needed to specify and provide the program instructions on what precise traits to look for in the data. These specialists would have to identify the traits that could suggest a certain ailment or disease, such as pneumonia, while dealing with medical imagery like X-rays. Due to human limits and biases, this manual feature engineering approach may be laborious, time-consuming, and prone to missing certain important qualities. On the other hand, deep learning models have the capacity to learn these characteristics directly from the data. Without explicit human direction, they independently detect patterns, forms, textures, and other pertinent elements within the photos. Because of this capability, the process is substantially more efficient and extremely adaptable to different jobs and data kinds. Deep learning algorithms excel in identifying intricate features that might not be seen to the human eye in the context of medical image analysis, including the identification of pneumonia from X-ray pictures. Due to the massive volumes of data and intricate network structures, this autonomous feature extraction produces more reliable and precise findings. Additionally, it implies that deep learning models may be used in a variety of fields, such as image identification and healthcare, where complicated and subtle characteristics must be found in the data.

- Healthcare has been transformed by deep learning's adaptability in medical image analysis. Aspects of medical diagnosis and image interpretation are included in its wide range of applications. One of the most well-known uses of deep learning algorithms is in computer-aided diagnosis, where they help medical professionals quickly and accurately diagnose a variety of medical disorders. The ability of these algorithms to recognize abnormalities in medical pictures, such as tumors in MRI and CT scans or symptoms of illnesses like pneumonia in X-rays, is unmatched. They make use of large datasets and are capable of identifying complex patterns and minute abnormalities that may be difficult for humans to comprehend. Deep learning also substantially facilitates the appropriate interpretation of complicated medical pictures, which may be difficult for medical personnel to do. Deep learning algorithms may automatically recognize and highlight pertinent structures or abnormalities on histopathology slides, echocardiograms, or 3D reconstructions, increasing the precision and speed of the interpretation process. Additionally, image fusion, which combines information from many imaging modalities to give a more thorough knowledge of a patient's health, expands the applicability of deep learning. In turn, this makes it possible for medical professionals to develop more accurate diagnosis and treatment strategies. Additionally, it is essential for image registration to monitor changes over time and improve image-guided treatments, including surgical operations, by providing real-time data processing for safer and more accurate interventions. Fundamentally, the applicability of deep learning in medical image processing greatly improves patient care and overall healthcare results.

- Beyond simply detecting illnesses like pneumonia, deep learning has a surprising ability for improved disease risk assessment. These algorithms are skilled at examining a broad range of data, including patient medical histories, clinical data, test results, and medical pictures. Deep learning algorithms provide a comprehensive picture of a patient's health and the particular condition in issue by synthesizing this copious amount of data. This method stands out because it can assess a disease's potential severity in addition to detecting its presence. For instance, while determining the severity and progression of pneumonia, deep learning algorithms take into account a number of variables, including the patient's age, medical history, and the pneumonia's features as shown in medical photographs. With the aid of this thorough risk assessment and severity estimation, medical professionals may better decide on treatment approaches, adjusting them to meet the individual needs of each patient. This individualized method of care improves the accuracy and efficacy of medical procedures, especially when a prompt and correct evaluation is critical to a patient's wellbeing.

Numerous studies have demonstrated the enormous potential of deep learning in thoracic medicine and pneumonia diagnosis. Convolutional neural networks (CNNs), which have shown to be extremely successful in the identification and localisation of pneumonia within chest X-ray images, are one noteworthy deep learning model advancement. These algorithms have shown extremely encouraging findings, demonstrating their capacity to precisely detect the presence and localize pneumonia within these pictures. The adaptability of these deep learning models increases their value. They have broadened their application's use beyond pneumonia to the classification of abnormalities in chest radiography. They have, for example, been extremely important in the diagnosis of conditions like idiopathic pulmonary fibrosis, a chronic lung ailment marked by the scarring of lung tissue. This expanded use of deep learning in thoracic imaging represents a substantial advance in the precision and effectiveness of illness diagnosis in the discipline of respiratory medicine.Deep learning's skills in lung ultrasound imaging have been investigated in certain research studies as a potential replacement for conventional X-ray imaging for categorizing pneumonia patients. In instances when X-ray equipment is not widely accessible or for particular patient demographics, lung ultrasonography provides a new technique to see lung problems. This strategy may provide medical personnel additional options for identifying and treating respiratory problems by broadening the range of imaging modalities that can profit from deep learning technology, thereby improving patient care and results.

In the context of our particular research work, we rigorously assessed a range of deep learning models to ascertain their applicability for correctly recognizing and classifying pneumonia in medical X-ray pictures. We came to a positive conclusion after extensive testing and analysis: MobileNet, especially when upgraded, appeared as a highly feasible option for this crucial duty. We used a dataset that contained X-ray pictures of pneumonia patients to confirm our results and demonstrate the dependability of MobileNet. To fully evaluate the effectiveness of these models, we used four well-known network models in addition to traditional convolution methods. In our review, we took into account a number of variables, with an emphasis on accuracy and other crucial performance measures.The findings of our study were quite convincing. In our experiments, the improved MobileNet consistently beat the other convolutional neural networks (CNNs), proving its superiority in terms of effectiveness and precision for diagnosing pneumonia from X-ray pictures. This result emphasizes the improved MobileNet's potential to be a crucial tool for healthcare professionals, providing the capacity to quickly and accurately detect instances of pneumonia.

CHAPTER 2: LITERATURE REVIEW:

A total of 40 research publications were meticulously analyzed throughout the course of this assessment of the literature, all of which concentrated on the crucial job of detecting pneumonia through the interpretation of chest X-ray pictures. This extensive investigation covered publications published between the years 2000 and 2023 and lasted over two decades. This comprehensive review's goal was to learn more about the rapidly changing field of diagnostic approaches in the context of pneumonia, a serious public health problem.

The result of this thorough investigation was the development of tables that classify the deep learning and machine learning methods used in the chosen publications. This classification provided a comprehensive look at the several approaches, techniques, and algorithms that scientists have created throughout time to improve the precision and effectiveness of pneumonia identification using chest X-ray pictures.

This literature review aims to offer a comprehensive overview of the state of the art in pneumonia detection and the rich landscape of approaches that have been investigated in the search for more effective diagnostic tools by presenting these findings in a tabulated format. This resource will be beneficial for researchers, clinicians, and stakeholders in the healthcare industry.

- Tabular Representation of Deep Learning Techniques used in Research Papers:-

Author Name	Year	Technique	Name of Classifier	Key findings	Dataset Used (dataset table name)	Accuracy (%)	Results
Che, Zhengping et al.	2015	Deep Learning for Clinical Time Series Data	Neural Networks	Deep learning models trained on clinical time series data, assisted by prior knowledge regularization, effective incremental learning, and causal inference algorithms, reveal significant physiological patterns connected to clinical phenotypes and health outcomes, providing promising	1- The first dataset, which includes multivariate clinical time series data from 8000 ICU units, is taken from the publicly available PhysioNet Challenge 2012. The second	N/A	Same as Key Findings.

				solutions for health "big data" problems.	dataset is made up of ICU clinical time series that were taken from an electronic health records (EHRs) system at a large hospital.		
Pranav Rajpurkar et al.	2017	Convolutional Neural Network (CNN)	CheXNet	Radiologists are outperformed by CheXNet, a 121-layer CNN, in the detection of pneumonia from X-rays. It provides binary findings and uses heatmaps to identify regions affected by pneumonia. The F1 score of CheXNet (0.435) is higher than that of radiologists (0.387), and it outperforms earlier techniques in identifying all 14 disorders in the ChestX-ray14 dataset.	ChestX-ray14	On the same test, CheXNet outperformed radiologists with an F1 score of 0.435 as opposed to an average F1 score of 0.387.	F1 score of 0.435 against 0.387 for pneumonia diagnosis.It obtains cutting-edge results with strong AUROC values across 14 diseases.
Gu, Xianghong et al.	2018	AlexNet	Deep Convolutional Neural Network (DCNN) with Transfer Learning and	For the purpose of identifying lung regions, the FCN model obtained DSC values of 0.9142 to 0.9657 for JSRT and 0.7637 to 0.9548 for MC datasets. For the classification of pneumonia, the DCNN model with transfer	Using the JSRT and MC datasets, the FCN Model can identify the lung regions. Classification of pneumonia using the Guangzhou	Accuracy: 80.48 % Sensitivity: 77.55 % AUC (Area	Same as Key Findings.

			Support Vector Machines (SVM)	learning demonstrated accuracy of 0.80480.0202, sensitivity of 0.77550.0296 and AUC of 0.81600.0162. The AUC was slightly raised to 0.82340.0014 by a collection of diverse attributes.	Women and Children's Medical Center dataset and the DCNN model.	Under the Curve) : 81.60 %	
Halil Murat Ünver et al.	2019	Convolutional Neural Networks - CNNs)	Xception and Vgg16 CNN models	50 epochs, cross-entropy loss, RMSprop optimizer, 1e-4 learning rate, 0.9 weight decay, 16 batch sizes, augmented data, batch normalization, dropout, and transfer learning are the experimental parameters. evaluated for F1 score, recall, sensitivity, specificity, accuracy, and precision. Vgg16 excels in detecting typical cases with an accuracy of 87%. Xception: 82% accuracy is better at spotting pneumonia.	The study used a dataset consisting of 5,856 frontal chest X-ray images, with 1,583 normal cases and 4,273 pneumonia cases.	Xception: 82% Vgg16: 87%	N/A
Elgendi, M.et al.	2020	The deep learning technique used in this research paper is "DarkNet-19."	N/A	The key finding related to deep learning is that DarkNet-19 achieved an overall accuracy of 94.28% for detecting radiographic features of COVID-19 pneumonia.	Dataset 1: CoronaHack-Chest X-Ray-Dataset (50 COVID-19 images and 50 healthy images) Dataset 2: A local dataset collected from Vancouver General Hospital (58 chest radiographs with COVID-19 and other pulmonary findings)	The accuracy achieved by DarkNet-19 is 94.28 %.	ResNet-50 and 17 pre-trained neural networks were surpassed by DarkNet-19.

Mahmud et al.	2020	Convolutional neural network (CNN)	"CovXNet," which is based on a deep convolutional neural network (CNN) utilizing depthwise convolution with varying dilation rates.	The design leverages transfer learning from a sizable database for COVID-19 X-rays, uses depthwise convolution with a range of dilation rates for X-ray analysis, optimizes with a stacking approach, and creates a class activation map for anomalous zone localization.	X-rays from the Guangzhou Medical Center are included in dataset 1, COVID-19 X-rays from the Sylhet Medical College are included in dataset 2, and a balanced dataset for transfer learning is included in dataset 3.	COVID/Normal: 97.4%, COVID/Viral pneumonia: 96.9%, COVID/Bacterial pneumonia: 94.7%, and COVID/Multiclass: 90.2%.	CovXNet uses transfer learning, a class activation map for accurate localization.
Hashmi MF et al.	2020	Convolutional Neural Network , Transfer Learning,ResNet18 Xception InceptionV3 DenseNet121 MobileNetV3	weighted classifier	With the help of transfer learning and data augmentation, the weighted classifier performs better than individual models. On the pneumonia dataset, the final classifier achieves a test accuracy of 98.43% and an AUC of 99.76.	Guangzhou Women and Children’s Medical Center pneumonia dataset	Test Accuracy: 98.43 % AUC Score: 99.76 %	The study demonstrates F1 Score.
Toğaçar et al..	2020	CNN models , including AlexNet, VGG-16,	Linear Discriminant Analysis (LDA)	The identification of pneumonia was improved by combining deep features from AlexNet, VGG-16, and VGG-19. LDA obtained the maximum accuracy at 99.41% when dimensionality was	The "pneumonia dataset" contains a total of 5,849 images, including 1,583 normal and 4,266 pneumonia images.	achieved the highest accuracy of 99.41 %	N/A

		and VGG-19		minimized by the use of mRMR feature selection.			
Račić, Luka et al.	2021	convolutional neural network (CNN).	N/A	The key findings related to deep learning include the successful application of a CNN-based algorithm to classify chest X-ray images as either showing changes consistent with pneumonia or not. The model achieved an accuracy of nearly 90%.	The dataset used in this research is provided by the Guangzhou Women and Children's Medical Center, Guangzhou, and is available on Kaggle .	The model achieved an accuracy of approximately 90%.	Training, validation accuracy, loss, and confusion matrix.
Masad et al.	2021	Hybrid system: CNN	SVM, KNN, RF, Softmax for X-ray pneumonia detection.	Hybrid systems matched CNN+Softmax in most aspects except RF. KNN was fastest, followed by SVM, Softmax, and RF.	The chest X-ray images dataset used in this study was published online at https://data.mendeley.com/datasets/rscbjbr9sj/3 by Kermany et al.	Softmax: 99% KNN: 99.3% SVM: 99% RF: 98.6%	Softmax: High sensitivity, specificity, and precision.
Ahmmad Musha et al.	2022	COVID-CXDNetV2, a deep learning-based model	YOLOv2 with ResNet	The model can detect two diseases, COVID-19 and pneumonia, from X-ray images with high accuracy.	Kaggle: COVID-19 Radiography Database [Link].	Multiclass accuracy: 97.9%, COVID-19/normal binary accuracy: 99.8%.	COVID-19: High sensitivity, specificity, precision, F1 score. Pneumonia: High sensitivity, specificity, precision, F1 score.

Nitin Arora et al.	2023	CBIR with deep learning: VGG, Xception, Inception, and more.	VGG-16	VGG-16 achieved the highest precision of 99% and a mean Average Precision (mAP) of 94.34%.	Chest X-ray images dataset with four classes (COVID-19, Pneumonia, and Normal), sourced from Qatar University, Doha, Qatar, and the University of Dhaka, Bangladesh.	Precision of 99% for the VGG-16 model.	Deep learning model performance compared, VGG-16 excels.
Kadali, Vasavi et al.	2023	CNN	RESNET 50 model (pre-trained on ImageNet) and fine-tuning	Study employs RESNET50 for pneumonia diagnosis from X-rays. Transfer learning, feature combination, surpasses state-of-the-art with 94.01% accuracy.	Chest X-ray dataset for pneumonia diagnosis.	94.01 %	Same as Key Findings.

- Tabular Representation of Machine Learning Techniques used in Research Papers:-

Author Name	Year	Technique	Name of Classifier	Key findings	Dataset Used (dataset table name)	Accuracy (%)	Results
Joshua P. Metlay et al.	1997	Evaluation of symptoms in individuals with community-acquired pneumonia at presentation, a review of how age	N/A	The symptoms that have the greatest decline in prevalence in older individuals are those associated	Dataset 1: Age-related characteristics of patient respondents. Dataset 2: Median	The study did not provide a single accuracy percentage since it did not include a	Compared to younger patients, those who have pneumonia report fewer respiratory and

		affects symptom reporting, Multivariate linear regression analysis to account for clinical and demographic traits.		with the febrile reaction (fever and chills) as well as those associated with pain (chest discomfort, headache, and myalgia).	Symptom Duration Prior to Presentation for Patient Respondents by Age Groups.	binary classification task but rather evaluated the prevalence and impact of age on symptom reporting.	nonrespiratory symptoms.
Gregory F. Coopera et al.	1997	Learning using neural networks, rule learning, causal discovery techniques, a straightforward Bayesian classifier, logistic regression, and the K-nearest neighbor algorithm are some examples.	Bayesian classifier	Aiming to help clinicians choose whether to treat a patient in the hospital or at home based on their initial presentation, the models were built using 9847 patient cases and evaluated on 4352 additional cases. The primary evaluation metric was the error rate in predicting	Dataset 1: The proportion of inaccurate patient survival estimates that occur for a certain fps level over a given number of techniques Dataset 2: Means and standard deviations were calculated using cross validation with 11 trials for the neural network	All models exhibited an error rate of less than 1.5% when predicting the survival of about 30% of patients.	There were considerable differences in the number of variables and parameters among the models, with some having as few as nine variables and 10 parameters and others having more than 600.

				survival as a function of the fraction of patients predicted to survive.	approach and 101 trials for the KNN method, respectively.		
Abdullah F. Owayed et al.	2000	laboratory testing, pulmonary function tests, radiographic studies, and clinical assessments.	N/A	92% of kids with recurrent pneumonia received a diagnosis of an underlying disease.	Dataset 1: Patients With Underlying Causes of Recurrent Pneumonia Dataset 2: Relationship Between the Number of Pneumonia Episodes and the Timing of the Underlying Illness Diagnosis	There was no mention of accuracy percentages in the text.	The age and location of pneumonia recurrences might reveal symptoms of underlying diseases.
Richard Ambrosino et al.	1995	Rule induction using Rule Learner (RL) and post-processing with Optimizer (OP).	The model is rule-based and consists of rules generated by Rule Learner (RL)	When proposing outpatient therapy, the model strives for a high positive predictive value (PPV), which means that it should reduce the number of	Dataset 1 has a misclassification matrix with a 10:1 FP:FN cost ratio. Dataset 2: Misclassification matrix applied with OP. Dataset 3: Table of insufficient outcomes.	When "low risk" is anticipated, the clinically meaningful range for PPV is in the vicinity of 0.990, which equates to a 1% fatality	As PPV and the FP:FN cost ratio rise, classification accuracy and the proportion of patients classified as "low risk" decline.

				erroneous positive predictions for inpatients.		rate among hospitalized patients.	
Gregory F. Cooper a et al.	2005	logistic regression, rule-based learning, neural networks, finite mixture model techniques, and simple Bayes methods	neural network model (NN.MTLR)	According to the research, implementing the NN model's suggestions might result in considerable cost reductions in healthcare delivery without sacrificing quality.	Dataset 1: The test set's 79 instances of disastrous results are classified into seven types. Dataset 2: The relationship between the modeling approach and the size of the training set under the ROC curve for predicting a bad result.	The neural network model produced an excellent prediction performance with an area under the ROC curve of 0.863.	The findings indicated that most models attained their optimal performance with 400 or fewer training examples, and that adding more training cases had no effect on model performance.
Sousa, Rafael T et al.	2013	The goal of the study was to enhance the PneumoCAD Computer-Aided Diagnosis (CAD) system's reliability and accuracy for identifying pneumonia in	Naïve Bayes, K-Nearest Neighbor (KNN), and Support Vector Machines (SVM).	By imitating the diagnostic skills of a professional, computer-aided diagnosis (CAD) systems can help to increase diagnostic accuracy.S	Dataset 1: Classifier accuracy results for each set of characteristics chosen by SFE.	77% accuracy was attained using SVM. 70% accuracy was attained using KNN. The accuracy	SVM performed better than the other classifiers and showed consistency with a range of training data. The accuracy of the SVM

		newborns using radiographic images.		VM outperformed the other classifiers in terms of overall performance.		of Naive Bayes was 68%.	classifier beat that of prior PneumoCAD iterations as well as medical resident diagnoses.
Cosmin Adrian Bejan et al.	2012	natural language processing (NLP)	supervised machine learning framework, using feature selection techniques	On limited and unrestricted datasets, respectively, the system's top results (85.71% and 81.67% F1-measure) beat the baseline results (50.70% and 49.10% F1-measure).	Dataset 1: Corpus statistics broken down by the number of unique patients and the frequency of report kinds. Dataset 2: According to 2 and t statistics, the top 10 most helpful uni-grams, bi-grams, and Unified Medical Language System (UMLS) ideas for pneumonia detection.	On the confined and unrestricted datasets, the system obtained F1-measure scores of 85.71% and 81.67%, respectively.	The machine learning-based system fared worse than the baseline, while the rule-based system utilizing assertion values did better. The dataset has flaws, such as incomplete reports and a dearth of positive pneumonia cases.
Sara Lee et	2020	Convolutional	K-Nearest	The cost-	Dataset 1:	The most	Overall,

al.		Neural Network (CNN) based feature extraction, InceptionV3 CNN	Neighbor, Neural Network, Support Vector Machines	effective way for identifying pneumonia is chest X-ray imaging.CNNs like InceptionV3 are appropriate for extracting features from X-ray pictures.	Analysis of the confusion matrix. Confusion matrix for the KNN model is in dataset 2. Dataset 3: Confusion matrix for the neural network model. Dataset 4: Confusion Matrix for SVM Model.	sensitive system was the neural network, at 84.1%. A sensitivity of 83.5% was attained using support vector machines. The sensitivity of the K-Nearest Neighbor algorithm was 83.3%. SVM had the greatest AUC, which was 93.1%.	NN fared better in terms of sensitivity, accuracy, and precision than kNN and SVM.
Yar Muhammad et al.	2021	CNN models, including AlexNet, VGG-16, and VGG-19, Inception-V3 Architecture	CNN, Artificial Neural Network (ANN), Logistic Regression (LR), SVM,	After 200 training iterations, the accuracy of the CNN model stabilized at 92.30%. The suggested system	Dataset 1: Epidemics in the past developed throughout time. Dataset 2: Performance of every classifier utilizing the	CNN: 92.30%, ANN - 96.97%, LR - 96.24%, SVM - 52.03% , LR - 96.82%, ANN - 96.56%,	The suggested system used several ML and DL algorithms to diagnose pneumonia with excellent

				performed better and was more accurate than earlier approaches.	AlexNet transfer learning architecture.	SVM - 50.30%, ANN - 97.01%, LR - 96.92%, SVM - 50.32%, ANN - 97.19%, LR - 97.08%, SVM - 50.32%, Proposed System - 97.19%,	accuracy. The maximum accuracy was achieved by Inception-V3 using an ANN, at 97.19%. The accuracy of the suggested system's pneumonia diagnosis was higher than that of earlier techniques

CHAPTER 3: METHODOLOGY

- 3.1. Depthwise Separable Convolution:

Filtering and merging inputs to create a new set of outputs allows for a standard convolution to be completed in one step. This factorization has the effect of drastically reducing the amount of computation and model size. A depth wise separable convolution splits the data into two layers: one layer for filtering and the other layer for merging.

The input pictures comprise red, green, and blue channels, which are used for the depthwise separable convolution. There may be several channels in the pictures after several convolutions. A different interpretation of the image may be used for each channel of imaging.

The "red" channel, "blue" channel, and "green" channel, for instance, each explain "red," "blue," and "green" for each individual pixel. There are 64 alternative ways to interpret a picture with 64 channels. A depthwise separable convolution, which is a separate regular convolution, consists of a depthwise convolution (DW) and a pointwise convolution (PW). Here, DW deals with modeling spatial relationships using 2D channelwise convolutions, while PW deals with modeling cross-channel relationships using 1 1 convolution across channels, its factorization form is described by DW + PW .

The computational cost of a depth wise separable convolution vs a standard convolution will then be compared in order to demonstrate that the former has greater performance.

A DF× DF ×N feature map G is created when the DF ×DF ×M feature map F of the standard convolution layer is used as input. DF stands for the spatial width and height of the square input feature map 1, M for the quantity of input channels (input depth), DG for the spatial width and height of the square output Computational Intelligence and Neuroscience feature map, and N for the quantity of output channels (output depth).

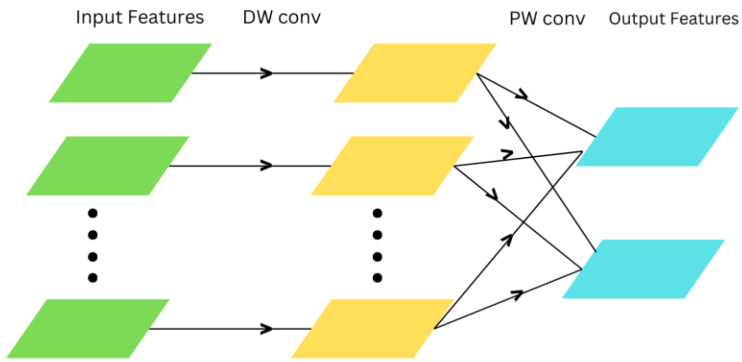


Fig 1. A depthwise separable convolution.[1]

The regular convolutional layer is specified by a convolution kernel K of size DK ×DK× M× N. DK stands for the kernel's assumed square spatial dimension, M for the number of input channels, and N for the number of output channels.
Regular convolution's output feature map, assuming stride 1 and padding, is calculated as

$$G_{k,l,n} = \sum_{i,j,m} \mathbf{K}_{i,j,m,n} \cdot \mathbf{F}_{k+i-1,l+j-1,m} \qquad (1)$$

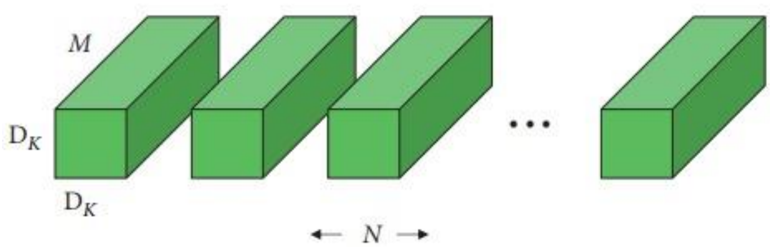


Fig 2. The regular convolution layer.[2]

The cost of computing the regular convolution CR is:-

$$C_R = D_K \,.\, D_K \,.\, M \,.\, N \,.\, D_F \,.\, D_{F'} \qquad (2)$$

where the number of input channels M, the number of output channels N, the kernel size DF ×DF, and the feature map size DF ×DF all affect the computational cost.

A depthwise separable convolution was previously described as having two layers: a depthwise convolution and a pointwise convolution. To apply a single filter to each input channel (input depth), depthwise convolution is utilized. En, we use pointwise convolution, a straightforward 1× 1 convolution, to combine the depth wise layer's output linearly. The depthwise convolution with one filter per input channel (input depth) can be defined as follows:

$$\hat{G}_{k,l,m} = \Sigma_{i,j}\, \hat{k}_{i,j,m} \,.\, F_{k+i-1,l+j-1,m'} \qquad (3)$$

where $\hat{k}$ is the DF ×DF ×M depthwise convolutional kernel; the mth filter in $\hat{k}$ is applied to the mth channel in F to form the mth channel of the filtered output feature map $\hat{G}$. The depthwise convolution CD's computational cost is

$$C_D = D_K \,.\, D_K \,.\, M \,.\, D_F \,.\, D_{F'} \qquad (4)$$

The pointwise convolution CP's computational cost is:

$$C_P = M \,.\, N \,.\, D_F \,.\, D_{F'} \qquad (5)$$

Therefore, the depthwise separable convolution CDP's computational expense is:

$$C_{DP} = D_K \,.\, D_K \,.\, M \,.\, D_F \,.\, D_F + M \,.\, N \,.\, D_F \,.\, D_{F'} \qquad (6)$$

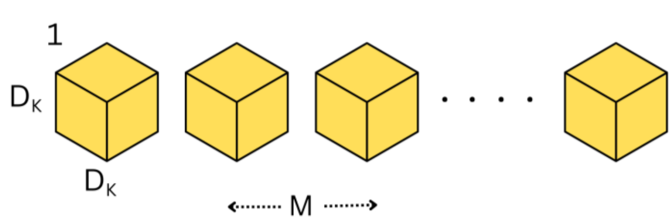


Fig 3. The depthwise convolution layer.[3]

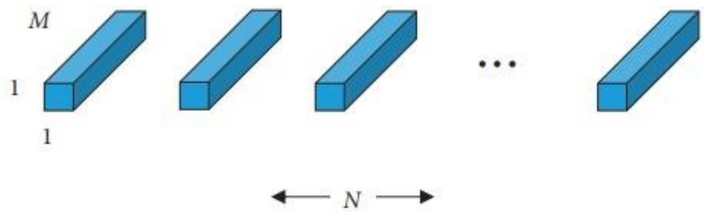


Fig 4. The pointwise convolution layer.[4]

This is the depthwise and one-to-one pointwise convolution added together. Convolution is divided into a 2-step procedure of convolution.

Using filtering and merging, we calculate a reduction R for :

$$R = (D_K . D_K . M . D_F . D_F + M . N . D_F . D_F) / (D_K . D_K . M . N . D_F . D_F) = (1 / N) + (1 / D_k^2) \quad (7)$$

It is so argued that the depthwise separable convolution can significantly lower the amount of computing cost.

Additionally, in an effort to eliminate redundancy, we tried lowering the number of filters. The first filter banks for edge identification are built using Howard's network model, which employs 32 filters in a complete 3×3 convolution. Through examination of the experiment data, we discovered that lowering the number of filters from 32 to 16 might preserve accuracy while saving an extra 2 ms.

- 3.2. Model Evaluation Metrics :

We use the confusion matrix , a common structure for expressing accuracy evaluation, to assess the performance of the deep learning model. The following standards are used for evaluation in accordance with this confusion matrix:

1. The number of samples successfully identified by the classification model divided by the total number of samples for a certain test data set is the accuracy. The following formula may be used to represent it:

$$Accuracy = (TP + TN) / (TP + TN + FP + FN') \quad (8)$$

2. Recall is the likelihood that the classification model correctly predicted a positive sample from the first sample, which is represented by the original sample's positive sample. The formula below can be used to represent it:

$$\text{Recall} = TP / (TP + FN') \qquad (9)$$

Table 1: Confusion matrix.

	Actual Positive	Actual Negative
Predicted Positive	TP	FP
Predicted Negative	FN	TN

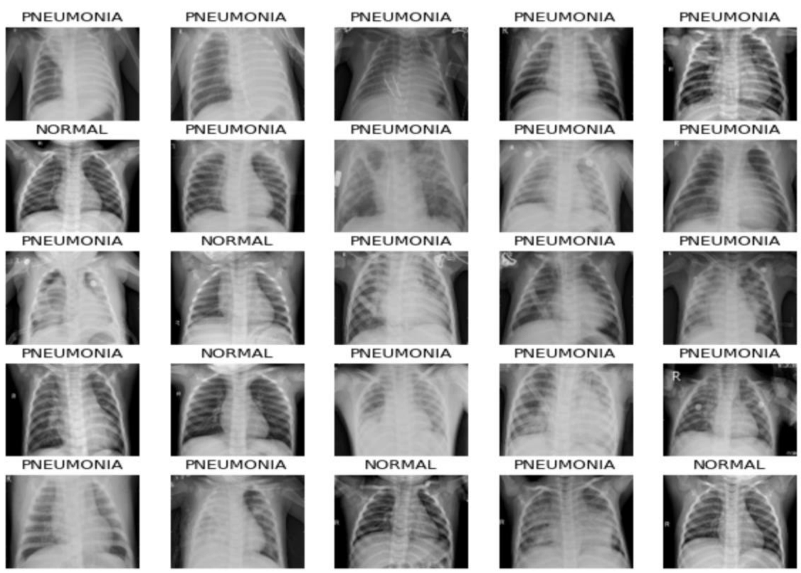


Fig 5. Chest X-ray images (pneumonia/normal).[5]

CHAPTER 4: RESULTS AND DISCUSSION

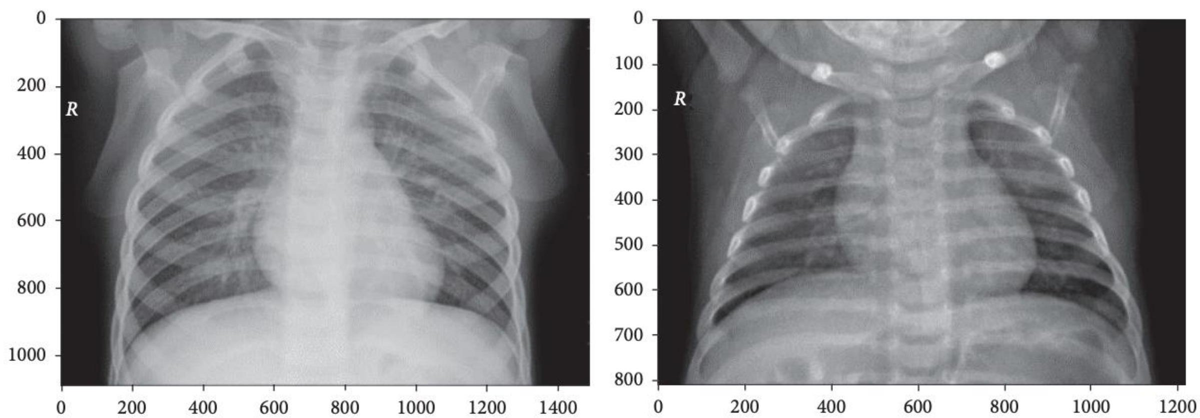
In this study, we set out to evaluate five different Convolutional Neural Network (CNN) models thoroughly, and we based our evaluation on a number of important performance indicators. These parameters included [14] the accuracy of the training set, the loss of the training set, the accuracy and loss of the validation set. We meticulously standardized the training procedure by setting up all models to train across 25 epochs in order to provide a fair and meaningful comparison between these models. We were able to evaluate the speed and effectiveness of each algorithm's learning thanks to this method, which made sure that each algorithm endured the same amount of training rounds.To balance training time and precision was a key objective of our investigation. This balance is essential, particularly when dealing with time-sensitive situations like the quick detection of novel pneumonia strains. In situations like these, when the prompt and accurate detection of newly developing pneumonia variants is crucial, researchers require tools that can quickly and successfully address new difficulties.

The results of our analysis showed that MobileNet's performance was particularly impressive. This model successfully detected pneumonia with an astounding accuracy rate of up to 92.79% and a high recall rate of 98.90%. These findings were generated from the application of the five trained models to the test dataset in our studies. MobileNet outperformed other network topologies in terms of accuracy and decreased loss in spite of these resource-saving features. This made it a desirable option for practical applications, particularly those requiring quick and accurate medical diagnostics.

Additionally, the distinctive advantages of MobileNet, notably its lightweight design, were underlined by our testing results. MobileNet outperformed other CNN models in terms of classification accuracy while having a substantially smaller number of parameters. The use of depthwise separable convolution, a method that minimizes processing needs while retaining high accuracy in categorizing medical pictures, was credited with this extraordinary accomplishment. Particularly in resource-constrained settings where both medical equipment and qualified personnel may be scarce, this idea has enormous promise.

(a) The process of converting a lung image with pneumonia, obtained from the dataset, into a NumPy array is a fundamental step in preparing medical image data for analysis or machine learning applications. This conversion allows the image to be represented as a multi-dimensional array of numerical values, which is essential for further processing. The resulting NumPy array can be used for tasks such as feature extraction, model training, or deep learning, enabling the development of diagnostic tools for pneumonia detection.

(b) Similarly, the conversion of a normal lung image, obtained from the training set, into a NumPy array is a crucial preprocessing step in the analysis of medical images. It transforms the image into a structured numerical format that can be manipulated and analyzed computationally. This NumPy array can then be used for tasks like image segmentation, comparison with pneumonia-affected images, or to serve as input data for machine learning algorithms that differentiate between healthy and diseased lung conditions. This process is vital for building accurate and efficient medical image analysis systems.



(a) (b)

Fig 6. (a) Conversion of the lung with pneumonia image obtained from the dataset into a NumPy array; (b) conversion of the normal lung image obtained from the train set into a NumPy array.[6]

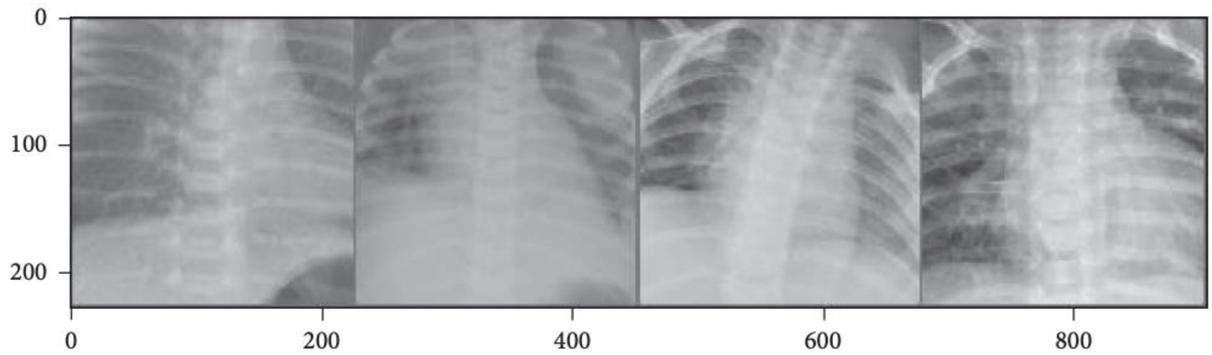


Fig 7. The sizes of images are changed to 226 × 226.[7]

Five distinct Convolutional Neural Networks (CNNs) are shown in this graphic with their training set accuracy. How effectively these CNNs work when applied to the data they were trained on is measured by training set accuracy. The graph most likely depicts how each CNN's accuracy changes throughout training, giving information on their capacity for learning and convergence over time. This data is essential for determining how well the models can recognize and learn from data patterns.

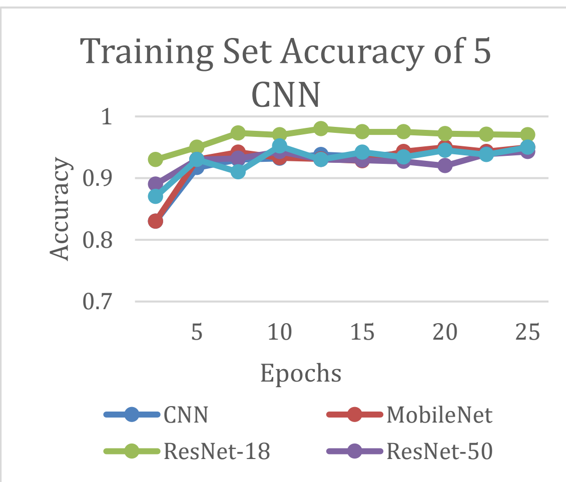


Fig 8. The training set accuracy of five CNNs [8].

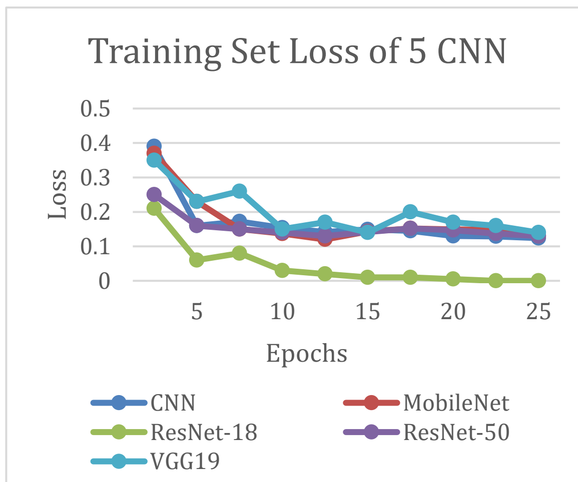
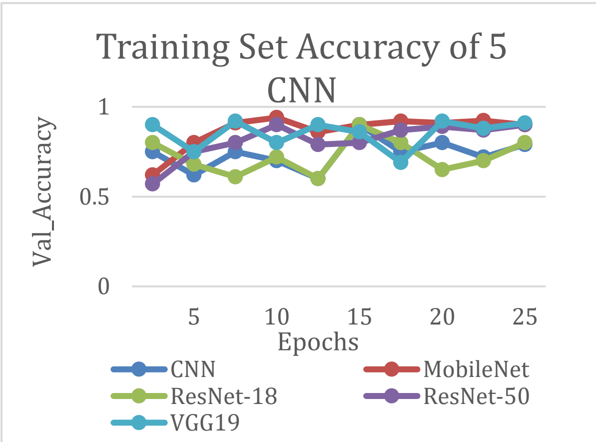


Fig 9. The training set loss of five CNNs [9]

On a validation dataset, it shows how five Convolutional Neural Networks (CNNs) performed. This accuracy metric measures how effectively these CNN models can identify or predict data that they haven't seen before during training. A greater validation set accuracy shows that the models are more successful at applying their discovered patterns to fresh, unexplored data. Making an informed selection when selecting a model for a certain job requires understanding which CNN architecture performs better in terms of accuracy, which can be learned through analyzing this graph.



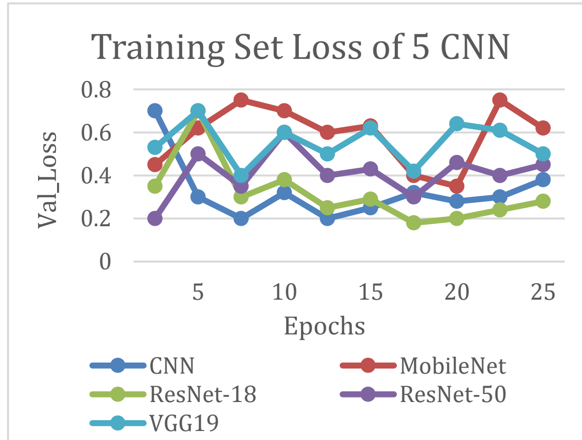


Fig 10:The validation set accuracy of five CNNs[10]

Fig 11:The validation set loss of five CNNs[11]

Table 2. The five CNNs' average of their training set accuracy, training set loss, validation set accuracy, and validation set loss.

	Accuracy	Loss	Val_accuracy	Val_loss
MobileNet	0.94454	0.15300	0.87119	0.25509
ResNet-18	0.98795	0.03783	0.85388	0.28453
ResNet-50	0.94342	0.13564	0.82982	0.37387
VGG19	0.94318	0.18500	0.86044	0.50610
CNN	0.93980	0.15152	0.72090	0.51290

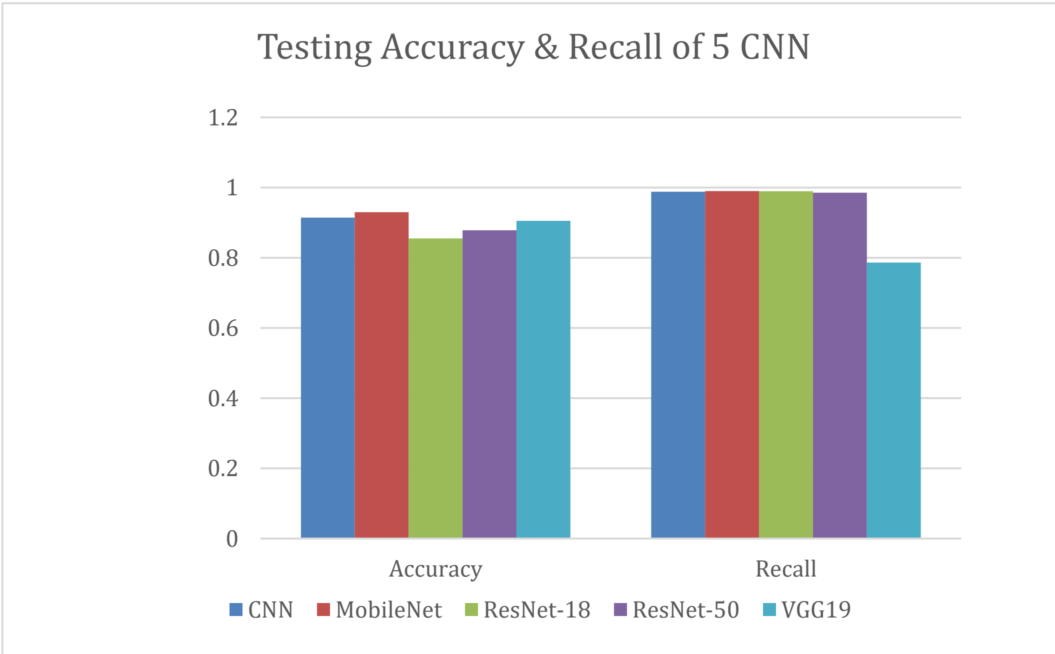


Fig 12:Bar Graph Plot of Testing Accuracy & Recall Of 5 CNN [12]

Table 3: The five CNNs' testing accuracy and recall.

	Accuracy	Recall
MobileNet	0.92986	0.98984
ResNet-18	0.85515	0.98947
ResNet-50	0.87486	0.98531
VGG19	0.90529	0.78635
CNN	0.91446	0.98813

CHAPTER 5: CONCLUSION & FUTURE WORK

As a result of its high incidence and fatality rates, pneumonia is a concern for global health and requires an early diagnosis in order to be effectively treated. Chest X-ray interpretation by qualified radiologists has been shown to be a bottleneck, especially in areas with limited access to healthcare. Deep learning and artificial intelligence developments, however, provide a strong resolution to this problem. The transformational potential of these technologies in the medical industry was highlighted by our study, which concentrated on the potential of deep learning models for pneumonia identification.

Our thorough analysis of five Convolutional Neural Network (CNN) models revealed MobileNet's outstanding performance. This compact design outperformed other CNN models while utilizing much less parameters, and it also demonstrated good detection accuracy for pneumonia. This balance between economy and precision was made possible in large part by the depthwise separable convolution approach. MobileNet is a useful tool for medical practitioners because to its speed and accuracy, which enables speedy and accurate pneumonia diagnosis even in areas with limited resources.

There are a number of promising directions for future study and advancement in this area. Here are some possible headings:

- Large-Scale Deployment: Incorporating MobileNet-style models into clinical practice is one of the near-term potential. This would entail creating user-friendly user interfaces and making sure that such technologies complied with medical requirements. AI-driven pneumonia diagnosis that is widely implemented can dramatically improve patient access to care.

- Transfer Learning: By using transfer learning techniques more broadly, the requirement for better generality and accuracy in identifying different pneumonia kinds may be addressed. This is particularly helpful in identifying lobar pneumonia from bronchiolitis or interstitial infiltration.

- Multimodal Imaging: The range of AI applications in healthcare may be increased by looking at the possibilities of deep learning in conjunction with other imaging modalities, such ultrasound or MRI, for the diagnosis and monitoring of pneumonia.

- Real-Time Diagnosis: It is essential, especially in emergency situations, to develop real-time diagnostic technologies that can deliver right away conclusions from X-ray pictures. To do this, deep learning model speed would need to be optimized for quick deployment.

- Continuous Learning: To guarantee that the technology stays successful over time, it is crucial to investigate ways for models to continuously learn from and adapt to new variations of pneumonia strains and developing medical knowledge.

- Resource-Constrained Settings: In areas with little access to modern medical technology and qualified radiologists, adapting AI models to function well with few computational resources has the potential to revolutionize healthcare.

The influence of deep learning in the diagnosis of pneumonia and other areas of healthcare may be increased by incorporating these upcoming initiatives, which will eventually result in better patient care and health outcomes.

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