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Empowering Diagnosis: A Review On Deep Learning Applications for COVID-19 and Pneumonia in X-Ray Images

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Abstract – The emergence of COVID-19, a highly contagious virus capable of infecting both the upper and lower respiratory tracts, has led to one of the deadliest pandemics in modern history, claiming millions of lives worldwide. Early and accurate detection of this rapidly spreading disease is crucial for effective containment and saving lives. Chest X-ray (CXR) stands out as a promising diagnostic tool due to its accessibility, affordability, and long-term sample preservation. However, distinguishing COVID-19 pneumonia from other respiratory ailments poses a significant challenge. This article delves into various approaches utilized for COVID-19 detection and the hurdles encountered in this endeavor. The imperative for developing automated detection systems to mitigate virus transmission via contact is underscored. Notably, deep learning architectures such as ResNet, Inception and Googlenet have been deployed for COVID-19 detection, albeit with a focus on identifying pneumonia cases. Discriminating between COVID-19-induced pneumonia and pneumonia caused by other pathogens remains a formidable task, demanding innovative solutions for accurate and timely diagnosis.
Keywords – COVID-19, Pandemic, Detection, Chest X-ray (CXR), Deep learning.

I. INTRODUCTION

In December 2019, the global crisis of COVID-19 erupted from Wuhan, China, rapidly becoming a major public health concern due to its highly contagious nature. This pandemic, caused by the Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2), marks a novel addition to the coronavirus family, which includes viruses responsible for ailments like the common cold, Middle East Respiratory Syndrome (MERS), and severe acute respiratory syndrome (SARS) [1] . COVID-19, believed to have zoonotic origins, is transmitted from animals to humans, similar to its predecessors like SARS-CoV and MERS-CoV. The virus primarily spreads through respiratory droplets and physical contact, with asymptomatic or mildly symptomatic individuals posing significant transmission risks. Alarmingly, a quarter of COVID-19 cases show no symptoms at all. As of April 7, 2020, there have been approximately 1,359,010 confirmed cases globally, resulting in 75,901 fatalities and 293,454 recoveries. The mortality rate stands at 5%, while 95% of infected individuals have a chance of recovery [2]. COVID-19 primarily affects the respiratory system, manifesting symptoms such as dyspnea, fever, and cough, with severe cases progressing to pneumonia, septic shock, and organ failure, often resulting in death. Men are more susceptible to infection due to increased exposure, while mortality among children aged 0-9 years remains uncommon [3].

Notably, COVID-19-induced pneumonia progresses more rapidly than other forms of pneumonia. Given its respiratory impact, chest radiology scans, particularly Chest X-rays (CXR), play a pivotal role in early diagnosis and management. CXR serves as a frontline diagnostic tool in several countries, offering rapid assessment of lung conditions and disease progression. Radiologists have observed various abnormalities in COVID-19 patients' CXR images, including bilateral ground-glass opacities (GGO) and consolidations. Deep learning (DL) techniques, particularly Convolutional Neural Networks (CNNs), have shown promise in enhancing the analysis of medical images, including CXR scans. Since the onset of the pandemic, DL approaches have been extensively explored to aid in COVID-19 diagnosis via CXR images. This paper reviews recent research endeavors in applying DL for COVID-19 detection from CXR scans, examining existing technologies, addressing challenges, and outlining future research directions. Through the critical assessment of preprint and published reports spanning the last five years, this review aims to elucidate how CNNs and DL architectures can facilitate the diagnosis of COVID-19 using CXR images [4].

The aim of this paper is to review recent research endeavors in applying Deep Learning (DL) techniques, particularly Convolutional Neural Networks (CNNs), for the detection of COVID-19 from Chest X-ray (CXR) scans. The COVID-19 pandemic, caused by the Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2), has highlighted the urgent need for efficient diagnostic tools due to its highly contagious nature and significant impact on global public health. With CXR serving as a frontline diagnostic tool for assessing lung conditions, this review seeks to explore the effectiveness of DL approaches in enhancing the analysis of CXR images for COVID-19 diagnosis. By critically assessing preprint and published reports, the paper aims to elucidate the potential of CNNs and DL architectures in facilitating early and accurate diagnosis, addressing existing challenges, and outlining future research directions in this critical area of medical imaging.

Section two offers an extensive examination of deep learning (DL) applications in analyzing CXR images for COVID-19, covering the employed architectures and datasets [5]. Section Three outlines the methodological analysis and performance evaluations across different DL models. Section Four emphasizes existing challenges, addressing issues such as the establishment of public datasets, model optimization, handling model uncertainty, and understanding the opaque decisions made by DL

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models. Lastly, Section five provides suggestions for future research directions, concluding the paper.

II. LITERATURE REVIEW:

While vaccines have been created, the most effective approach to containing the disease remains isolating individuals who are infected. Yet, swiftly distinguishing between healthy and infected individuals poses a challenge. Since the onset of the COVID-19 pandemic, scientists have endeavored to leverage machine learning and deep neural networks for automated detection of the virus. The following sections provide an overview of recent studies concerning COVID-19 detection and the use of DL classifiers. In [16] explored three comprehensive transfer scenarios for detecting pneumonia disease, encompassing normal cases, COVID-19, bacterial, and viral pneumonia. They employed three deep transfer models: AlexNet, GoogLeNet, and ResNet18. To address the challenge of limited training data, they leveraged Generative Adversarial Networks (GANs) to generate X-ray images effectively. In the initial scenario, the dataset was divided into four classes, with GoogLeNet serving as the primary transfer model. The second scenario focused on three classes, with AlexNet chosen as the base model for deep transfer. The third scenario narrowed down to two classes, normal and COVID-19, with GoogLeNet as the base architecture. The achieved accuracy for the classification of three classes reached 85.2%.In [17] conducted a study to assess the effectiveness of a multi-CNN (Convolutional Neural Network) system in automatically detecting COVID-19 in X-ray images. They employed a multi-CNN combined with Correlation Feature Selection (CFS) and a Bayes net classifier for COVID-19 prediction. The proposed methodology was tested on two distinct public datasets, yielding promising outcomes in both cases. The initial dataset consisted of 453 COVID-19 images and 497 non-COVID images, achieving an Area Under Curve (AUC) of 0.963 and an accuracy of 91.16%. When applied to the second dataset, which comprised 71 COVID-19 images and seven non-COVID images, the method achieved an AUC of 0.911 and an accuracy of 97.44%.The researcher [18] conducted an initial experiment employing image texture feature descriptors, specifically the Gray Level Co-Occurrence Matrix (GLCM) and Local Binary Patterns (LBP), alongside a feed-forward network and a CNN. They utilized newly constructed datasets comprising COVID-19 images, with the aim of laying groundwork for the future development of a system capable of automatically detecting COVID-19 in chest X-rays and CT images of the lungs. Integration of two distinct databases was performed, and the most effective technique achieved an accuracy of 97.40% on the validation set. This was achieved by utilizing a feed-forward neural network and incorporating flattened images along with texture information as inputs.In [19] introduced a novel approach for automated detection of COVID-19 using deep neural networks. Their framework employed generative adversarial networks in conjunction with transfer learning and Long Short-Term Memory (LSTM) networks, eliminating the need for feature extraction in COVID-19 diagnosis. This method effectively distinguished COVID-19 cases from the healthy group with a remarkable accuracy of 99%. Additionally, various other deep transfer learning networks such as VGG16, Inception-ResNet V2, VGG16, and MobileNet, which have been extensively utilized in pneumonia detection research, were compared to the proposed model. The results demonstrated that the suggested model exhibited significant promise in terms of accuracy, precision, sensitivity, and specificity compared to existing deep transfer learning systems. In [20] introduced a computerized approach aimed at optimizing hyperparameters. They investigated the individual tuning of learning rates for each layer of the network to refine the parameters. Additionally, the authors addressed the high computational demand of deep models by employing memory- and computationally-efficient mixed-precision training, thereby reducing the training time. Despite the limited availability of datasets, the model demonstrated outstanding performance and generalization. Specifically, the proposed Model 11 achieved a validation accuracy of 96.83% and sensitivity and specificity rates of 96.26% and 95.54%, respectively. Moreover, the model attained an accuracy level of 97% when tested on a completely new dataset without undergoing any additional training. Lastly, the model showcased its potential to aid radiologists in rapidly screening patients for COVID-19 symptoms.In the researcher [21] proposed a model utilizing chest radiographs due to the widespread use of these imaging modalities in clinical diagnosis, owing to their rapidity and cost-effectiveness. The study utilized a dataset comprising 1428 chest radiographs, encompassing healthy cases (no infection), as well as cases with common bacterial pneumonia and COVID-19 positivity. Furthermore, the study assessed the VGG-16 model's capability for categorization. Employing transfer learning with fine-tuning, the network was trained on the dataset of small chest radiographs. The experimental results showcased an accuracy of 96% for cases with two output classes and 92.5% for cases with three output classes, respectively. The research conducted by [22] improved the Snapshot Ensemble technique for classifying COVID-19 chest X-rays using deep learning. This approach also utilized the ResNet-50 model, which is pre-trained, as the foundation for transfer learning. A publicly available dataset comprising 2905 images, including COVID-19, normal, and pneumonia chest X-rays, was employed. The model demonstrated a 95% correct classification rate. Furthermore, it achieved a multi-class micro-average of 97% specificity, along with 95% f1-score and classification accuracy. The results indicate that the proposed approach outperforms several existing methods.In [23] introduced a novel approach to utilizing CXR images for improved screening and classification of COVID-19 disease in patients. Departing from the conventional heavy reliance on extensive datasets and the intricate features extracted by deep learning models, their strategy combined generative adversarial networks (GANs) with traditional data augmentation methods to address data limitations. Additionally, they employed Sobel, Laplacian of Gaussian (LoG), and Gabor filters to extract additional features from the data. This methodology was applied to various deep transfer models, and the results were compared. The

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researchers utilized a dataset of 4560 CXR images encompassing patients with viral, bacterial, fungal, and other diseases to train the models. Among these, 360 images were classified as COVID-19 cases, while the rest represented other diseases. The test results indicated an accuracy increase of up to 32% within 45 iterations when utilizing the Gabor filter bank, based on evaluation criteria. Their proposed model utilized the DenseNet-201 architecture and its detection accuracy was evaluated against 10 existing COVID-19 detection methods, achieving a two-class classification accuracy of 98.5%. In [24] introduced a deep learning architecture (DLA) along with optimization algorithms aimed at streamlining the automated detection of Covid-19. They proposed models utilizing convolutional neural networks for feature extraction from images. Deep-feature-based methods, including data augmentation and fine-tuning, were employed to enhance the model's performance. Additionally, the authors utilized two factors, namely the degree of opacity and geographic area, to improve visualization and quantify the disease severity level through image enhancement and saliency maps. Various parameters of Otsu thresholding and contrast-limited adaptive histogram equalization were explored to evaluate their impact on visualization outcomes. The proposed technique was compared against other pre-trained DLAs, showcasing outstanding classification accuracy (97.36%) and sensitivity (95.24%). The performance metrics of DenseNet were particularly noteworthy, demonstrating high efficacy for the proposed work and rendering them comparable to other models. The [25] developed an X-ray-based approach for diagnosing coronavirus infection. They utilized the DenseNet169 Deep Neural Network (DNN) to extract features from X-ray images obtained from patients' chests. Subsequently, the Extreme Gradient Boosting (XGBoost) technique was applied to these features for classification purposes. The proposed method demonstrated higher accuracy and efficiency compared to existing approaches, exhibiting satisfactory performance in detecting COVID-19 cases from X-ray images when assessed and compared with recent methodologies. In the experiments, the proposed approach achieved accuracies of 98.23% and 89.70%, and sensitivities of 92.08% and 95.20% for two- and three-class scenarios, respectively. In [26] the author introduced COVDC-Net; a classification approach based on Deep Convolutional Networks. This method aims to identify individuals infected with SARS-CoV-2 among healthy individuals and pneumonia patients by analyzing chest X-ray images. COVDC-Net employs two modified pre-trained models, MobileNetV2 and VGG16, originally trained on ImageNet, but without their classifier layers. These models are then combined using the Confidence fusion method to enhance classification accuracy on publicly available datasets. Through extensive testing, it was found that COVDC-Net achieved an overall classification accuracy of 96.48% when applied to three-class classification tasks involving COVID-19, Normal, and Pneumonia cases. The experimental results indicate that COVDC-Net outperforms existing deep learning methods proposed for similar tasks in ongoing COVID-19 competitions. In [27] introduced Conv-CapsNet, a novel model that combines Capsule Networks and convolutional layers for detecting COVID-19 in X-Ray scans. The proposed model achieves high accuracy rates of 96.47% for multi-class and 97.69% for binary classification. By utilizing a shallow architecture with 23M parameters, the model demonstrates effectiveness in classifying X-Ray images into COVID-19, No Findings, and Viral Pneumonia classes. The study concludes that Capsule Networks outperform Convolutional Neural Networks for smaller datasets, offering promising results for accurate COVID-19 detection in medical imaging. The study [28] presented "RADIC" an automated tool utilizing three deep learning (DL) models trained on radiomics-derived images to detect COVID- Initially, four radiomics methods analyze original CT and X-ray images. Subsequently, each DL model is trained on distinct sets of radiomics, X-ray, and CT images. Deep features are extracted from each DL model and transformed using Fast Walsh Hadamard Transform to generate a time-frequency representation of COVID-19 patterns. The discrete cosine transform combines these features, and four classification models are employed for classification. RADIC achieves 99.4% and 99% accuracy on two benchmark datasets for CT and X-ray respectively, outperforming related studies. The results demonstrate that DL models trained on radiomics-generated images are more effective for COVID-19 detection than those trained on original images. Additionally, incorporating deep features from DL models trained on various radiomics methods enhances diagnostic accuracy. The researcher in [29] explored the potential of combining X-ray imaging with deep learning algorithms to quickly and accurately diagnose COVID-19 patients. The proposed method enhances detection accuracy by fine-tuning established transfer learning models with appropriate layers. The study used a dataset of 2000 COVID-19 X-ray images for experimentation. Remarkable accuracy rates were achieved, ranging from 97.32% to 100% across various models, with EfficientNetB4 demonstrating outstanding performance. Furthermore, EfficientNetB4 showed excellent results in identifying lung diseases using a separate dataset of 4,350 Chest X-ray images. The findings underscore the effectiveness of fine-tuned transfer learning for efficient lung detection in medical imaging, particularly with X-ray images. This research presents a valuable tool for radiologists to aid in rapid and precise COVID-19 diagnosis and provides essential support for healthcare professionals in accurately identifying affected patients. In [30] the author investigated available CXR image datasets, comprising a total of 15,153 (dataset 1) and 4575 (dataset 2) images, were utilized. Three neural network models were trained using balanced subsets of dataset 1 (1345 images per class), balanced dataset 2 (1525 images per class), and an unbalanced full dataset 1. These models, including VGG16 and Inception Resnet (IR) utilizing transfer learning, alongside a custom-made Convolutional Neural Network (CNN), were employed. The accuracy, sensitivity, specificity, and F1 score for each model were assessed. VGG16 achieved an accuracy, sensitivity, specificity, and F1 score of 96%, 97.8%, 95.92%, and 97% respectively. IR attained an accuracy, sensitivity, specificity, and F1 score of 97%, 98.51%, 97.28%, and 99% respectively. The CNN model, identified as the top performer, yielded an accuracy, sensitivity, specificity, and F1 score of 97%, 98.21%,

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96.62%, and 98% respectively. These performance metrics were evaluated using the balanced dataset 1, and all models underwent 80:10:10 cross-validation. The highest accuracy rates of 97%, 96%, and 93% across all three datasets respectively were demonstrated by CNN. To ensure authentic pathology markers were employed for generalization, Gradient-weighted Class Activation Mapping (Grad-CAM) was utilized. The authors [31] introduced three advanced deep-learning models designed to detect specific lung ailments using chest X-rays. The first model, dubbed "CovCXR-Net," focuses on identifying COVID-19 (with two possible outcomes: COVID-19 present or normal). The second model, labeled "MDCXR3-Net," extends its scope to detect both COVID-19 and pneumonia (with three potential outcomes: COVID-19, pneumonia, or normal). Lastly, the "MDCXR4-Net" model is tailored to recognize COVID-19, pneumonia, and pulmonary opacity (with four potential outcomes: COVID-19, pneumonia, pulmonary opacity, or normal). These models outperform existing ones and achieve impressive accuracies of 99.09%, 97.74%, and 90.37% respectively across three benchmarks. In [32] introduced a robust method for classifying lung diseases from chest X-ray (CXR) images. To achieve accurate classification, three finely-tuned models are presented. Their effectiveness is assessed using a recently constructed CXR image dataset. Experimental results demonstrate that these fine-tuned models surpass existing lung disease classification methods, achieving an accuracy of 98%. The proposed approach shows promise for effective lung disease categorization. The researcher in [33] introduced a transfer learning method for predicting pneumonia using a collection of chest X-ray images. These images will be categorized into two groups based on specific parameters. The proposed model achieved an average accuracy of 94.54% on the dataset. Compared to prior quantitative and qualitative research, the proposed model (PDTLA) demonstrated strong performance. The modified model, named Pneumonia Detection Transfer Learning Algorithm (PDTLA), showed notable effectiveness in pneumonia detection.

III. RESEARCH METHODOLOGY

2.1 Deep Learning

In recent years, neural networks have made significant strides, particularly in computer vision tasks like image classification, generation, and object detection. Deep learning, characterized by networks with numerous layers of processing units, has been pivotal in these advancements. These networks, by passing the output of one layer to the input of the next, can extract complex hierarchical features from large datasets[6] . Feature extraction is fundamental to deep learning, utilizing multiple layers to pinpoint specific characteristics in incoming data. Unlike traditional models with fixed equations, deep learning algorithms directly extract valuable insights from data through computational methods, resembling human learning through experience. This approach has greatly improved the effectiveness of machine learning. Additionally, advancements in computer hardware have accelerated the pace of deep learning, enabling more efficient processing of vast amounts of data [7].

2.2.1 Convolutional Neural Networks

CNNs, widely utilized for image recognition tasks, are highly efficient deep learning models adept at handling high-dimensional data like images and videos[37]. They function similarly to ANN, employing two-dimensional filters to automatically detect important spatial and temporal features within image data. Comprising layers of convolutions and filters, CNNs serve as feature extractors, with lower layers identifying basic features such as edges, middle layers extracting color and shape information, and deeper layers recognizing objects [8]. Their success stems from their capability to learn hierarchical representations, mirroring the hierarchical learning process in biological brains. Input images are transformed into feature maps through convolutional layers, and CNN models are trained and evaluated by passing images through layers containing kernel-based filters, pooling, fully connected layers, and softmax for classification[36].

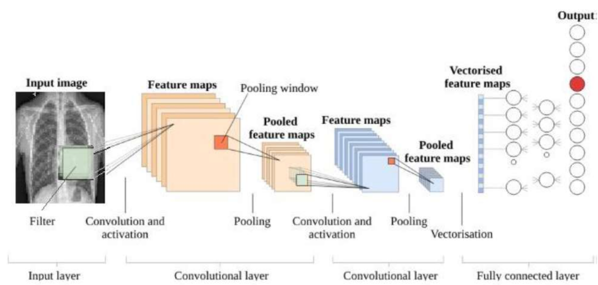

Fig. 1: Building blocks of CNN architecture

2.2.2 Pre-trained CNN Models

In the realm of deep learning, CNNs undergo initial training tailored to specific tasks, such as classification, utilizing large datasets to efficiently extract crucial image features. However, in medical data analysis, like pneumonia or COVID-19 detection, dataset sizes can be constrained, impeding accurate feature extraction and classification. Transfer learning addresses this obstacle by retraining models previously trained on akin tasks, improving learning in new challenges by transferring knowledge. This involves repurposing pre-trained weights in model layers as a starting point, adjusting them to suit the current task [9]. Transfer learning proves particularly advantageous in CNN implementations with limited data, enabling models trained on expansive datasets like ImageNet to serve in applications with smaller datasets.

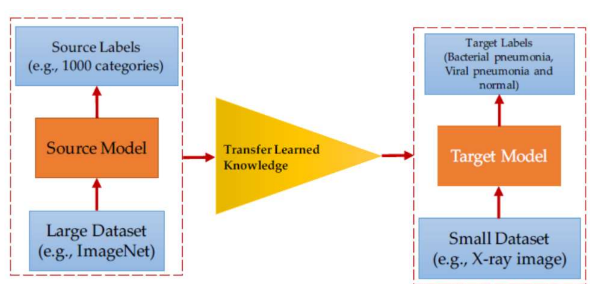

Fig 2: Diagram of Transfer Learning

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Many popular CNNs have been pre-trained using DL, like VGG-16, ResNet, AlexNet, DenseNet, XceptionNet, and MobileNet, have been used for COVID-19 and pneumonia detection.

2.2.2.1 VGG

The VGG (Visual Geometry Group) pre-training model is a convolutional neural network architecture developed by the University of Oxford, renowned for its depth and uniform structure. Featuring typically 16 or 19 layers, it employs small 3x3 filters in convolutional layers and 2x2 filters in max-pooling layers. Pre-trained on vast datasets like ImageNet, it learns general image features, facilitating transfer learning for specific tasks with smaller datasets. This versatility and effectiveness make VGG a widely used tool in computer vision, particularly for image classification and object detection tasks [10].

2.2.2.2 ResNet

The ResNet (Residual Network) pre-training model, introduced by Microsoft Research, addresses the challenge of training very deep neural networks by incorporating skip connections or residual connections. These connections allow information from earlier layers to bypass certain layers and be added directly to later layers, mitigating the vanishing gradient problem. The ResNet architecture consists of convolutional layers followed by residual blocks containing multiple convolutional layers with shortcut connections[35]. Typically, pre-trained on large datasets like ImageNet, ResNet models learn general features that can be fine-tuned for specific tasks. This approach, known as transfer learning, enhances performance on new tasks with limited data. ResNet is recognized for its effectiveness in training deep networks and its versatility in various computer vision tasks [11].

2.2.2.3 AlexNet

AlexNet is a landmark convolutional neural network architecture that revolutionized the field of computer vision with its exceptional performance in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2012. Developed by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, AlexNet features five convolutional layers followed by three fully connected layers, incorporating max-pooling layers and ReLU activation functions. Notably, it introduced dropout regularization to combat overfitting and leveraged parallel computing resources using multiple GPUs for efficient training on the massive ImageNet dataset. AlexNet's success demonstrated the effectiveness of deep learning for image classification tasks and laid the foundation for subsequent advancements in the field [12].

2.2.2.4 DenseNet

DenseNet, also known as Dense Convolutional Network, is a deep learning framework distinguished by its dense interconnection structure among layers. Developed by Gao Huang et al. in 2017, DenseNet combats the vanishing gradient problem by establishing direct links between all layers, allowing each layer to access feature maps from every preceding layer. This dense connectivity promotes effective feature propagation, encourages feature reuse, and facilitates gradient flow across the network, resulting in improved performance and parameter efficiency. DenseNet comprises densely connected dense blocks, featuring multiple layers with direct connections, often followed by transition layers to manage feature map growth. Typically, during training, DenseNet models are pre-trained on large datasets like ImageNet, where they learn general features adaptable to specific tasks through fine-tuning. This pre-training, alongside dense connectivity and efficient parameter sharing, enhances DenseNet's efficacy across a range of computer vision tasks, encompassing image classification, object detection, and segmentation [13].

2.2.2.5 XceptionNet

XceptionNet, abbreviated from Extreme Inception, is an advanced deep learning framework developed by François Chollet in 2017 as a refinement of the Inception architecture, aimed at enhancing efficiency and efficacy in image classification tasks. It distinguishes itself with its utilization of depthwise separable convolutions, which segregate spatial and channel-wise operations within convolutional layers. This segregation serves to decrease computational complexity and parameter count while preserving or enhancing model performance [14]. The XceptionNet structure comprises sequences of depthwise separable convolutional blocks, interspersed with max-pooling layers, and optionally followed by fully connected layers for classification purposes. Typically, XceptionNet models undergo pre-training on extensive datasets like ImageNet to grasp general features, subsequently fine-tuning for specific tasks. The integration of depthwise separable convolutions, coupled with pre-training and fine-tuning processes, underpins XceptionNet's efficacy across a spectrum of computer vision applications, encompassing image classification, object detection, and segmentation.

2.2.2.6 MobileNet

MobileNet is a convolutional neural network architecture optimized for mobile and embedded devices with limited computational resources, devised by Andrew G. Howard et al. in 2017. It employs depth wise separable convolutions to reduce computational complexity and model size while maintaining performance. Depth wise convolutions apply filters per input channel, followed by pointwise convolutions to combine outputs, significantly cutting down computation compared to traditional convolutionsClick or tap here to enter text.. MobileNet architectures typically feature a sequence of depth wise separable convolutional layers with optional down sampling layers to decrease spatial dimensions. These models are often pre-trained on large datasets like ImageNet for general feature learning, with subsequent fine-tuning for specific tasks. MobileNet's lightweight design and efficiency make it suitable for deployment on mobile and embedded devices, enabling tasks such as image classification, object detection, and semantic segmentation with constrained resources [15].

A. Table Description

The comments and results of related works of Deep Learning Techniques are summarized in Table (1).

Table 1. summary table

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	Study Dataset Case Classify Techniques Performance (Accuracy %)		
	Loey et al., 2020 69 COVID-19, 79 Normal, 79 Pneumonia bacterial, and 79 Pneumonia virus. Three classes GAN and Transfer learning (Alexnet, Googlenet, and Resnet18) Acc = 85.19% Acc = 81.48% Acc = 81.48%		
	Abraham and Nair, 2020 Two dataset X-ray 950 and 78 Covid-19 = (453&71) Normal = (497&7) Binary class CFS technique and Bayesnet classifier Dataset1 = 91.2 % Dataset2=97.36 %		
	Varela-Santos and Melin, 2020 Cohen’s and Kermany’s database 255 COVID-19 X-rays and 255 No Findings X-rays Binary class GLCM+CNN Acc = 97.4 %		
	Sheykhivand et al., 2021 X-ray images COVID-19 = 371 Pneumonia Bacterial = 2778 Pneumonia Viral = 2840 Normal = 2923 Binary class GANs and Transfer learning and LSTM Acc= 99 %		
	Adedigba et al., 2021 oseph Cohen, two dataset X-ray Covid-19 = (258&219) Normal = (4&1341) Binary class DFT and Transfer learning Acc= 97%		
	Pandit et al., 2021 X-ray images COVID-19 = 224, Pneumonia = 700, and Normal = 504 Three classes Transfer learning (VGG16) Acc = 92.53%		
	P and Annavarapu, 2021 219 COVID-19, 1345 Pneumonia, and 1341 Normal. Three classes ResNet-50 model Acc = 95.18%		
	Barshooi and Amirkhani, 2022 X-ray images COVID-19 = 360 Normal = 4200 Binary class Preprocessing (Gabor filter, Sobel, and LoG), DenseNet-201 Acc=98.50%		
	Syarif et al., 2022 X-ray images COVID-19 = 676 Normal = 804 Binary class Preprocessing CLAHE, UNAS-Net (CNN) Acc=97.36%		
	Nasiri and Hasani, 2022 Chest X-ray images: COVID-19 (125), Pneumonia (500), and no findings (500). Three classes DenseNet169 and XGBoost Acc = 89.70%		
	Sharma et al., 2022 Chest X-ray images: COVID-19 (1784), Pneumonia (1345), and Healthy (1755) Three classes COVDC-Net Acc = 96.48%		
	Verma, B et al., 2023 Radiography Database, which includes chest X-Ray scans of COVID-19, Normal, and Viral Pneumonia. Binary class		

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	Study Dataset Case Classify Techniques Performance (Accuracy %)		
	And three classes Conv-CapsNet Acc=96.47% for multi class Acc=97.69% for binary Attallah et al., 2023 two benchmark datasets (CT and X-Ray) for COVID-19 are employed Three classes RADIC Acc= 99% For First dataset Acc=99.4% For second dataset Talukder et al., 2023 used a dataset of 2000 COVID-19 X-ray images Binary class Xception InceptionResNetV2 ResNet50 ResNet50V2 EfficientNetB0 Proposed (EfficientNetB4) Acc= 99.55%, Acc= 97.32%, Acc=99.11%, Acc=99.55%, Acc=99.11% Acc=100% Mohan et al., 2024 uses two open source CXR image dataset having a total of 15,153 (dataset 1), and 4575 (dataset 2) Three classes VGG16 and Inception Resnet (IR) Acc= 96% Acc=97% Bennour et al., 2024 CIDC, CXRP, CRD dataset Binary classes and Three classes CovCXR-Net, MDCXR3-Net MDCXR4-Net 99,09 %, for binary class 97.74 %, for multi class and 90,37 for multi class Shimja et al., 2024 CXR image dataset Multi classes VGG-16 98% Baig et al., 2024 uses a public dataset available on Kaggle [34] Binary classes PDTLA model 94.54%		

IV. RESULTS AND DISCUSSION

This paper delves into the utilization of deep learning (DL) techniques for diagnosing COVID-19 and pneumonia through the analysis of X-ray images, synthesizing findings from 18 studies from (2020 to 2024) show cased in Table The common thread across these studies is the adoption of DL convolutional neural network CNN pre-training algorithms, which is instrumental in improving detection accuracy and overall performance. A notable observation is the disparity between binary and multi-class classification approaches: binary classification consistently demonstrates superior accuracy and performance metrics compared to its multi-class counterpart. employing binary classification leverage a diverse array of DL models, including Xception, InceptionResNetV2, and Efficient NetB4, achieving remarkable accuracy rates ranging from 97.32% to a perfect 100%. Conversely, multi-class classification poses inherent challenges, employs the RADIC technique to attain commendable accuracy rates of 99% and 99.4% across two distinct datasets. While binary classification excels in precision, multi-class classification offers opportunities for refinement through innovative methodologies like RADIC. These insights underscore the transformative potential of DL in medical imaging, promising enhanced diagnostic accuracy and patient care outcomes in combating infectious diseases.

V. CONCLUSION

The emergence of COVID-19 as a global pandemic has underscored the critical need for accurate and timely detection to mitigate its spread and save lives. Chest X-ray (CXR) imaging offers a promising avenue for diagnosis due to its accessibility and preservation capabilities. However, distinguishing COVID-19 pneumonia from other respiratory ailments presents a formidable challenge. This comparative analysis of deep learning (DL) techniques in COVID-19 diagnosis highlights the pivotal role of binary and multi-class classification approaches. While binary classification consistently outperforms in accuracy and performance metrics, multi-class classification, particularly through innovative techniques like RADIC, shows potential for refinement. The deployment of sophisticated DL models such as Efficient NetB4 demonstrates remarkable accuracy rates, emphasizing their efficacy in

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discerning COVID-19 and pneumonia. Moving forward, integrating the strengths of both classification approaches is essential for advancing DL-based medical image analysis and empowering clinicians with robust diagnostic tools to combat infectious diseases effectively.

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