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Comprehensive Review of Deep Learning Techniques for Pneumonia Detection using Chest X-Ray Imaging

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***Abstract*—Introduction: According to the World Health Organization, in 2019, 2.5 million people died from pneumonia, with children aged 0-5 years accounting for 14% of these deaths. Pneumonia remains a major health problem worldwide. The high death rate emphasizes the importance of receiving a diagnosis as soon as possible to avoid serious health consequences. Specifically, deep learning (DL) methods. convolutional neural networks (CNNs), pre-trained models, and ensemble models, have shown promise in improving pneumonia detection due to their superior performance and ability to automatically extract features from datasets.**

Methodology and Contribution: This systematic literature evaluation (SLR) provides a radical analysis of the structures and methods concerned in a variety of DL methods for pneumo- nia analysis. The evaluate divides models into 3 categories: ensemble, pre-trained, and CNN-based fashions., providing insights into their performance measures, hyperparameters, and fine-tuning processes. By identifying research gaps and proposing potential solutions, the review contributes to a deeper understanding of the models' effectiveness and suitability for medical applications. Results: The analysis highlights the robustness and superior performance of ensemble models in pneumonia detection tasks. These models, which combine multiple DL techniques, demon- strate enhanced accuracy and reliability in medical diagnostics. The review also emphasizes the importance of optimizing hyper- parameters and fine-tuning models to achieve the best outcomes in detecting pneumonia from medical images.

Conclusion: In conclusion, while DL models offer significant advantages for pneumonia detection, there are still areas for improvement. The review identifies existing research gaps and suggests that addressing these could further enhance model performance. Future research could focus on refining model architectures and exploring innovative solutions to overcome current limitations, ultimately improving the early diagnosis and treatment of pneumonia.

***keywords*—Pneumonia, Machine learning, Deep learning, Convolutional neural network, Pre-trained models, Ensemble models**

I. INTRODUCTION

Pneumonia is a critical lung disease gives a severe hazard to health, particularly for inclined populations along with the elderly and people with underlying medical troubles. Reducing demise rates calls for early and specific detection, mainly in regions with little scientific resources. How deep gaining knowledge of, a sort of synthetic intelligence, can help radiologists understand pneumonia in chest X-ray pix. Using methods like YOLOv3 for detection and SVM for class, the recommended approach makes use of a deep gaining knowledge of version to phase X-ray images and properly categorise pneumonia instances. The approach also looks at how properly anisotropic diffusion filtering reduces noise [1]

The COVID-19 pandemic, which began in [2], soon spread globally, forcing the World Health Organization to proclaim it a public health emergency and later a pandemic. COVID-19, part of the Coronaviridae family, shares similari- ties with SARS and MERS and is believed to have originated in bats [3]–[5]. Symptoms range from mild to severe, including fever, cough, and lung inflammation. Diagnostic methods like CT scans, Nucleic Acid Tests, and X-rays are used, with CT scans being particularly effective for assessing lung inflam- mation. The pandemic has overwhelmed healthcare systems, causing a shortage of radiologists and delayed diagnoses. This has driven the development of AI-based systems to automate pneumonia diagnosis by analyzing CT scans [6]–[8]. The pa- per proposes an AI engine to classify lung inflammation levels in COVID-19 patients using a two-phase model involving morphological analysis and a modified Convolutional Neural Network combined with k-Nearest Neighbor for classification, aiming to improve diagnostic efficiency and accuracy.

Doctors commonly use X-ray images to detect pneumonia, as the disease typically manifests as areas of increased turbid- ity in lung images. This is visually represented by contrasting colors, with red indicating pneumonia-affected regions and green highlighting normal lung areas. The presence of pre- existing lung disorders in many patients complicates pneu- monia diagnosis, which is further challenged by symptoms such as fever, muscle aches, coughing, and difficulty breathing [9], [10]. Despite its ancient history, pneumonia remains a highly contagious disease, causing significant morbidity and mortality worldwide. In 2016, pneumonia was responsible for nearly 700,000 deaths among World Health Organization Definition: Children under 2 years of age, early diagnosis of pneumonia, radiology, including CT scans and X- rays. It is important to determine the severity of the disease and determine the direction of the patient's care plan (Figure 1). X-rays are not only used for diagnosing lung disorders but also for monitoring the progression of illnesses in patients' lungs. Radiologists use detailed examinations of Deep studying (DL) has tested to be an powerful tool for the early diagnosis of pneumonia because of its proficiency in picture recognition and category. Researchers from quite a few technical and healthcare fields have advanced numerous DL fashions to enhance the accuracy of pneumonia predictions. Radiographs are used to evaluate the diploma of recuperation or deterioration, which allows plan future remedy strategies. These models leverage the capabilities of DL to process lung X-ray data, offering improved outcomes

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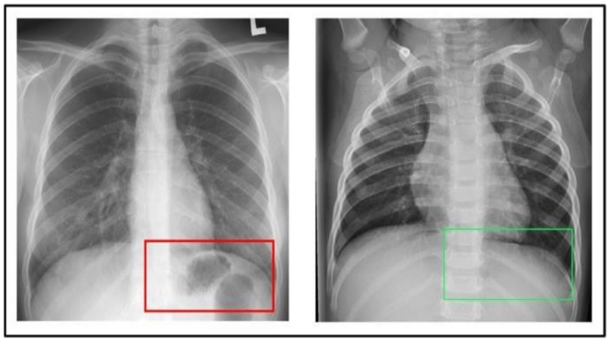

Fig. 1. Pneumonia Vs. normal lung

in predicting health concerns such as pneumonia and COVID- 19. Pneumonia is a significant health concern, responsible for 14% of all fatalities in children under five, with 740,180 deaths reported in 2019 according to the World Health Organization. The disease is primarily caused by bacteria, viruses, and fungi. Preventative measures such as the incidence of pneumonia can be reduced by vaccination. Eating nutritious food and a healthy environment, only 1 in 3 children with severe bacterial pneumonia receive the antibiotics they need. Therefore, there are still difficulties in treatment. The high death rate is the result of insufficient vaccination and delayed treatment. Effective treatment and reduced mortality depend on early detection [9] by outlining the basic resources and key elements required to build predictive models for the diagnosis of pneumonia. This article attempts to assist researchers by highlighting the value of empirical research to improve early detection and treatment approaches...

This systematic overview's contribution is listed under:

- Taxonomy of DL-Based Models: The work presents a comprehensive taxonomy for deep learning-based pneu- monia detection models, categorizing them into Ensemble and pre-trained models from CNN, providing detailed descriptions of the design and operating procedures of the models. To detect pneumonia in the early stages
- Analytical Discussion on Model Parameters: The ar- ticle offers an in-detailed analysis of the ensemble model advance training and CNN-based models, hyperparameter tuning search includes various topics. Including productivity tools Learning rate, batch size, epoch, and training/testing ratio. Data set size How to optimize data and performance indicators such as accuracy, sensitivity, precision, AUC, and recall. has also been summarized.
- Identification of Research Gaps: The study attracts attention to current research gaps in pre-educated, CNN- based, and seem fashions. It identifies the challenges and limitations within these models, providing a foundation for future research to address these issues.
- Proposed Solutions for Model Improvement: Beyond identifying gaps, the article offers a possible way to overcome the difficulties and limitations in the field of deep learning models for pneumonia detection. The purpose of this guidance is to help researchers create more reliable and efficient models for diagnosing pneumonia.

Table I provide the abbreviations used in the review.

II. LITERATURE REVIEW

The paper explores various methodologies and techniques for detecting and classifying respiratory disease using deep learning and machine learning techniques Synthetic Minority Oversampling Technique (SMOTE), which corrects class imbalance by generating synthetic samples for minority classes. It is one of the main guidelines that cover. However, SMOTE can lead to over-generalization, prompting the development of enhanced methods like SSCMIO by Wang Xiao, which uses k-nearest neighbors to assign selection weights and avoid over-generalization by focusing on safer neighboring directions. Additionally, under-sampling tech- niques such as LOFCUS, proposed by Hartono, utilize local outlier factors and boxplots to clean noisy samples and man- age class overlap, while tocreate a balanced data set Krawczyk's clustering under sampling (CUS) technique groups instances of the majority class and undersamples those that are most informative [1 The study also emphasizes a two- step method, e.g. Arefin's OCSV-US, which increases computation time and classification accuracy by combining evolutionary algorithms with dynamic sampling methods. under-sampling Methods that use sampling to reduce noise or overlapping data, such as those summarized by Xu, sample important minority classes. and sample the majority of influential classes according to the safety criteria. [11]. Data augmentation is emphasized for its role in preventing overfitting and im- proving model accuracy, with various studies employing deep learning models like CNNs for medical image classification, particularly in detecting COVID-19 and pneumonia from X- ray images [11]. The paper also discusses the significance of edge detection in medical imaging, evaluating techniques like Gaussian blurring, which performed well in the proposed RESDETECT system. Despite these advancements, challenges remain in medical image segmentation due to low contrast and artifacts, underscoring the need for automated and semi- automated techniques to enhance accuracy and efficiency [12]. Overall, while existing methods have shown promise, limitations such as over-generalization, class overlap, and segmentation challenges highlight areas for further research and development.

Feature selection in CNN-based classification involves ex- tracting relevant features from CNNs to enhance the accu- racy of the classification stage. However, these features can sometimes include noise, artifacts, or other information that may interfere with the accuracy of the classification. To reduce this problem, it is necessary to look for and select the most revealing and distinguishing characteristics. This approach has been successfully

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TABLE I
ABBREVIATION TABLE

Abbreviatio	Definition	Field of Use	Example/Description
AI	**Artificial Intelligence:** Systems that perform tasks requiring human intelligence.	Computer Science, Healthcare	Image recognition, natural language processing
ANN	**Artificial Neural Network:** A system that mimics the brain's neurons to process information.	Deep Learning, Computer Vision	Handwritten digit recognition
BRISK	**Binary Robust Invariant Scalable Key-points:** Detects and describes key points in images.	Computer Vision	Object recognition in images
CAD	**Computer Aided Diagnosis:** Assists doctors in interpreting medical images.	Medical Imaging	X-ray, MRI diagnostics
CGAN	**Conditional Generative Adversarial Network:** Generates new data based on specific conditions.	AI, Image Synthesis	Generating images of certain objects under conditions
CNN	**Convolutional Neural Network:** Specialized neural network for analyzing visual data.	Image Recognition, Medical Imaging	Analyzing chest X-rays
DBN	**Deep Belief Network:** A deep learning model used for unsupervised learning.	Unsupervised Learning	Dimensionality reduction in high- dimensional data
DL	**Deep Learning:** A subset of ML involving neural networks with many layers.	AI, Big Data Analytics	Image recognition, voice recognition
DNN	**Deep Neural Network:** A neural network with multiple layers to model complex patterns.	AI, Natural Language Processing	Text classification, speech recognition
EDCNN	**Enhanced Deep Learning-aided CNN:** Incorporates advanced techniques for improved performance.	Medical Imaging, Object Detection	Enhanced image feature extraction
EDs	**Emergency Departments:** Hospital units treating urgent medical conditions.	Healthcare	Treatment of trauma or sudden illness
FaNet	**Fast Assessment Network:** A network designed to quickly process data.	AI, Medical Imaging	Rapid image segmentation for diagnostics
FFNN	**Feed Forward Neural Network:** A basic neural network with no cycles.	AI, Pattern Recognition	Recognizing handwritten digits
GOM	**Grande Ospedale Metropolitano:** Refers to a large metropolitan hospital.	Healthcare, Medical Research	Advanced hospital infrastructure
HIPAA	**Health Insurance Portability and Accountability Act:** Protects patient health information.	Healthcare	Privacy protection in patient records
ICU	**Intensive Care Unit:** Special hospital unit for critically ill patients.	Healthcare	Treating patients with life-threatening conditions
KNN	**K-Nearest Neighbor:** A simple machine learning algorithm for classification.	Classification, Regression	Classifying images, predicting housing prices
LSTM	**Long Short Term Memory:** A recurrent neural network capable of learning long-term dependencies.	Time Series Analysis, NLP	Language translation, speech recognition
ML	**Machine Learning:** Training algorithms to learn from data and make predictions.	AI, Data Science	Predicting stock market trends
MLP	**Multi-Layer Perceptron:** A feedforward neural network with multiple layers.	AI, Image Processing	Recognizing digits in MNIST dataset
M R-CNN	**Mask Recurrent-CNN:** A neural network for object detection and image segmentation.	Image Recognition, Medical Imaging	Identifying and segmenting organs in medical scans
NLP	**Natural Language Processing:** AI that enables computers to understand human language.	AI, Linguistics	Sentiment analysis, language translation
NMS	**Non Maximum Suppression:** Eliminates redundant overlapping boxes in object detection.	Computer Vision	Removing redundant bounding boxes in object detection
NN	**Neural Network:** A system of algorithms mimicking the human brain to recognize patterns in data.	AI, Pattern Recognition	Predicting stock prices
PCA	**Principal Component Analysis:** A method to reduce the dimensionality of large datasets.	Data Analysis, ML	Reducing the complexity of datasets for visualization
ReLU	**Rectified Linear Unit:** An activation function in neural networks introducing non-linearity.	Neural Networks, Deep Learning	Used in image classification tasks
RF	**Random Forest:** An ensemble method that uses multiple decision trees for accurate predictions.	Classification, Regression	Predicting customer churn, classifying images
RMSprop	**Root Mean Squared Propagation:** An optimization algorithm for training neural networks.	Deep Learning, Optimization	Improving model convergence during training
RNN	**Recurrent Neural Network:** A neural network capable of processing sequences of data.	NLP, Time Series Analysis	Predicting stock prices, language modeling
RSNA	**Radiological Society of North America:** A professional association for radiologists.	Healthcare, Medical Imaging	Organizes conferences, provides resources for medical imaging
sCNN	**Self Customized Simple CNN:** A simplified and customized version of CNN for specific tasks.	Image Classification, Object Detection	Customized model for detecting objects in satellite images
SCR	**Segmentation in Chest X-ray:** Divides chest X-ray images for detailed analysis.	Medical Imaging	Identifying lung abnormalities in X-ray scans
SLR	**Systematic Literature Review:** A methodical review of existing research.	Research, Medical Studies	Synthesizing research on AI in medical imaging
SVM	**Support Vector Machine:** A supervised machine learning model used for classification and regression.	Classification, Regression	Classifying emails as spam or not
SVR	**Support Vector Regression:** A type of SVM used for predicting continuous values.	Regression Analysis, Time Series	Predicting housing prices
VAP	**Ventilator Associated Pneumonia:** A lung infection in patients on mechanical ventilation.	Healthcare, Hospital Infection Control	A common infection in ICU patients on ventilators

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applied across various domains, such as agriculture, audio classification, and medicine, including tasks like to figuring out dangerous tumours, classifying cells, and diagnosing sicknesses. Although COVID-19 detection investigations have hired wrapper techniques, which can be based totally on evolutionary algorithms, they often necessitate looking a extensive search area and can be time-consuming due to the education process. Filter-based totally function selection techniques, on the other hand, provide a quicker choice because they do not need schooling and have verified effective. To improve the overall overall performance of type models, this work uses an iterative characteristic selection manner that makes use of strategies like Chi-Square and mRMR to find the most beneficial capabilities for every CNN version [13]–[22] from Table II.

III. METHODOLOGY

A. Dataset Preparation

A dataset of 6000 chest x-ray images was created, with 1500 from Debark hospital and 3000 from an online archive. The images were divided into training, testing, and validation categories, and image augmentation techniques like shifts, flips, and rotations were used to increase data quantity. Pre-processing involved enhancing image clarity and balancing data by removing unnecessary details. Images were resized to 224x224 pixels to make processing faster and cheaper. The images were converted into a NumPy array using Keras, and OpenCV was used for image scaling, ensuring efficient data handling for further analysis [24].

B. Research questions identification and formalization

The systematic literature review (SLR) from Table III aims to provide an intensive evaluation of the ultra-modern in early pneumonia detection, with an emphasis on device gaining knowledge of (ML) and deep getting to know (DL) techniques. The essential aim is to teach readers at the SLR's scope by way of going over key ideas approximately pneumonia detection. This involves seeking, investigating, and integrating existing resources concerning various research types, subjects, methods, and identifying research gaps. Additionally, the SLR aims to highlight contributions in the domain of early pneumonia prediction and classification, ensuring a thorough understanding of the methodologies and advancements in this critical field.

Research Question 1: What makes early pneumonia detection a vital vicinity of have a look at?
Since pneumonia is a major cause of demise, generally due to delayed prognosis and inadequate assets, early diagnosis is essential. By facilitating greater efficient treatment, early discovery can dramatically lower death fees. In order to deal with this difficulty, the research attempts to find out technology which can help early and particular prediction of pneumonia.

Research Question 2: What relevant reviews are on hand on this discipline, and what flaws had been referred to within the SLRs which are now in lifestyles? What relevant opinions are on hand on this field, and what flaws have been cited within the SLRs which might be now in lifestyles?
The review identifies existing studies in the domain of pneumonia diagnosis and highlights their shortcomings, such as gaps in topic coverage. These reviews are discussed in Section 2, providing insights into the limitations of current systematic literature reviews (SLRs).

Research Question 3: Which technique is maximum suitable for appearing an SLR to diagnose pneumonia?
The most useful technique for carrying out an SLR in this area is decided to be the PRISMA methodology. This includes a methodical manner that is explained in Section three and consists of key-word looking, publishing facts, and article selection criteria.
Research Question 4: Which DL techniques and their frameworks are used to diagnose pneumonia early?
With an emphasis on version architectures, the study gives quite a few deep mastering (DL) techniques and frameworks for diagnosing pneumonia. Section four gives thorough causes of numerous DL-based totally fashions, inclusive of ensemble models, pre-educated fashions, and convolutional neural networks.

IV. REVIEW OF THE LITERATURE ON MODELS FOR PNEUMONIA DETECTION BASED ON DEEP LEARNING

Pneumonia can be identified through symptoms such as colored mucus from coughing, fever, and difficulty in breath- ing, among others. Early detection is crucial for timely treat- ment and prevention. To nicely diagnose pneumonia, researchers have created a number of machines studying (ML) and deep gaining knowledge of (DL) methods. This discipline has seen a outstanding deal of studies, generating a whole lot of fashions with one-of-a-kind prediction fulfillment costs. The use of DL and ML models for detecting lung diseases from X-ray images has proven successful and is increasingly used in healthcare for disease diagnosis. Additionally, DL- based systems have been developed to automatically diagnose pneumonia in COVID- 19 patients using radiology images, demonstrating the adapt- ability of these technologies in addressing new healthcare challenges [36].
CNN-primarily based, pre-trained, and ensemble models are all covered in the taxonomy of pneumonia detection fashions. Using convolutional, pooling, and completely related layers, CNN fashions—which can be regularly employed in pc imaginative and prescient—are made to discover and extract hierarchical traits from visible records [37]. CNNs are powerful for photograph class duties due to the fact those layers cooperate to locate patterns and spatial correlations in images. In contrast, pre-trained models are developed by training on large datasets, allowing them to transfer learned skills to new tasks. This approach enables them to apply their understanding of data trends to unforeseen tasks effectively. Ensemble models enhance accuracy and performance by combining predictions from multiple individual models, which can be either homogeneous (identical models) or heterogeneous (different modelsTo similarly explore information traits and diversify predictions, each model in an ensemble is trained in my view the usage of several techniques or subsets of training records [38] []. CNN-based totally, pre-trained, and ensemble models are all covered in the taxonomy of pneumonia detection models. CNN fashions are regularly hired in laptop vision and are intended to identify and extract

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TABLE II
SUMMARY OF APPROACHES USED TO IMPLEMENT CNNS FOR PNEUMONIA DETECTION

Study/Reference	CNN Approach	Dataset	Model Type	Performance (Accuracy %)
Yi et al. [23]	Customized CNN Model	Kermany [24]	52-layer Customized CNN Model	96.09%
Siddiqi [25]	Customized CNN Model	Kermany [24]	18-layer Customized CNN Model	94.39%
Stephen et al. [26]	Customized CNN Model	Kermany [24]	4-layer Customized CNN Model	93.73%
Kermany et al. [24]	Transfer Learning	Kermany [24]	Inception V3	92.8%
Rajkupar et al. [27]	Transfer Learning	ChestXray14 [28]	DenseNet	76.8%
Fernandes et al. [29]	Transfer Learning	Kermany [24]	VGG16	96.40%
Wang et al. [28]	Transfer Learning	Kermany [24]	DenseNet	92.8%
Liang and Zheng [30]	Transfer Learning	Kermany [24]	49-layer Custom Model	90.5%
Manickam et al. [31]	Transfer Learning	Kermany [24]	ResNet50, InceptionV3, InceptionRes-NetV2	93.06%
Mabrouk et al. [32]	Ensemble Learning	Kermany [24]	DenseNet169, MobileNetV2, Vision-Transformer	93.91%
Vrbancic and Podgorelec [33]	Ensemble Learning	Kermany [24]	Stephan et al. [30]'s Model	96.26%
Chouhan et al. [34]	Ensemble Learning	Kermany [24]	AlexNet, DenseNet121, InceptionV3, ResNet18, GoogLeNet	96.39%
Liz et al. [35]	Ensemble Learning	Kermany [24]	Custom Models (3- and 4-layer CNNs), AUC: 97.6%	AUC: 97.6

TABLE III
KEYWORDS AND PHRASES USED FOR SYSTEMATIC LITERATURE REVIEW

Search	Keywords and Phrases	Field of Application
Search 1	”Deep Learning models” in ”COVID-19 pneumonia detection using chest X-ray images”	COVID-19 pneumonia detection using medical imaging
Search 2	”Machine Learning” for ”automated pneumonia classification” using ”medical imaging”	Automated pneumonia classification with AI models
Search 3	”Convolutional Neural Networks (CNN)” for ”chest X-ray analysis in pneumonia detection”	Neural networks for pneumonia detection in medical imaging
Search 4	”Artificial Intelligence” in ”predicting COVID-19 severity from chest X-ray scans”	Predicting COVID-19 severity with AI and medical imaging
Search 5	”AI-based models” for ”early pneumonia diagnosis” using ”radiological images”	Early pneumonia diagnosis using AI and radiological analysis
Search 6	”Transfer Learning techniques” applied to ”COVID-19 pneumonia prediction”	Transfer learning methods for COVID-19 pneumonia prediction
Search 7	”Recurrent Neural Networks (RNN)” in ”tracking pneumonia progression in patients”	RNN models for tracking pneumonia progression in patients
Search 8	”Neural Networks” for ”multi-class pneumonia detection” in ”chest X-ray datasets”	Multi-class pneumonia detection using neural networks
Search 9	”Hybrid AI methods” for ”pneumonia detection” using ”deep learning and feature extraction”	Hybrid AI methods for pneumonia detection using feature extraction
Search 10	”Deep Learning” for ”pneumonia detection” with ”COVID-19 labeled datasets”	Deep learning models applied to COVID-19 pneumonia datasets
Search 11	”Machine Learning classifiers” for ”differentiating bacterial and viral pneumonia”	Differentiating bacterial and viral pneumonia using ML
Search 12	”AI-driven chest X-ray analysis” for ”predicting pneumonia outcomes”	AI-driven image analysis for predicting pneumonia outcomes

hierarchical features from image data through Fully connected layers, clustering, and convolution [37] CNNs are effective for image classification tasks. Because these layers cooperate to find patterns and spatial relationships in images, in turn, pre-trained models can apply their acquired skills to new tasks. Because it is created by training on a large dataset. This approach enables them to apply their understanding of data trends to unforeseen tasks effectively. Ensemble models enhance accuracy and performance by combining predictions from multiple individual models, which can be either homogeneous (identical models) or heterogeneous (different models).

To similarly explore records tendencies and diversify predictions, each version in an ensemble is skilled independently the usage of distinct techniques or subsets of schooling facts [38] [39].

The classification of all of them are seeking for to locate pneumonia in chest X-ray (CXR) photographs, pneumonia detection fashions may be divided into CNN-based, pre-educated, and ensemble classes in line with their layout and strategies of operation. To extract characteristics from images, CNN-primarily based models are comprised of the ground up and skilled on massive datasets. Conversely, pre-trained fashions are subtle on unique datasets to perceive a extensive variety of characteristics, leveraging

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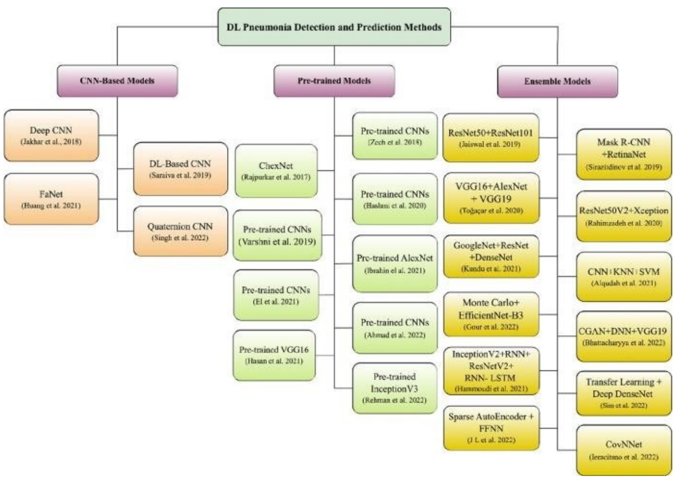

Fig. 2. Classification of deep studying techniques for the prognosis and prediction of pneumonia

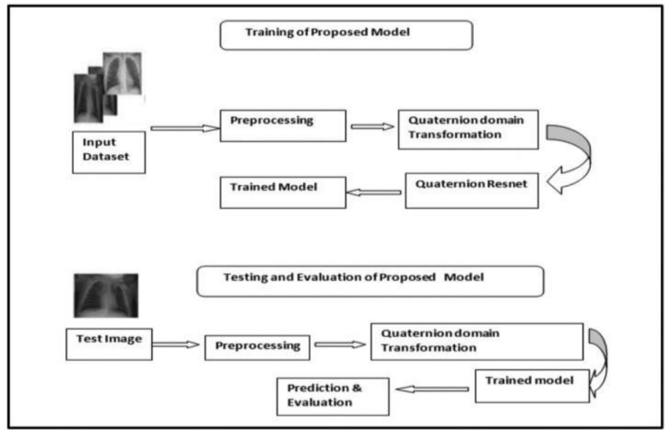

Fig. 3. Pneumonia diagnosis model proposed in [10]

prior training on extensive datasets. Ensemble models combine different deep learning techniques to enhance performance by integrating predictions from various models from fig 2. These categories reflect the diverse approaches used to achieve the common goal of pneumonia detection in CXR images.

A. Evaluation of CNN-based models for diagnosing pneumonia

1) FaNet: The FaNet model is a deep learning-based dual-task network designed to quickly identify and predict COVID-19 symptoms by utilizing a combination of Medical symptoms and a dataset of 3-d CT snap shots. Particularly, this version is used for CT scans that provide details on COVID-19 symptoms. Three convolutional layers make up the FaNet structure, with batch normalisation coming after the second convolutional layer. The version makes use of 512×512×a hundred and sixty as its enter photo size, and its kernel sizes are 1×1×64×32, 1×1×32×2, and 3x3x32x3, in that order. The examine's authors have shown that the FaNet version detects COVID-19 with a prediction accuracy of 98.28% and a severity prediction accuracy of 94.43% [40].

2) Quaternion CNN: The authors [10] utilized A Quaternion residual community technique the use of a publicly to be had large chest radiograph dataset from Kaggle, accomplishing a classification accuracy of 93.75% and an F1- rating of 0.94. Batch normalisation, quaternion convolution for characteristic extraction, residual blocks, pooling, and activation functions are a number of the steps that make up the model architecture. The training procedure is sped up through normalisations, whilst dimensionality reduction and mitigation are assisted via pooling and ReLU (the variety is displayed in Eq. 1) activation functions, the vanishing gradient problem. The study compared the Quaternion residual network with existing CNN models, demonstrating that it outperformed other algorithms in classification tasks. 3

$$f(x) = max(0, x) \tag{1}$$

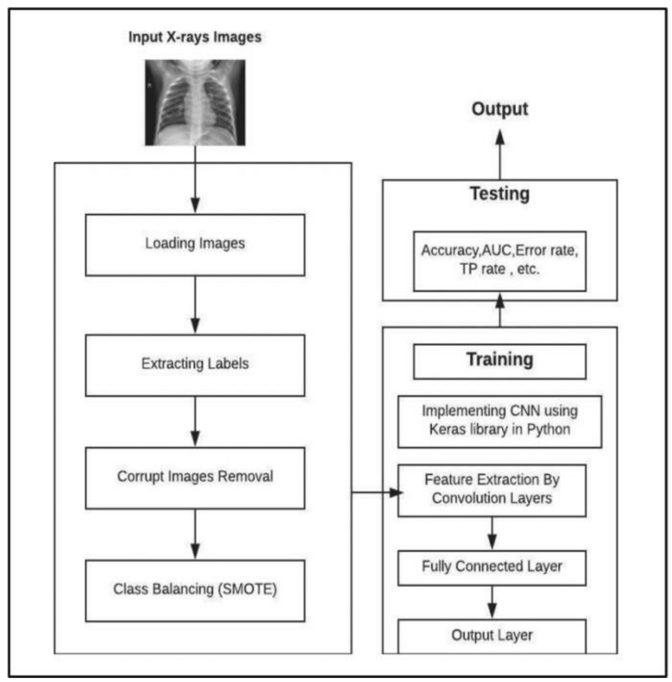

Fig. 4. Deep CNN model proposed in [41]

3) Deep CNN: Using a sizeable dataset for training and more than one deep layers, the authors [41] provided a Deep CNN model intended for the best prediction of pneumonia. Several pre-processing and facts-cleansing processes stepped forward the statistics's pleasant. Following function extraction from notable radiological imaging statistics, 84% prediction accuracy turned into attained by means of the version implementation.

4) DL-based CNN: In [42], The authors analysed 5,863 chest X-ray (CXR) snap shots using a convolutional neural network (CNN) model primarily based on deep mastering. Ten layers made up the CNN structure; the primary seven layers have been convolutional layers, and the final three layers covered a softmax feature. The input photographs have been scaled to three hundred x three hundred pixels by using the version. In order to enhance overall performance,

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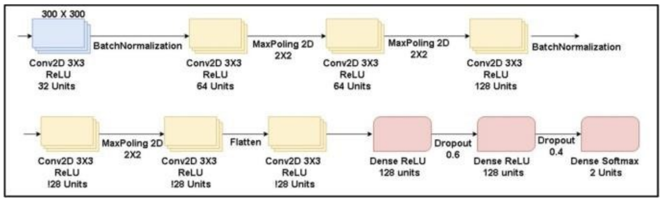

Fig. 5. Pneumonia diagnosis using CNN network presented in [42]

In each convolutional layer five, the Adam optimiser and ReLU activation characteristic had been used. K-fold cross-validation, a way that aids in evaluating the model's generalisability, was used to refine the version's parameters. An accuracy of 95.3% became attained by the version, whose performance information have been displayed as a confusion matrix.

B. Review of pre-trained models for pneumonia diagnosis Neural networks which have been considerably educated on giant datasets—commonly for obligations requiring a excessive diploma of picture type and prediction—are known as pre-educated models. Through switch getting to know, these fashions can be tailored for sure sports, that is useful because it cuts down at the time and effort needed for version layout development and training. Numerous studies have proven the blessings of figuring out and classifying photos using pre-educated classifiers. Several pre-educated models for predicting pneumonia have been diagnosed inside the systematic literature review (SLR) that became supplied. This suggests how powerful these fashions are in lowering computational sources while nonetheless accomplishing good performance in medical image analysis duties.

1) CheXNet: CheXNet Is a model primarily based on DenseNet architecture, offering 121 dense layers, and is skilled on the chestX-ray14 dataset, which incorporates 100,000 frontal view radiology pics overlaying 14 sicknesses. This dataset is currently the biggest publicly available series of chest X-ray pictures. CheXNet complements gradient waft and facts optimization in the model, improving overall performance. It uses a sigmoid activation characteristic on the fully related layer to discover all 14 diseases. The model's input pics are resized to 224×224 pixels, and each layer is interconnected to beautify architecture, lessen mistakes, and enhance overall performance from Eq.
2. In assessments annotated by using four educational radiologists, CheXNet outperformed different models, accomplishing the highest accuracy and powerful performance, particularly in the F1 metric [27].

$$S(x) = \frac{1}{1 + e^{-1}} \qquad (2)$$

2) Pre-trained CNN Models: Using pre-trained DenseNet121 and ResNet50 CNN models, two CNN fashions have been created in [44] and trained on pooled facts from multiple websites, each with a distinct pneumonia occurrence price. The dataset com- prised 158,323 chest X-ray images, with mean patient ages of 63.2, 46.9, and 49.6 years from Mount Sanai, NIH, and Indiana University, respectively. The percentage of female patients was 44.8%, 43.5%, and 57.3% for these institutions. The models

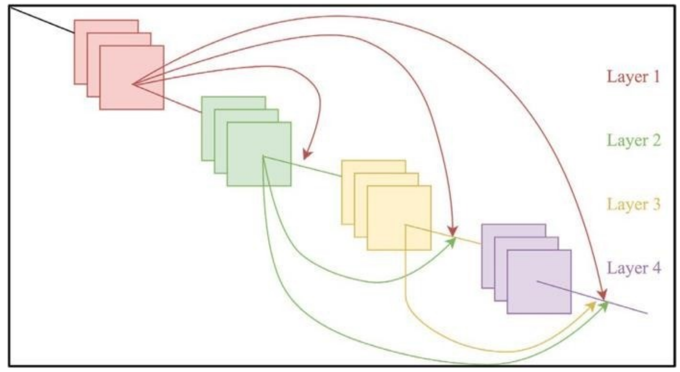

Fig. 6. DenseNet framework [43]

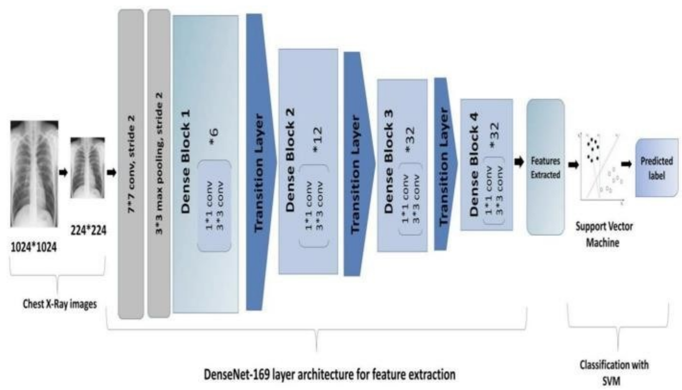

Fig. 7. Pre-trained CNNs proposed in [43].

demonstrated high accuracy in identifying pneumonia, with performance evaluated using the AUC metric. The results had been contrasted with pre-existing fashions the usage of Delong's approach, a famous device for comparing AUC effects across diverse deep learning and machine learning approaches so that you can perceive the top-appearing version. Additionally, cross-sectional frameworks were employed to assess the generalizability of the models across different sites using a validation method called "test-split".

3) Pre-trained CNNs: The study utilized In order to detect pneumonia contamination, pre-trained CNN fashions—inclusive of VGG16, ResNet50, DenseNet121, VGG19, and DenseNet169—for function extraction are used along side supervised machine getting to know classifiers, such as SVM, KNN, Naive Bayes, and Random Forest. This approach combines characteristic extraction with DenseNet169, in comparison to traditional fashions that most effective use switch gaining knowledge of. and classification using an SVM classifier, achieving an AUC of 0.8002. The DenseNet169 model features 169 layers, each serving as a feature extractor, with outputs feeding into sub-sequent layers. It incorporates four dense blocks, each with two convolutional layers (1x1 and 3x3 sizes) 7. The final classification layer employs 7x7 average pooling followed by a fully connected layer with softmax activation to enhance performance outcomes [43].

4) Pre-trained CNNs: The authors [45] proposed a frame-work for detecting pneumonia using chest radiographs, which

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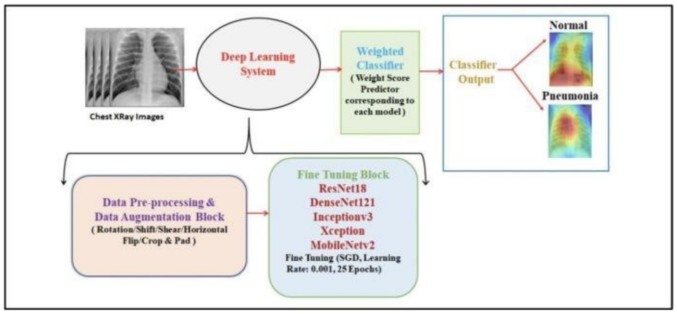

Fig. 8. Pneumonia detection framewrk using pre-trained models [45]

Consists of a pre-processing and facts augmentation block that makes use of operations like rotation, shift, shear, flip, crop, and pad to enhance the dataset. A quality-tuning block containing pre-skilled models like MobileNetv2, ResNet18, InceptionV3, DenseNet121, and Xception is covered into the deep studying machine predicting pneumonia by aggregating each model's outcomes. Different pre-trained architectures necessitate varying input image sizes; thus, images were resized to 224x224 for DenseNet121, MobileNetv2, and ResNet18, and 299x299 for the others. Initially, the dataset comprised 5,156 images, but augmentation increased it to 7,022 to mitigate overfitting. The model's development utilized an SGD optimizer with a learning rate of 0.001, momentum of 0.9, and 25 epochs for effective pneumonia prediction fig 8.

5) Pre-trained CNNs: The authors [46] compared various inceptionResNetV2, VGG19, VGG16, Incep-tionV3, DenseNet201, MobileNetv2, Xception, and ResNet50 are examples of great-tuning fashions for the binary classification of pneumonia using chest X-ray pics (CXR) using modern Deep CNN frameworks. A dataset of one,583 regular and four,273 pneumonia CT snap shots and 5,856 CXR photographs that were upgraded thru information augmentation had been blanketed within the evaluation. Images were resized to 224x224 pixels for most models, except InceptionV3, which used 229x229. The Adam optimiser become used to educate the models with a gaining knowledge of rate of zero.00001 and a batch length of 32,300 epochs. With an accuracy of 96.61%, ResNet50 outperformed the other fashions. InceptionResNetV2, VGG19, VGG16, DenseNet201, MobileNetv2, Xception, and InceptionV3 had accuracies of 96.09%, 85.94 %, 86.26%, 9366%, 96.27%, 83.14%, and 94.59%, respectively.

6) Pneumonia detection model using pre-trained AlexNet: A pre-skilled AlexNet was utilized by the authors [47] to propose a version for binary and multiclass illness category. COVID-19 and normal lungs, bacterial pneumonia and normal lungs, viral pneumonia and everyday lungs, and COVID-19 and bacterial lungs were all prominent via the model in binary class. It made a distinction between COVID-19, bacterial pneumonia, viral pneumonia, and everyday lungs for the purposes of multiclass category. Five convolutional layers with 3x3 filter out sizes and 2x2 padding for the max pooling layer had been used inside the AlexNet model. The input image size was 227x227x3, and the convolutional layers processed input sizes of 55x55x96, 27x27x256, 13x13x384, 13x13x384, and 13x13x256, respectively. The first two layers underwent max pooling and normalization, resulting in outputs of 27x27x256 and 13x13x256. The subsequent two layers did not use max pooling, producing outputs of 13x13x384. The final layer was followed by max pooling, yielding a 6x6x256 output. The model concluded with two fully connected layers and an output layer for pneumonia classification Fig. 9.

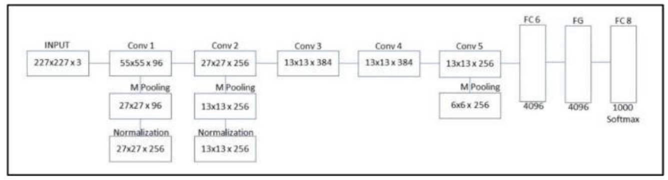

Fig. 9. Pneumonia detection model using pre-trained AlexNet proposed in [47]

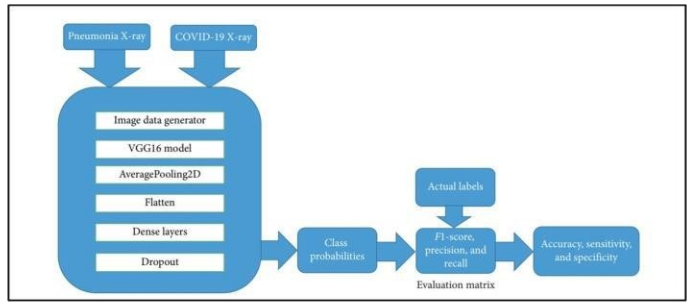

Fig. 10. Pneumonia detection model using pre-trained VGG16 proposed in [48]

7) Pneumonia detection model using pre-trained VGG16: A pre-trained VGG16 model become employed by the authors [48] to perceive pneumonia in chest X-ray (CXR) images that have been received from Kaggle. Data pre-processing and augmentation had been used to improve the dataset with the aid of increasing the variety of pictures and removing noise. For trying out and education, the dataset changed into divided in an 80:20 ratio. Convolutional layers got here after three absolutely connected (FC) layers in the VGG16 layout. The batch size turned into 16 and the mastering rate turned into set at zero.001 during schooling. Image flattening was used to convert n-dimensional arrays into 1-dimensional arrays, and a classification layer was added for outcome prediction. The ML-based LabelBinarizer tool encoded labeled CXR images into categorical form. The model achieved an accuracy of 91.69% and a sensitivity of 95.92% fig 10.

8) Pneumonia disease progression model with sequence learning using pre-trained CNNs: A pneumonia identity version changed into proposed by way of the authors [49] the use of lung contamination datasets and a lot of pre-trained convolutional neural networks (CNNs), consisting of InceptionV3, ResNet50, EfficientNetB0, EfficientNetB2, ChexNet, and InceptionResNetV2. They created a technique that makes use of sequence modelling to extract each coarse- and first-rate-grained traits so as to pick out the route of a disorder. The model quantifies disease progression into positive and negative categories, paired with age-related risk parameters. To ensure effective sequence learning, the dataset

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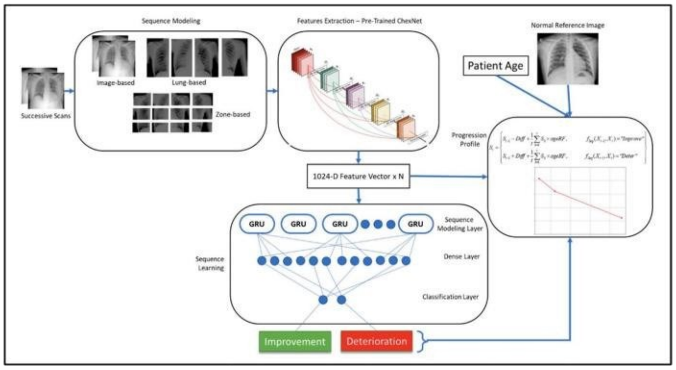

Fig. 11. Pneumonia disease progression model with sequence learning using pre-trained CNNs proposed in [49]

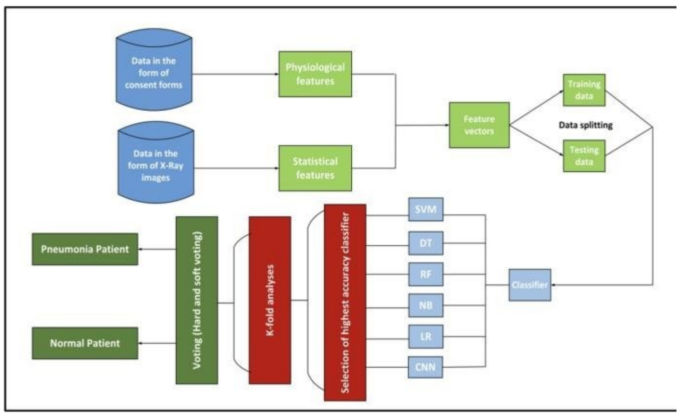

Fig. 12. Pneumonia prediction using pre-trained InceptionV3 [9]

includes images from patients with multiple scans, excluding those with only a single scan. To classify images into lung-primarily based, zone-based totally, and picture-primarily based sorts, the program makes use of series modelling. Notably, photo-based and lung-based totally strategies acquired AUCs of zero.Ninety two and zero.96, respectively, at the same time as ChexNet with region-based totally characteristic extraction produced the first-rate AUC of 0.98.

9) Pneumonia prediction using pre-trained InceptionV3: Using a dataset of chest X-ray (CXR) photos and a pre-educated InceptionV3, the authors [9] proposed a pneumonia detection model. From the CXR pics, this approach extracts a number of physiological features, inclusive of fever, chest pain, cough, terrible energy, flu, respiratory issues, perspiration, appetite loss, exhaustion, and headache. Two pooling layers, two convolutional layers, and a knocking down layer had been brought to the InceptionV3 version to refine it. The N-dimensional array turns into a 1-dimensional array as a result. The pre-skilled InceptionV3 accomplished a 97% accuracy fee inside the category phase. The authors also used a number of gadget learning fashions, including Random Forest (RF), Support Vector Machines (SVMs), Naive Bayes, and selection bushes, and they got here to the conclusion that the advised InceptionV3 version finished higher than all the others (Fig. 12).

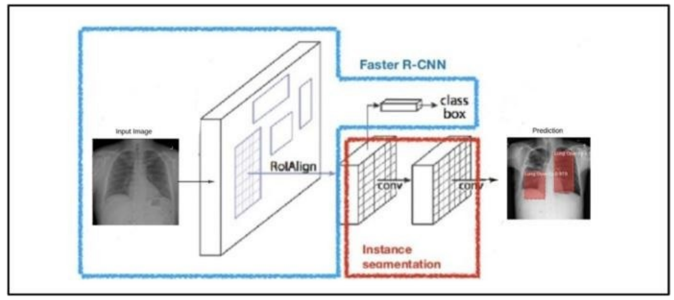

Fig. 13. Mask R-CNN proposed in [50]

C. Review on ensemble models for pneumonia diagnosis

Ensemble deep learning models for pneumonia prediction are created by integrating consistent and logical CNN classifiers to boost model performance and prediction accuracy. These fashions frequently integrate popular architectures like GoogleNet, AlexNet, VGG16, and VGG19 and make use of transfer gaining knowledge of strategies. In order to reduce the generalisation blunders inside the prediction outcomes, the ensemble technique integrates predictions from exceptional CNN models. This technique, which mixes the advantages of numerous models to produce extra accurate effects, is being investigated for the early prediction of pneumonia.

ResNet50 + ResNet101: The proposed ensemble model [50], named Mask R-CNN, integrates ResNet50 and ResNet101 to identify pneumonia in chest X-ray (CXR) im- ages. This model utilizes images sized 512x512 and performs pixel-wise segmentation by identifying both local and global features from fig 13. The CXR images are categorized into two stages, stage 1 and stage 2, to enhance the segmentation process. The model achieves robustness by incorporating a novel post-processing step that combines bounding boxes from various models, thereby enhancing the training procedure. This approach allows Mask R-CNN to outperform the fast R-CNN by achieving a better threshold value of 0.218051 for pneumonia prediction.

1) Mask R-CNN + RetinaNet: Using 512x512 input pictures, the authors [51] proposed an ensemble model that combines RetinaNet and Mask R-CNN for pneumonia classification and identity. The base models for RetinaNet and Mask R-CNN are ResNet50 and ResNet101, respectively, and the Adam optimiser is used with gaining knowledge of quotes of 0.0001 for RetinaNet and zero.001 for Mask R-CNN. The version is examined and validated using a publicly to be had dataset of 26,684 pictures from Kaggle, as proven in fig. 14, with item detectors extracted and overlapping bounding boxes removed using the NMS algorithm. A comparative evaluation with DenseNet121 and ResNet50 shows that the proposed ensemble version achieves precision, bear in mind, and F1-rating of 0.758, 0.793, and 0.775, respectively. Notably, the ensemble model demonstrates advanced remember compared to DenseNet121 and ResNet50, highlighting its effectiveness in pneumonia detection.

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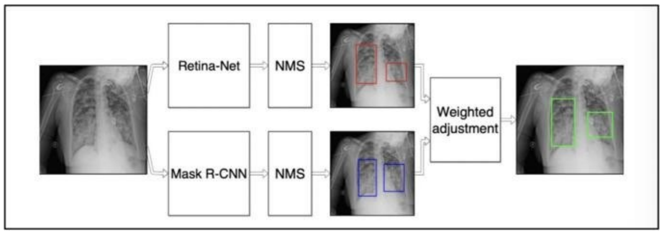

Fig. 14. Mask R-CNN + RetinaNet framework proposed in [51]

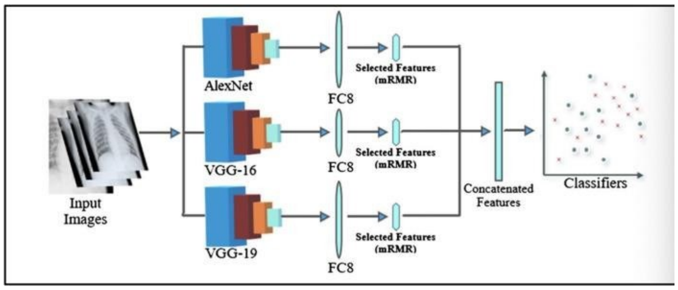

Fig. 15. VGG16 + AlexNet + VGG19 framework proposed in [52]

2) VGG16 + AlexNet + VGG19: Based on a conventional CNN structure, the authors [52] suggested an ensemble version that integrates VGG16, AlexNet, and VGG19. Each version procedures the enter pictures independently. The enter photograph length for AlexNet is 227x227 with 3x3/5x5 filters, but the enter length for VGG16 and VGG19 is 224x224 with 3x3 filters. The low redundancy most relevance (mRMR) approach from Figure 15 is used to lessen the a thousand capabilities that every version extracts from the dataset to 100. For classification, the ensemble version uses a lot of system mastering classifiers, consisting of SVM, KNN, choice bushes, linear regression, and linear discriminant evaluation. With an accuracy of 99.Forty one%, linear discriminant analysis is the maximum accurate of these.

3) ResNet50V2 + Xception: A pneumonia detection version that integrates functions from the ResNet50V2 and Xception fashions into an ensemble framework changed into advanced by the authors [53]. Using the Nadam optimiser, the concatenated features, which have dimensions of 10x10x4096, are fed right into a convolutional layer that has 1024 filters and a 1x1 kernel. After that, the functions are compressed into a 102,four hundred-through-1-dimensional array. The output is predicted the use of a softmax activation characteristic in a dropout layer. The outputs from Figure sixteen may be categorised as COVID-19, pneumonia, and ordinary the usage of this model's binary and multiclass category competencies. It obtains 91.4% overall accuracy for multiclass class and 99.5% accuracy for binary type between COVID-19 and pneumonia.

4) GoogleNet + ResNet + DenseNet: The authors [54] developed an ensemble framework for pneumonia prediction by integrating GoogleNet, DenseNet, and ResNet models, which consist of 22, 121, and 18 layers, respectively. This model was constructed using the RSNA and Kermany's datasets, with image sizes ranging from 127x384x3 to 2713x2517x3.

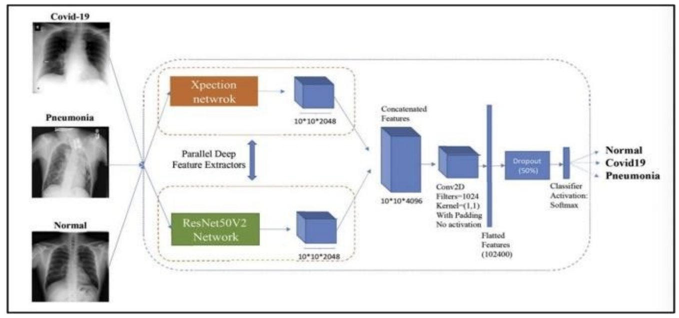

Fig. 16. ResNet50V2 + Xception framework for pneumonia detection proposed in [47]

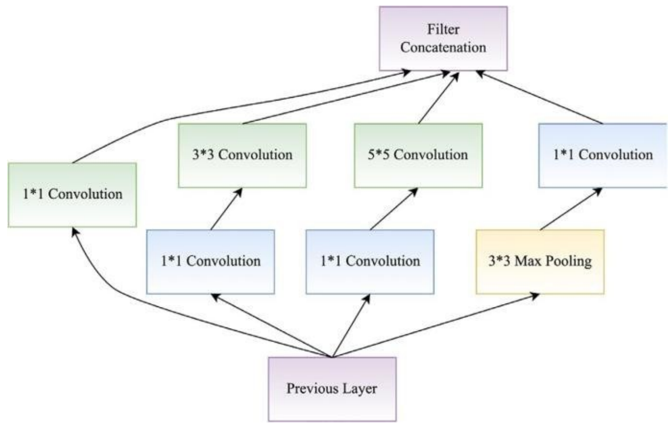

Fig. 17. Inception module to decrease the complexity of GoogleNet architecture [54]

The input picture size turned into standardised to 224x224x3 by way of preprocessing. The framework uses the residual block from ResNet to lower temporal complexity by way of omitting connections and the inception module from GoogleNet to improve performance. The effectiveness of the ensemble is extended through the usage of DenseNet to extract the most substantive functions. On Kermany's dataset, the version's accuracy, sensitivity, and precision have been 98.81%, 98.80%, and98.82%, respectively. On the RSNA dataset, the corresponding scores have been 86.85% for accuracy, 87.02% for sensitivity, and 86.89% for precision. Figure 17 illustrates the inception module from GoogleNet architecture, Fig. 18 shows a residual block of the ResNet model.

5) CNN + KNN + SVM: Using chest X-ray (CXR) photos of various sizes, the authors [55] offered an AI-based device for the prediction and classification of pneumonia. The model makes use of classifiers, K-Nearest Neighbours (KNN) and Support Vector Machine (SVM), for sickness classification, and a Convolutional Neural Network (CNN) for characteristic extraction. 5,852 radiographs from Figure 19 make up the dataset, that's separated for training, trying out, and validation purposes. For multiclass category, the recommended version had an accuracy of 93.9% the usage of the KNN classifier and 94% the usage of the SVM classifier. The CNN architecture used in the ensemble model is illustrated in Figure 25.

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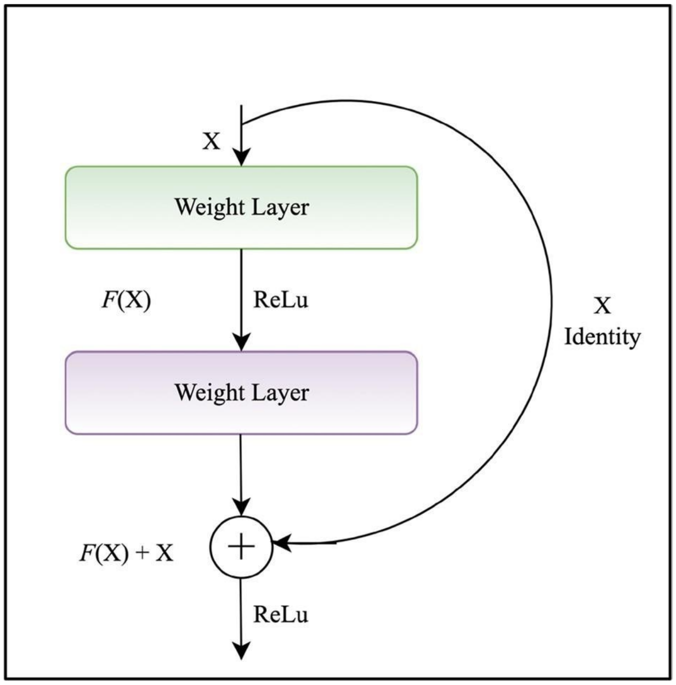

Fig. 18. Residual block in ResNet model [54]

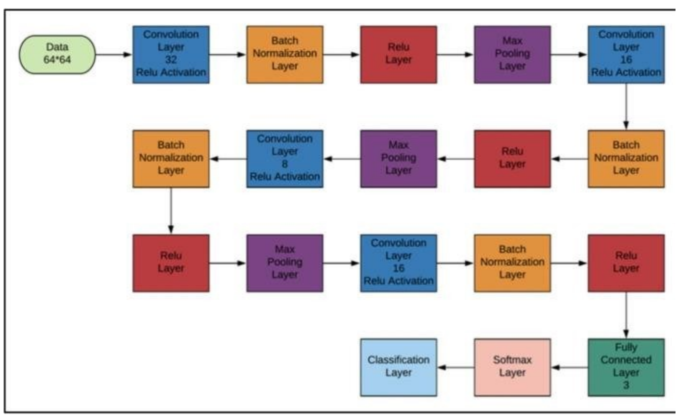

Fig. 19. CNN architecture used in ensemble model for pneumonia prediction presented in [55]

6) Monte Carlo + EfficientNet-B3: The authors [36] used the EfficientNet-B3 version and Monte Carlo dropout (MC-dropout) to advise an ensemble technique for identifying chest X-ray (CXR) pix. To refine the photos, a CNN-primarily based pre-educated model called EfficientNet-B3 is used. To enhance community generalization and decrease over fitting, the Monte Carlo approach is applied. A generative predictive distribution is computed to evaluate the model's suggest prediction score and uncertainty. EfficientNet-B3 is converted right into a reliable Bayesian version by means of making use of MC- dropout. Images are downsized to 224x224x3 pixels and normalised to a range of 0-1, as a part of the education manner. The ensemble version structure employing Monte Carlo and EfficientNet-B3 is shown in Figure 26.

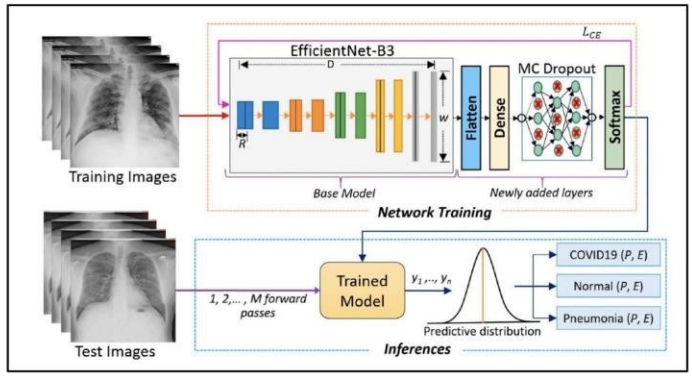

Fig. 20. Monte Carlo + EfficientNet-B3 ensemble model for pneumonia prediction proposed in [36]

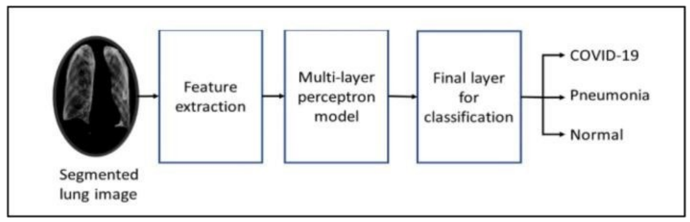

Fig. 21. CGAN + DNN + VGG19 ensemble model architecture for pneumonia detection proposed in [56]

7) CGAN + DNN + VGG19: Using chest X-ray (CXR) pix, the authors [56] presented an ensemble approach for figuring out COVID-19, pneumo-nia, and regular lungs. The CXR information is first segmented the use of a Conditional Generative Adversarial Network (CGAN). A educated Deep Neural Network (DNN) then strategies the segmented lung radiographs with a view to extract discriminatory features. Then, using the Adam optimiser, a specific loss feature, a gaining knowledge of charge of 0.01 and 100 epochs, the VGG19 version is applied to multiclass type. The multiclass classification accuracy of this ensemble version is 96.6%. The architecture of the CGAN + DNN + VGG19 ensemble model is shown in Figure 27.

8) InceptionV2 + RNN + ResNetV2 + RNN-LSTM: To locate pneumonia infections, the authors [57] created an ensemble version that blended Incep-tionV2, ResNetV2, RNN, and RNN-LSTM. This method uses an RNN-LSTM model to are expecting the final results, at the same time as InceptionV2, ResNetV2, and RNN are mixed to classify enter categories. For training and testing, pix have been decreased to 310x310 pixels to house the dataset's variable photo sizes. The goal of this model is to offer realistic fitness signs for monitoring the risk and infection charge of COVID-19 pneumonia. Three one of a kind styles of chest X-ray (CXR) pictures—bacterial, viral, and everyday—were used in its implementation. Furthermore, as shown in Figure 22, a twin technique was created to explain the split of input images.

9) Transfer learning + Deep DenseNet: The authors [58] proposed using the DenseNet121 model to detect pneumonia, utilizing the NIH chest-14 open-source dataset, which contains

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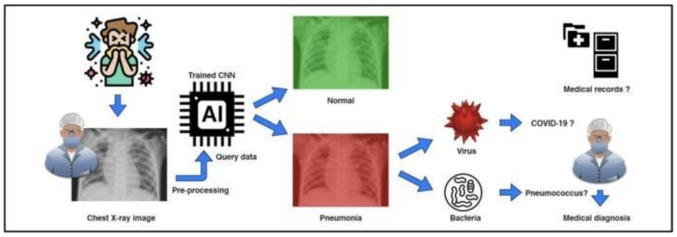

Fig. 22. An ensemble model using InceptionV2 + RNN + ResNetV2 + RNN-LSTM to classify pneumonia proposed in [57]

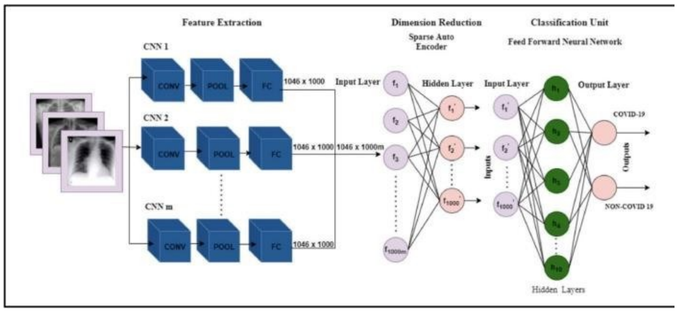

Fig. 23. An ensemble model using using Sparse Autoencoder + FFNN for the covid-19 and non covid-19 pneumonia prediction proposed in [59]

4000 radiograph images. The model to begin with plays characteristic extraction, and all weights, except for the final layer's, are used to initialize the DenseNet121 model. The Tan Tock Seng Hospital (TTSH) dataset became great-tuned. The suggested model obtained an F1-score of zero.9120, an AUC of zero.95, sensitivity of 79%, and specificity of 97%.

10) Sparse Autoencoder + FFNN: Using a combination of FFNN and Sparse Autoencoder, the authors of the study [59] created a CAD model for identifying COVID-19 pneumonia from chest radiographs. The version works in three levels. First, functions are extracted from the dataset the usage of a CNN version. To dispose of features that would impair overall performance, a Sparse Autoencoder is used for dimensionality discount in the second degree. Lastly, an FFNN is used for binary class inside the 0.33 phase to differentiate between COVID-19 and non-COVID-19 pneumonia cases from Figure 23. The accuracy of the model is meant to be improved with the aid of the use of Sparse Autoencoder and integrating a couple of pre-skilled networks into the feature extraction process.

11) CovNNet-based ensemble model for pneumonia detection: The authors [60] developed a CovNNet model and an ensemble model based on the CovNNet framework for classifying pneumonia. The CovNNet model is designed with a ReLU activation function, three convolutional layers, pool- ing layers, two fully connected layers, and a softmax layer. It is specifically tailored to predict pneumonia presence in COVID-19 chest X-ray images. This model employs a fuzzy logic-based deep learning technique to differentiate between interstitial pneumonia and COVID-19 pneumonia in chest X- rays 24. In the CovNNet model, inputs from chest X-rays and images generated by a fuzzy algorithm are combined for

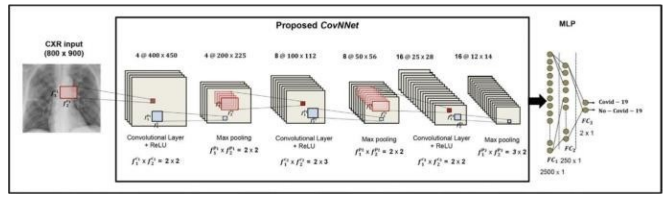

Fig. 24. CovNNet model for covid-19 and non covid-19 pneumonia prediction presented in [28]

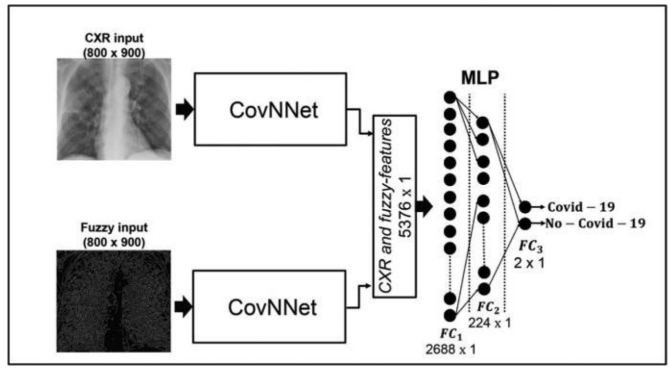

Fig. 25. Ensemble CovNNet model proposed in [28]

feature extraction, while the classification task is performed using a multilayer perceptron (MLP).

Chest X-ray (CXR) and fuzzy version-generated photographs are processed independently through specific CovNNet models for feature extraction inside the CovNNet-based totally ensemble model. For photograph class, these amassed characteristics are sooner or later integrated and fed into a multilayer perceptron (MLP) 25. While the accuracy of the CovNNet-based totally ensemble model extended to 81%, the accuracy of the CovNNet version on my own turned into best 67.2%. This illustrates how the ensemble technique performs higher in predicting pneumonia.

V. CONCLUSION AND FUTURE DIRECTION

Significant studies has been performed within the healthcare enterprise lately, specifically within the improvement of deep getting to know (DL) fashions for the early prediction of pneumonia. Even with the improvements, this place nevertheless has space for improvement. This systematic literature evaluate (SLR) offers a radical evaluation of the architectures and improvement tactics of pneumonia detection models by way of classifying them into CNN-based totally, pre-educated, and ensemble fashions. In order to provide insights into the version configurations and education tactics, it additionally explores hyper parameter parameters including optimizers, learning fees, epochs, batch sizes, and education/checking out ratios. The study highlights research gaps in these DL fashions and talks about possible fixes for problems that researchers encountered while developing the models.

The paper emphasizes that while healthcare records accumulating gives problems due to privateness considerations, enhancing datasets could improve DL version overall performance results. Strict privateness approaches are required to keep affected person confidentiality and adhere to laws like

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HIPAA considering the fact that healthcare records, consisting of clinical history and personally identifying records, is sensitive. The paper recommends investigating federated gaining knowledge of-based totally DL fashions for pneumonia identity in chest X-ray pictures in order to overcome those difficulties. This method should defend facts privacy even as utilizing dispersed facts assets.

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