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# Lung Pathology Detection: A Qualitative and Comprehensive Survey of Deep Neural Networks Utilising CT, MRI, and PET Imaging Modalities

**Yellepeddi Samba Siva Krishna Assish[1], Kuppusamy P.[2]**

School of Computer Science and Engineering, VIT-AP University, Andhra Pradesh, India.

**E-mail:** [1]yellepeddi.22phd7108@vitap.ac.in, [2]drpkscse@gmail.com

**Orchid ID:** [1]0009-0007-5432-7868, [2]0000-0001-5369-8121

**Abstract**

In March 2020, the World Health Organisation (WHO) identified COVID-19 as a global pandemic brought about by the SARS-CoV-2 virus. RT-PCR continued to be the first line of diagnosis, but its slow turnaround emphasized the need for faster, complementary diagnostic modalities. Imaging techniques like chest X-rays (CXR), computed tomography (CT) scans, and ultrasound were soon in high demand; yet manual assessment was time-consuming and susceptible to faults. To overcome these challenges, artificial intelligence (AI), and more so deep learning (DL), has proven to be a revolutionary instrument through feature extraction automation and enhanced diagnostic accuracy. This survey differentiates itself from reviews that have already been conducted by providing an exhaustive review of state-of-the-art DL architectures engineered for COVID-19 analysis on various imaging modalities, also highlighting under-investigated aspects like prognostics, rehabilitation assistance, and the role played by uncertainty quantification (UQ) in achieving clinical trustworthiness. The survey identifies areas of research gaps, such as the scarcity of multimodal datasets, difficulties in generalising models across populations, and the absence of standardised evaluation benchmarks. Systematically resolving these gaps, this work highlights the practical significance of AI-based computer-aided diagnosis (CAD) systems toward accelerating faster, more robust, and scalable pandemic response tools. In addition, it gives researchers and clinicians a blueprint for developing AI-based healthcare, allowing for both short-term use in managing COVID-19 and long-term relevance in future public health emergencies.

**Keywords:** COVID-19, Systematic Review, Deep Learning, Medical Imaging, Artificial Intelligence, Classification, Segmentation.

## 1. Introduction

In recent years, the world has struggled with numerous harmful infectious pathogens constantly emerging and reemerging. New viral zoonotic disease outbreaks are increasing frequent. "These infections" refer to diseases caused by different viruses. SARS, influenza A (H5N1), and MERS-CoV are severe respiratory illnesses. These elements and others have detrimental consequences on public health [1]. Several reasons contributed to the COVID-19 epidemic. First, the novel SARS-CoV-2 is spreading globally (without any prior human


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exposure or immunity). Second, SARS-CoV-2 is a highly mutagenic ribonucleic acid (RNA) virus that allows for rapid diversification at the expense of producing non-viable offspring. The COVID-19 epidemic revealed flaws in the medical systems of many nations, and the incapacity of these institutions to effectively address concerns. Lack of distinctiveness in clinical detection techniques is a significant factor in COVID-19's rapid dissemination [2]. Identifying the infected and immunizing the susceptible are crucial in controlling and eradicating COVID-19. Although it takes longer to analyze the specimen and obtain results, the reverse-transcription-polymerase-vchain-reaction (RT-PCR) test is currently considered the most reliable method for detecting COVID-19. According to recent observations, many individuals may test positive for COVID-19 after recovering. Due to the successful application of deep learning in computer vision and biomedicine, researchers are looking at AI-based approaches for detecting COVID-19 using CXR and CT-scan images. While still in its infancy, research on COVID-19 has shown enormous promise and is progressing quickly [3].

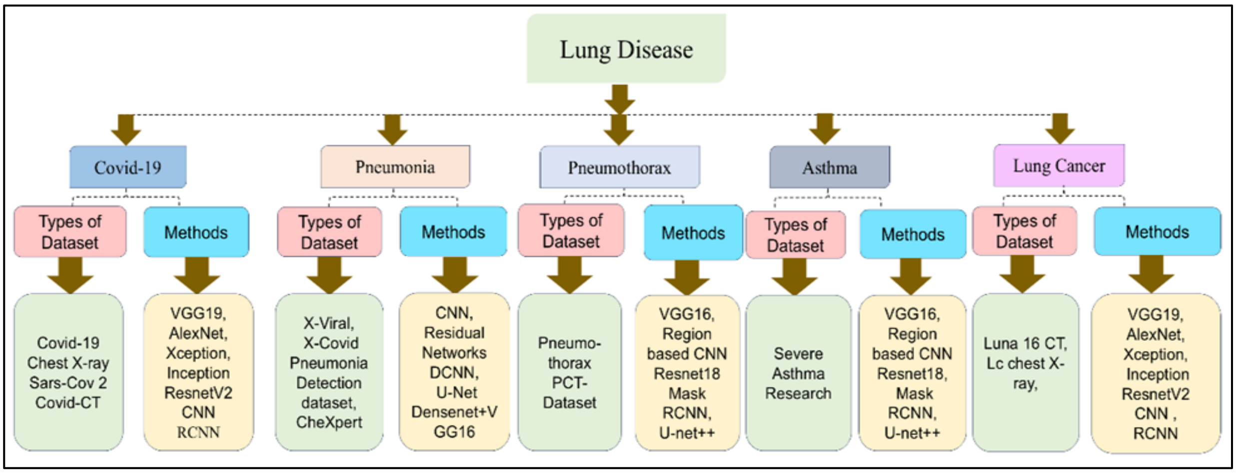


**Figure 1.** Lung Disease Classification

We also provide recommendations for future studies on the potential applications of AI and ML to counteract epidemics other than COVID-19 [4]. Researchers are concentrating on the limitations of the RT-PCR test to enhance the medical evaluation and identification of COVID-19. Moreover, diagnostic procedures such as lung needle biopsy, chest magnetic resonance image (MRI), CT, and CXR are also suggested in Fig 2.[5].

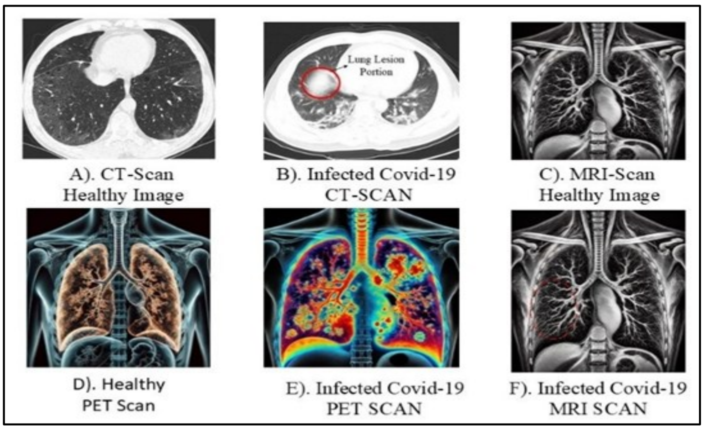


**Figure 2.** Availability of Different Types of Lung Scans

Here, the study makes the following four significant contributions:

- Explored the various datasets for classification and segmentation
- Investigated the strategies that use deep learning for COVID-19 detection from clinical scans, along with their main advantages and disadvantages.
- Given an overview of the chosen articles.
- A taxonomy of lung classification is provided.
- This paper might be helpful for those who are working on DL-based lung disease identification in real-time and guides future researchers in the right direction.

In Fig. 2 above, the lung CT-scan health image information is at the top, beside an infected COVID-19 CT-scan image. Below are the two chest X-rays, which are healthy and infected scans. Existing reviews are insufficient because they are either modality-specific (mainly CT or X-ray) or limited to early COVID-19 detection tasks. They rarely provide a systematic taxonomy of both classification and segmentation, nor do they evaluate clinical barriers to deployment. This survey addresses these gaps by analyzing CT, MRI, and PET collectively, providing structured comparisons, and offering direct clinical guidance. The work is structured as follows: Section 2 discusses various datasets used by researchers for analysing lung diseases. Section 3 discusses related studies on lung disease classification and segmentation, and Section 4 presents a computer-aided diagnosis system utilising CNN for COVID-19. Finally, Section 5 presents results and discussion, and Section 6 concludes this study.

## 2. Related Work

Lung disease datasets include patient information, medical history, test results, and medical images, such as CT and MRI scans.

### 2.1 CT-Scan Dataset

Regarding the MRI lung segmentation and the diagnosis of COVID-19, publicly accessible datasets for SARS-CoV-2, offered by the Open Access Series of Imaging Studies for COVID-19 Disease, are presented in Table 1. The details of the datasets for SARS-CoV-2, COVID-CT, and COVID-CT-MD are provided. The survey begins with a quick overview of lung MRI before describing the unique characteristics of the datasets.

#### 2.1.1 SARS-CoV-2 Dataset

Researchers created the COVID-19 CT dataset. The dataset comprises 2,482 CT scan images, divided into 1,252 images for SARS-CoV-2-infected patients and 1,230 for non-infected patients [6].

#### 2.1.2 Covid-CT

The researchers gathered 349 CT scans that were identified as positive for COVID-19. The sizes of these CT images vary: 153, 491, and 1,853 are the smallest, average, and largest heights, respectively. There are three different widths: 124, 383, and 1485. It includes 397 non-COVID-19 CT images and 349 COVID-19 CT images [7].

### 2.1.3 Covid-CT-MD

The COVID-CT-MD dataset is used to test and improve COVID-19 image segmentation. In addition to the MRI data, the collection contains the outcomes of a manually guided expert segmentation. The image's dimensions are 256 x 256 x 128 pixels [8].

## 2.2 Lung MRI Scan

Lung MRI utilises magnetic fields and radio waves to produce precise images of the internal structures of organs. MRI, unlike CT scans, does not utilise ionising radiation. This makes MRI a safer option for pregnant women and children, as well as for people who need to have repeated imaging tests.

**Table 1.** Overview of COVID-19 CT and PET Scan Datasets and COVID-19 Lung CT Datasets

| S.No | Datasets | Class | No of Images |
|---|---|---|---|
| 1 | SARS-CoV-2 [6] | COVID-19 | 1252 |
| | | Non-Covid-19 | 1230 |
| 2 | Covid-CT [7] | COVID-19 | 349 |
| | | Non-Covid-19 | 397 |
| 3 | COVID-CT-MD [8] | COVID-19 | 60 |
| | | Non-Covid-19 | 76 |
| 4 | Covid-19 MRI | COVID-19 | 350 |
| | | Pneumonia | 400 |
| | | Normal | 150 |
| 5 | Radiological Society of North America (RSNA) [9] | COVID-19 | 284 |
| | | Healthy | 500 |
| 6 | National Institutes of Health (NIH) [10] | COVID-19 | 500 |
| | | Healthy | 500 |
| 7 | Chinese Medical Association (CMA) [11] | COVID-19 | 500 |
| 8 | Lung PET Scan Dataset for Pneumonia Detection [12] | Pneumonia | - |
| 9 | Lung PET Scan Dataset for COPD Detection [13] | COPD | - |
| 10 | Lung PET Scan Dataset for Asthma Detection [14] | Asthma | - |

### 2.3 PET Scans

Positron Emission Tomography (PET) is a medical imaging method that utilises radioactive tracers to visualise the function of specific organs. Table 1 illustrates that CT and PET scans are used to diagnose and manage various conditions, including lung diseases. However, across these datasets, challenges such as class imbalance (over-representation of COVID-19 cases), variability in acquisition protocols across institutions, and limited availability of real-world clinical data persist. Public datasets are often small, biased toward specific populations, and inconsistently annotated, reducing generalization potential.

## 3. Related Study

To ensure a rigorous and systematic review, we established clear criteria for selecting studies included in this survey. The inclusion criteria are as follows: studies published between 2016 and 2024 that focus on DL applications for lung pathology detection using CT, MRI, or PET imaging. We included peer-reviewed articles and preprints addressing COVID-19, pneumonia, chronic obstructive pulmonary disease (COPD), or other lung diseases. This review adhered to the PRISMA 2020 guidelines. We conducted systematic database searches in PubMed, IEEE Xplore, SpringerLink, and arXiv. After removing duplicates, 120 records were screened, and 75 studies were included based on predefined eligibility criteria. The PRISMA flow diagram in Fig. 3 summarizes the selection process.

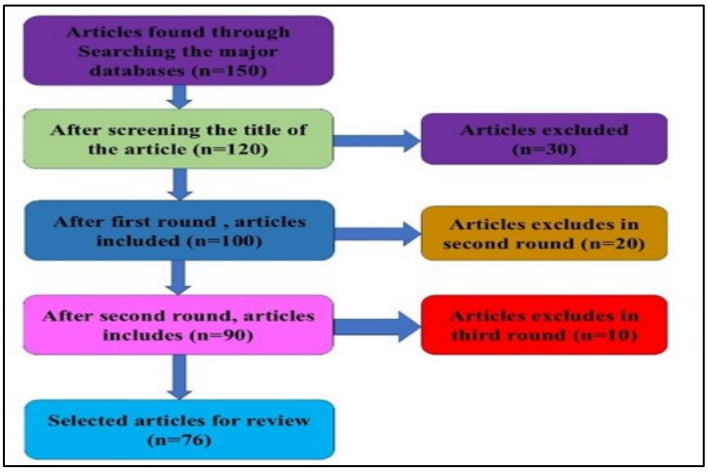


**Figure 3.** PRISMA Selection Criteria for Research

Exclusion Criteria: Studies lacking empirical results, non-DL approaches, or those not involving CT, MRI, or PET imaging were excluded. Databases Searched: PubMed, IEEE Xplore, SpringerLink, and arXiv were searched using keywords such as “lung pathology,” “COVID-19 detection,” “CT imaging,” and “MRI segmentation.” Selection Process: From 350 retrieved articles, 120 were selected after abstract screening, and 75 were included after full-text review based on relevance and quality.

### 3.1 Impact of AI on Lung Disease Classification and Segmentation

To find COVID-19, researchers offered a thorough literature study on lung CT data's structural Segmentation and categorisation. Here, the section pertains to the previous researcher's years of work under a system that automatically detects COVID-19 using DL methods. DL for healthcare images and feature extraction is an excellent method. New, reliable, automatic techniques for accurate detection are essential to minimise medical professionals' exposure to the pandemic. X-ray imaging can aid in Diagnosis, and MobileNet is a CNN trained to classify features [15]. According to researchers, improved beetle antenna metaheuristics for exploration, swarm intelligence, ML, and an adaptable NFI system are all integrated into the proposed prediction model. The flexible NFI system parameters are chosen to enhance the beetle antenna search, which improves prediction model accuracy [16].

According to researchers, the dataset distribution consists of 33.3% each for "SARS-CoV-2" and "Covid-CT," 20.4% for "Covid-CT MD," and 13% for "CovidX-CT." This allocation emphasises the "SARS-CoV-2" and "Covid-CT" datasets, providing a balanced approach to COVID-19 data analysis, with additional insights from "Covid-CT MD" and "CovidX-CT" in Fig. 4.

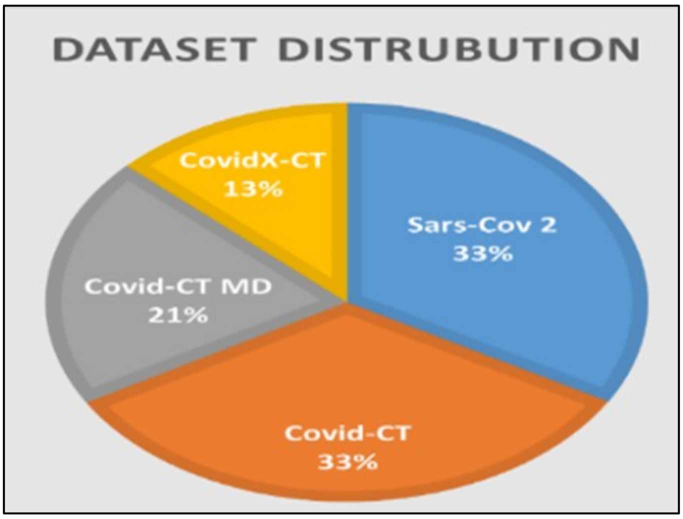


**Figure 4.** Dataset Used Across the Research

Using diverse datasets, the researcher aims to leverage knowledge from multiple associated tasks to enhance classification and segmentation performance and mitigate minor data issues [17]. The researcher presented a new method for analyzing lung CT scans, which identifies patients as COVID-19 positive or negative by utilizing models such as ResNet50 and VGG16 to determine CT lung scan results [18]. The illustration in Fig. 5 shows various diseases associated with the lungs and lung disease screening tests. Automated image analysis systems have been utilizing medical images, such as CXR, CT, and lung MRI, enhanced by AI and ML-based methodologies. Different ML and DL techniques are applied to COVID-19 medical images to detect, classify, segment, assess severity, and track patient progress. This work aims to review research on the detection and analysis of COVID-19 using ML, DL, and transfer learning models applied to medical image datasets for lung pathology detection [19].

Several DL techniques were evaluated, including hybrid CNN Restricted Boltzmann Machine (RBM), LSTM, hybrid Gated Recurrent Unit (GRU), and Long Short-Term Memory (LSTM- CNN). Standard ML techniques such as Logistic Regression (LR) and Support Vector Regression (SVR) were also examined. The long-term forecasting accuracy of COVID-19 future trends is anticipated to be improved using hybrid models (such as LSTM-CNN and GAN-GRU) [20]. The pre-trained VGG16 model extracts feature for the early detection of pneumonia, enabling prompt and effective therapy. To assist medical practitioners, a DL-based methodology categorises normal CXR radiographs as either pneumonia or normal [21].

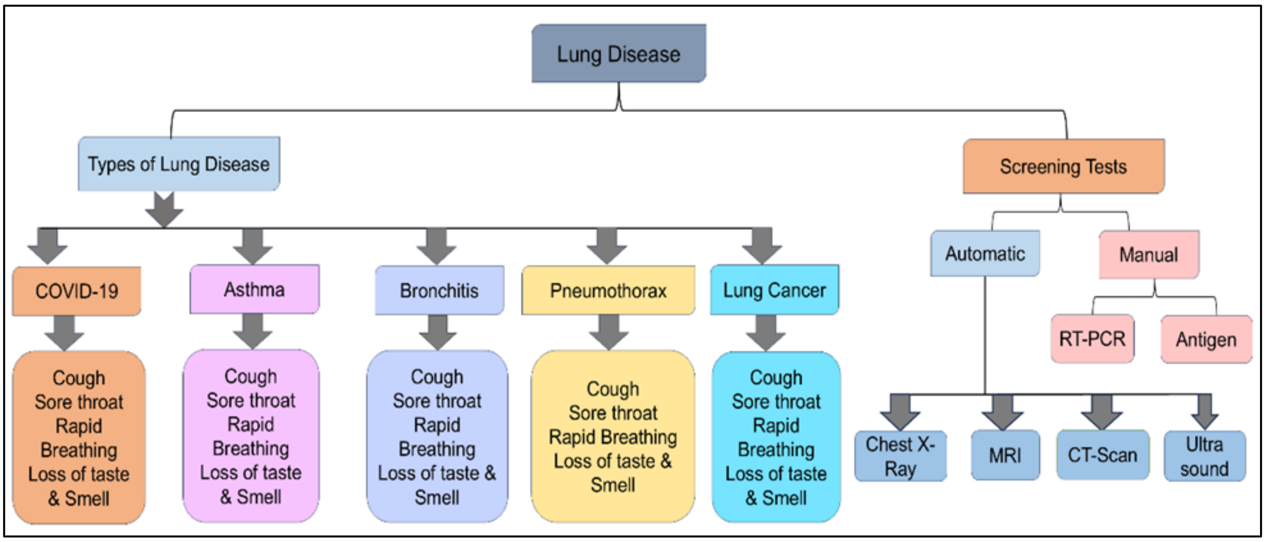


**Figure 5.** Taxonomy of Lung Classification Considered in this Research

**Table 2.** Performance of Various DL Models for COVID-19 Detection

| Model | Task | Accuracy (%) | Sensitivity (%) | Specificity (%) | Limitations |
|---|---|---|---|---|---|
| DenseNet121 [18] | Classification | 96 | 94 | 97 | Prone to overfitting on small data |
| InceptionV3 [19] | Classification | 95 | 93 | 96 | Limited generalizability |
| ResNet50 [20] | Classification | 98 | 96 | 97 | High computational cost |
| MobileNetV2 [21] | Classification | 87.6 | 85 | 88 | Misses complex clinical features |
| U-Net [22] | Segmentation | 88.0 | 85 | 90 | Requires large annotated datasets |

Frontline healthcare workers require faster and more accurate diagnostic options beyond nucleic acid-based laboratory tests. Researchers created an AI algorithm in this work by evaluating typical CT images with Inception V3 using transfer learning. Three primary operations comprise the architecture: input picture filters, mask size determination from ROI images, and training, which includes classification with two fully connected layers and a binary classifier [22]. The multitasking model with automatic segmentation and classification are proposed for identifying COVID-19 pneumonia using CT chest images. This method explained a shared encoder for feature representation, a singular processor for Segmentation, and an MLP for classification. It analysed three datasets and evaluated image size on model performance for multi-class and binary-class learning [23].

Researchers analysed and evaluated five DL models, ResNet50, ResNet101, DenseNet121, DenseNet169, and InceptionV3, to recognise COVID-19 from chest radiography images. This study demonstrates the potential of various DL algorithms in analysing CXR images related to COVID-19. The models were trained and verified on COVID-

19 CXR images from the largest publicly available source. AI-based DL methods have been extensively used. This approach aims to assess the efficiency of DL-based AI methods in detecting COVID-19 using chest radiography and CT scans. The study presents the limitations of current methods in detecting COVID-19 through DL techniques, such as finding datasets with extensive data and implementing them [24]. The study presents a robust framework for DL-based methods and chest CT scan images for automated COVID-19 testing. MobileNetV2, DarkNet19, and a new lightweight DLM can automatically detect COVID-19 in a dataset of 1,252 positive and 1,230 negative chest CT scans. DLM training, testing, and validation are conducted using a tenfold holdout validation approach [25]. The future medical applications of ML will become increasingly crucial. ML can speed up COVID-19 Diagnosis, but the technique needs improvement. The scarcity of COVID-19 data causes a lack of training data scans accessible to the general public, as well as a limited, publicly available, and varied dataset created by researchers who have studied COVID-19. To enhance the classification model's ability, it is also possible to create a model using multimodal data [26].

### 3.2 Computer-Aided Diagnosis System for the Usage of CNN for COVID-19 Diagnosis Classification

A Computer-Aided Diagnosis (CAD) system leverages CNN to assist in COVID-19 diagnosis by automatically analysing medical images, enabling faster and more accurate disease detection. One type of DL-based neural network that performs exceptionally well in image classification and recognition applications is the CNN [27]. It comprises several layers of data, each of which processes the input data in a particular way a CNN's convolutional layer gathers attributes from the input image. A convolutional layer is followed by a pooling layer, which reduces the dimension of the feature maps it produces. Several iterations of this procedure are carried out, with each layer picking up increasingly intricate details from the initial image. Establishing trust, researchers explore the use of AI-powered analysis of clinical reports for COVID-19 detection. They investigated various feature engineering techniques (TF-IDF, BOW, and report length) with classical and ensemble ML algorithms. TF-IDF identified crucial words and extracted unigrams and bigrams for feature representation. Among them, 40 relevant features were chosen and weighted for classification by ML algorithms. The approach demonstrates the potential of AI in analysing clinical reports for the detection of COVID-19 [28]. To ensure DL, utilising MobileNet v2 is demonstrated as an effective method for extracting complex features from medical images. It was trained on a dataset of 3905 X-ray images representing six diseases, and the approach successfully achieves excellent results for classification tasks [29]. Fig. 5 outlines the process of diagnosing COVID-19 by interpreting test results to determine whether a patient is positive or negative for the disease. The DL process is aimed at creating a system that can automatically classify a medical image as containing a healthy or COVID-19 infection. Enhancing time-series prediction algorithms is crucial for assessing and implementing possibilities during the COVID-19 outbreak. A hybrid model named CESBAS- ANFIS is introduced, which combines an Adaptive Neuro-Fuzzy Inference System (ANFIS), enhanced beetle antennae search swarm intelligence, and ML. The Beetle Antenna Search (BAS) algorithm and ANFIS are both computational techniques used in optimisation and prediction tasks [30]. To address the challenge of diagnosing COVID-19 from limited CT lung images, a novel framework utilising ResNet50 and VGG16 models for classification, coupled with U-Net for segmentation, was introduced. Preprocessing techniques, transfer learning, and data augmentation enhanced model robustness [31].

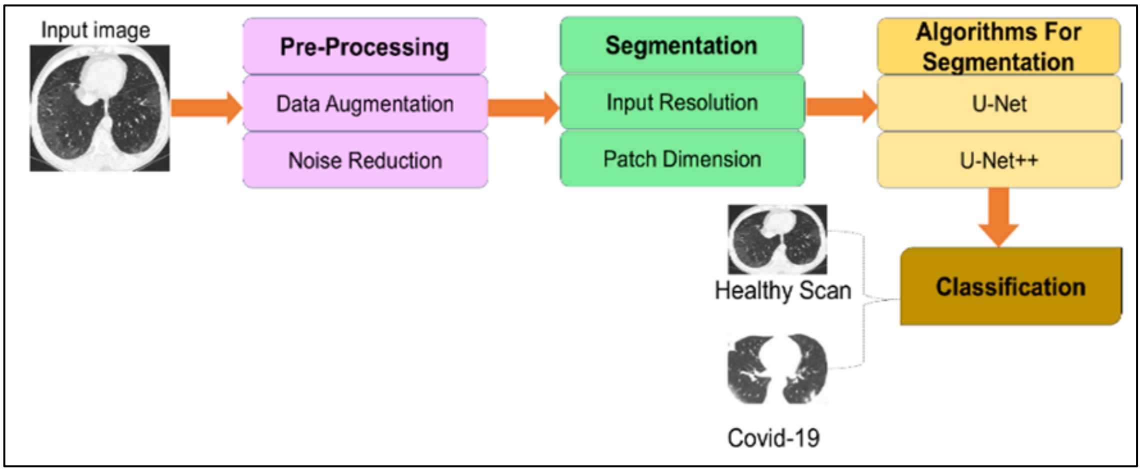


**Figure 6.** Conventional Block Diagram of COVID-19 Diagnosis

After evaluating a dataset of 1369 patients, including 449 with COVID-19, the model has shown promising results of 97% for classification [32]. In DL, multitask learning is a technique in which a single model can learn several interrelated tasks simultaneously, sharing knowledge and parameters to improve overall performance. A new DL model called CoroDet uses CT scans and CXRs automatically to detect COVID-19. CoroDet can classify images into 2, 3, or 4 categories, including COVID-19, standard, and many forms of pneumonia [33]. CoroDet, a 22-layer DL model, uses a wide range of metrics, including Accuracy, precision, and sensitivity, to evaluate its performance in three different classification tasks: two-class (COVID-19 vs. Healthy), three-class (by incorporating pneumonia that is not COVID-19), and four-class (further segregating pneumonia that is bacterial and viral). Table 3. describes the summary of previous researchers' work on COVID-19 diagnosis methods and different approaches with their pros and cons.

**Table 3.** Characteristics with the Datasets, Performance, and Limitations of the COVID-19 Detection Methods

| Methods /Models | Disease | Datasets used and Accuracy | Limitations |
|---|---|---|---|
| Fine-tuning Mobile Net [29] | Covid-19, Normal & Pneumonia | SARS-CoV-2 (87.6%) | Clinical Conditions are missing (symptoms, medical history, or relevant diagnoses) |
| Bettle Antenna Search algorithm and adaptive neuro-fuzzy [30] | Pneumonia & Covid-19 | RSNA Covid-19 dataset | The testing procedure reveals the limitations of the suggested technique. Therefore, modifying the metaheuristics' control parameters requires fresh simulation runs. |
| VGG16 Resnet50 U-net [31] | COVID-19 & Pneumonia | COVID-19 lung CT images from a public Source (98.98%) | Privacy concerns that the public cannot access the CT scan datasets utilised in such works. |

| | | | |
|---|---|---|---|
| Multi-task Learning (MTL)[32] | Covid-19 & Pneumonia | Customised CT-scan Dataset | To test our strategy on large data sets and determine its performance, we might investigate novel types of networks that account for additional important information. |
| CoroDet, a CNN model [33] | COVID-19, Normal Pneumonia, viral Pneumonia, bacteria | Chest X-ray image data | We must overcome hardware limitations to leverage larger image sets for training the suggested model and thereby improve its performance. |

## 3.3 Segmentation of Lung CT using Deep Learning

The term DL has been recently used to describe neural networks, a form of artificial intelligence that has existed for over 40 years. NN focuses on complex problems that are challenging for individuals to address. The disease investigation technique was used, the dataset was considered, and accuracy was determined based on our analysis of current computerised COVID-19 disease detection techniques [35].

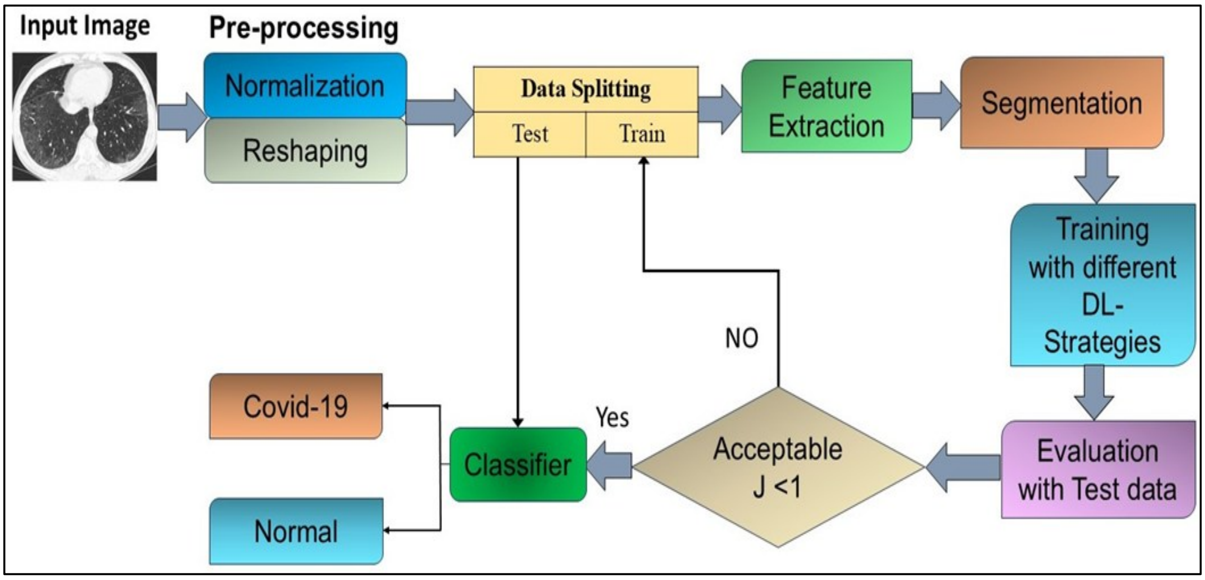


**Figure 7.** Generic Block Diagram of CAD COVID-19 Diagnosis

The illustration in Fig. 7 shows the typical steps involved in diagnosing COVID-19. CT slices must first be acquired. Preprocessing, which involves removing unnecessary information and rearranging the data for easier reading, is the next step in data preparation. DL segmentation extracts the essential characteristics from the pre-processed data from lung MRI scans.

**Table 4.** Fine-Tuning Based Methods for Lung Segmentation

| Authors | Methodologies | Applications |
|---|---|---|
| Mohit et al. [36] | DenseNet121, DenseNet169 models | Covid-19 Classification |

| | | |
|---|---|---|
| Shirin Kordnoori et al. [37] | Auto-encoder, multi-layer Perceptron & Decoder (MLP) | COVID-19 Segmentation and Classification |
| Emrah Irmak [38] | VGG-19 model | COVID-19 Disease Severity Classification |
| Saeed Mohagheghi and Mehdi Alizadeh et al. [39] | Inception V3, DenseNet & ResNet | COVID-19 Classification using VGG16 and ImageNet algorithms |
| Amyar and Romain et al. [40] | Auto-encoder & decoder model | Classification and Segmentation |
| sakib et al. [41] | DL-CRC | Classification |
| Wang & Siwen et al. [42] | Deep Fusion Architecture Ensemble Learning | Segmentation |
| Lin & Lixin et al [43] | Connect with U-net | Segmentation |

In Table 4. Mohit et al. utilise a customised CNN to categorise cases of COVID-19. The contributors recommended a multitask approach for efficient detection and segmentation of viral influenza with CT chest imaging. Here, the model features a typical encoder, segmentation decoder, and an approach that involves using a multi-layer perceptron for classification, demonstrating a significant improvement in results [37]. The researchers utilised a 16-layer customised CNN to categorise individuals with COVID-19 into different severity levels. The CNN model is explicitly designed for classification and is trained and evaluated using a dataset of 3,260 CXR images from COVID-19 patients. Twenty percent is spent on validation, twenty percent on testing, and sixty percent on training. The image Resolution is $227 * 227 * 3$. This model is recognised for its efficiency and effectiveness in processing large datasets and complex models.

The CNN model facilitates rapid training and optimisation of the model's parameters, yielding excellent accuracy in classifying COVID-19 patients into distinct sensitivity levels [38]. In the proposed method, a CNN is employed for diagnosing infections by analysing CXR images of healthy, COVID-19, and pneumonia cases, and calculating the probability of coronavirus infection. The CBMIR algorithm is designed to label medical images. The CNN and CBMIR algorithms are essential for accurately diagnosing and distinguishing COVID-19 from other conditions, offering valuable support for medical professionals [39]. A proposed multitask DL algorithm will recognize COVID-19 individuals while segmenting lesions. It generates superior outcomes, with a dice coefficient of more than 0.88 for segmentation and an area under the ROC curve of more than 97% for identification [40]. The existing research used several advanced models to enhance segmentation tasks effectively. sakib et al. [41] employed a DL-CRC hybrid (ResNet-50 with GAN) to achieve improved accuracy, thereby combining convolutional and sequential processing. Wang & Siwen et al. [42] applied Deep Fusion Architecture with Ensemble Learning to optimise performance through model fusion. Lin & Lixin et al. [43] utilised ConvNet with U-Net for fine-detail segmentation, combining convolutional and encoder-decoder architectures. These approaches highlight various methods for achieving precise segmentation.

## 3.4 High-Resolution Computed Tomography of Pneumonia

In hindsight, they gathered 46,096 anonymised photos from 106 hospitalised patients at Wuhan University's Renmin Hospital, comprising 51 individuals whose COVID-19 pneumonia was verified by a laboratory and 55 healthy people with various ailments [44]. On a different dataset, it obtained a 96% accuracy rate. The approach drastically reduced radiologists' reading time by 65%. Professional radiologists were outperformed by the DL model in terms of performance, greatly enhancing the effectiveness of radiologists in clinical settings. Supervised learning performed superior to the methods, achieving 92.9% accuracy. Recurrent supervised learning will improve accuracy [45].

**Table 5.** Performance of COVID-19 CT Imaging Techniques for Classification with Similar Datasets

| **Author Name** | **Dataset Name** | **Classification or Segmentation** | **Techniques** | **Metrics (%)** |
|---|---|---|---|---|
| Xu, Jingxiang et al [46] | SARS-CoV-2 | Image Sequence Classification | Covid-IRLNet | Accuracy 88<br>Precision 88<br>F1-Score 86 |
| Zhan & Guilin et al [47] | SARS-CoV-2 | Segmentation | EAswin-unet | Dice Similarity Coefficient 74<br>Sensitivity 72<br>Specificity 93 |
| Balaha & Hossam Magdy et al [48] | SARS-CoV-2 | Classification | Optimised Yolo V8 with Mosaic Augmentation | Accuracy 96<br>Recall 94<br>Specificity 97 |
| Moosavi & Abdoulreza et al [49] | SARS-CoV-2 | Segmentation & Classification | U-Net<br>DenseNet 121 | Accuracy 88<br>AUC 96<br>Specificity 82 |
| Tembhurne & Jitendra [50] | COVID-CT | Segmentation | Transfer Learning VGG16, Inception, Xception and Resnet50 | Dice Similarity Coefficient 83<br>Accuracy 84 |
| Liu & Weili et al [51] | COVID-CT | Classification | Effective Channel Expansion and Fusion (ECEF) | Accuracy 89<br>Precision 90<br>F1-Score 89 |
| Punitha S & Thompson Stephan et al [52] | COVID-CT | Segmentation & Classification | Artificial Bee Colony (ABC) optimised ANN (ABCNN) | Accuracy 90<br>Precision 89<br>F1-Score 89 |
| Yujia, Hak et al [53] | Covid-CT<br>Covidx-CT | Classification | DenseNet 121 | Accuracy 99<br>Precision 98<br>Specificity 98 |

| | | | | |
|---|---|---|---|---|
| Mouna, Riadh et al [54] | Covid-CT Covidx-CT | Segmentation | context fuse model (CFM), Attention mix module (AMM), and a Residual Convolutional Module (RCM). | Precision 93 F1-Score 94 Accuracy 96 |

Table 5 highlights advancements in COVID-19 CT imaging techniques for classification and segmentation. Researchers applied models such as Covid-IRLNet, which achieved 88% accuracy for SARS-CoV-2 classification, and the Efficient Attention (EA) mechanism with the U-Net (EAswin-unet), which obtained a 74% Dice Similarity score for segmentation. Optimised Yolo V8 with Mosaic Augmentation reached 96% accuracy, while the U-Net and DenseNet121 combination achieved a high AUC of 96%. Other approaches, such as the ECEF model with 89% accuracy and ABCNN with 90% accuracy on COVID-CT, further demonstrate progress in precision diagnostic methods. Techniques such as DenseNet121 and fusion models continue to make significant strides in COVID-19 CT diagnostics.

## 4. Challenges in Lung CT Segmentation

Lungs have diverse structures, varying with age, sex, and the presence of chronic obstructive pulmonary disorders.

- Lungs are challenging to examine due to their complex structure, which could result in more precise classifications of various structures. Experts on the human species frequently encounter this problem.

- Manually segmenting a lung CT requires much work and is prone to mistakes. Furthermore, a thorough knowledge of the lung's function is necessary.

Collecting enough ground truth data to build a segmentation model is challenging.

- The noisy background makes it challenging to label each pixel while precisely segmenting a typical image.

### 4.1 Challenges in the Diagnosis of COVID-19 Disease

The most challenging aspect of COVID-19 infection is the time needed to monitor and assess the patient's status. Due to the disease's dynamic nature, CT scans are not effective in diagnosing COVID-19.

- Multimodal data collection for the assessment of COVID-19 disease.

A prediction model constructed solely from multimodal data will be unreliable due to heterogeneity, as data from genetics and neuroimaging techniques such as CT, MRI, or PET, have different data distributions and levels of discriminative ability compared to singlenucleotide polymorphisms (SNPs) for COVID-19 diagnosis [55,56]. For instance, it has been found that the utility of raw SNP data in the context of COVID-19 illness is limited.

- High dimensionality problem

While a neuroimaging scan frequently contains millions of voxels, a subject's genetic data may have hundreds of SNPs linked to COVID-19. Table 5 summarises eight studies on lung disease diagnosis using various strategies, image types, critical methods, and datasets.

**Table 6.** Key Findings of DL-Based Lung Classification Techniques for CAD

| Author | Organ/ Disease | Modality used | Key-Method | Dataset | Limitation |
|---|---|---|---|---|---|
| Apostolopoulos et al. [57] 2020 | Lung | CT images | Transfer learning with MobileNet V2 | RSNA (1428) | Limited generalisation due to dataset imbalance and low diversity |
| K. Shankar et al. [58] 2020 | Covid-19 | CT images | A fusion model has been created using the DL features-based Inception v3 algorithm. | Chest CT Dataset | Model complexity increases computation time. |
| Shin, Hoo-Chang, et al. [59] 2016 | Lung | CT images | Transfer learning with CifarNet and AlexNet from pre-trained ImageNet | COVID-CT | Early work, outdated architectures, and limited accuracy |
| Xiaohong, Carl et al. [60] 2019 | Lung (TB) | CT images | A Depth Res-Net and ResNet-50 model | ImageCLEF2018(340) | A small dataset limits scalability and generalisation |

| | | | | | |
|---|---|---|---|---|---|
| Pietro Nardelli, Daniel et al.[61] 2018 | Lung | CT images | A proposed scale-space particle algorithm based on Patch dimensionality | COPD Gene Data | Patch-based analysis may miss the global context |
| S. Wang, Bo Kang et al. [62] 2021 | Lung | CT images | Inception V3 Model | SARS-COV-2 (1065) | Prone to overfitting with a small data size |
| Ouchicha, Ouafae Ammor et al. [63] 2020 | Lung | CT images | CVDNet | RSNA (2905) | No external validation to test generalizability |
| Javaheri et al. [64] | Lung | CT scans | The DL model called Covid-CTNet | A dataset with 335 cases was used. Out of 335 patients, 110 had COVID-19, while the remaining 115 were infected with the Community-Acquired Pneumonia dataset. Out of 335 patients, 110 had COVID-19, and the remaining 115 had CAP. | Small sample size and class imbalance |
| Saad et al. [65] | Lung | CT Images | Deep Feature Concatenation DFC mechanism, DCNN | The dataset includes 2628 COVID-19 positive images and 1620 non-COVID images. | Risk of feature redundancy and overfitting |
| Singh et al. [66] | Lung | CT Images | Ensemble DL models DCCNS, | 4-class CT-scanned images are collected from different sources, like | Combining models increases inference time |

| | | | | | |
|---|---|---|---|---|---|
| | | | ResNet152 V2, VGG16 | COVID-19, Pneumonia [67-69] | |
| N. A. Baghdadi et al [70] | Lung | CT images | MobileNet V3 Large | COVID-19, Pneumonia, Normal | A lightweight model may sacrifice fine-grained accuracy |
| R. Kundu et al [71] | Lung | CT images | Deep CNN ensemble | Covid-19, Pneumonia | Requires high computational resources |
| Nneji et al. [72] | Lung | Covid-CT | Siamese Capsule Network | Covid-19, Pneumonia | Capsule networks are harder to train and interpret |
| Khan, Asif et al [73] 2020 | Lung | CXR images | CoroNet | RSNA-27 | CXR modality offers lower resolution than CT for COVID-19 |

Here, researchers investigated using DL with X-ray imaging to detect COVID-19 disease automatically. They used two CXR image datasets to study COVID-19, bacterial pneumonia, viral pneumonia, and other specific cases. They utilised the DL models VGG-19 and MobileNet V2 to analyse the datasets. Researchers found that X-ray imaging in DL may extract significant biomarkers for COVID-19 diagnosis. Further research is needed to evaluate its effectiveness from various perspectives [57]. Eventually, with limited rapid tests during surges of COVID-19, researchers introduced a novel Fusion Model Handcrafted DL Features (FM-HCF-DLF) for accurate diagnosis and classification. Combining Local Binary Patterns (LBP) with DL (Inception v3), FM-HCF-DLF utilises optimisation techniques for improved performance. This model holds promise for precise COVID-19 detection [58]. The research addresses challenges in obtaining well-annotated medical imaging datasets, such as ImageNet. The study tests various CNNs, dataset sizes, and image contexts for detecting lymph nodes and lung disease in CAD [59].

Researchers presented a 3D block-based depth-ResNet to handle short datasets and restricted anomalies in CT and TB images, with promising results in severity prediction and tuberculosis categorisation [60]. A three-step deep learning pipeline (vessel isolation, 3D CNN, and graph-cut optimisation) achieved 94% accuracy on 18 clinical instances [61]. A modified Inception transfer-learning model achieved an external accuracy of 79.3%, detecting 85.2% of COVID-19 cases that were missed by nucleic acid tests [62]. These findings demonstrate the potential of AI for early COVID-19 diagnosis. CVDNet, trained on 219 COVID-19, 1341 normal, and 1345 viral pneumonia pictures, demonstrated potential as an automated diagnosis tool [63]. CoroNet obtained 89.6% accuracy, 93% precision, and 98.2% recall in detecting COVID-19 in three classes. CoroNet performed admirably in COVID-19 detection (3-class), achieving an overall accuracy of 89.6%, precision of 93%, recall of 98.2%, and 95% accuracy in 3-class classification. These promising results suggest CoroNet has potential for COVID-19 diagnosis, with further improvement expected as more data becomes available [64]. These contributions have revolutionised medical image segmentation, ushering in a new era of possibilities. While U-Net remains dominant for segmentation with strong performance on smaller datasets, it requires extensive annotations. Deep Fusion and ensemble approaches enhance accuracy but are computationally demanding. GAN-based hybrids generate realistic augmentations but often suffer from instability during training. The trade-off between efficiency and accuracy highlights the need for lightweight yet reliable segmentation models.

### 4.2 Multimodal Dataset Availability

Despite progress in CT-based datasets, there is a striking scarcity of multimodal repositories. CT dominates with datasets like SARS-CoV-2, COVID-CT, and RSNA, whereas MRI and PET datasets remain limited both in volume and annotations. This imbalance hinders fusion-based deep learning models, which require aligned CT, MRI, and PET scans to leverage complementary structural and functional insights.

Consequently, the availability of multimodal datasets represents a key gap restricting robust generalization. Surveyed studies have addressed this imbalance through weighted loss functions (e.g., class-balanced cross-entropy), oversampling of minority classes, and GAN-based synthetic augmentation. For example, Covid-CT studies often balanced datasets by generating synthetic pneumonia and normal cases.

## 5. Results and Discussion

The suggested DCNN design classifies CT images into two phases: COVID-19 and Normal. The model employs 16 weighted layers for image examination and classification. These layers include an input layer, three convolutional layers for feature extraction, three ReLU layers for non-linear activation, a normalization layer for data standardization, three max-pooling layers for dimensionality reduction, two fully connected layers for information integration, a dropout layer to prevent overfitting, a Softmax layer to generate probability distributions, and finally a classification layer to determine the final severity level. Two output layer neurons map to two possible severity levels. Of the imaging modalities, MRI still proves to be the most troublesome for training deep neural networks. The reasons include lower resolution for lung imaging, motion artifacts at scan time, smaller annotated datasets, and machine variability. PET imaging, while clinically useful for functional imaging, also presents challenges with extremely small dataset sizes and patient privacy issues.

The accuracy, recall, and precision of the DCNN CT-Scan model in classifying COVID-19 and normal classes have decreased by 85% and 93%, respectively, in comparison to the current VGG19 X-ray images (Fig. 8).

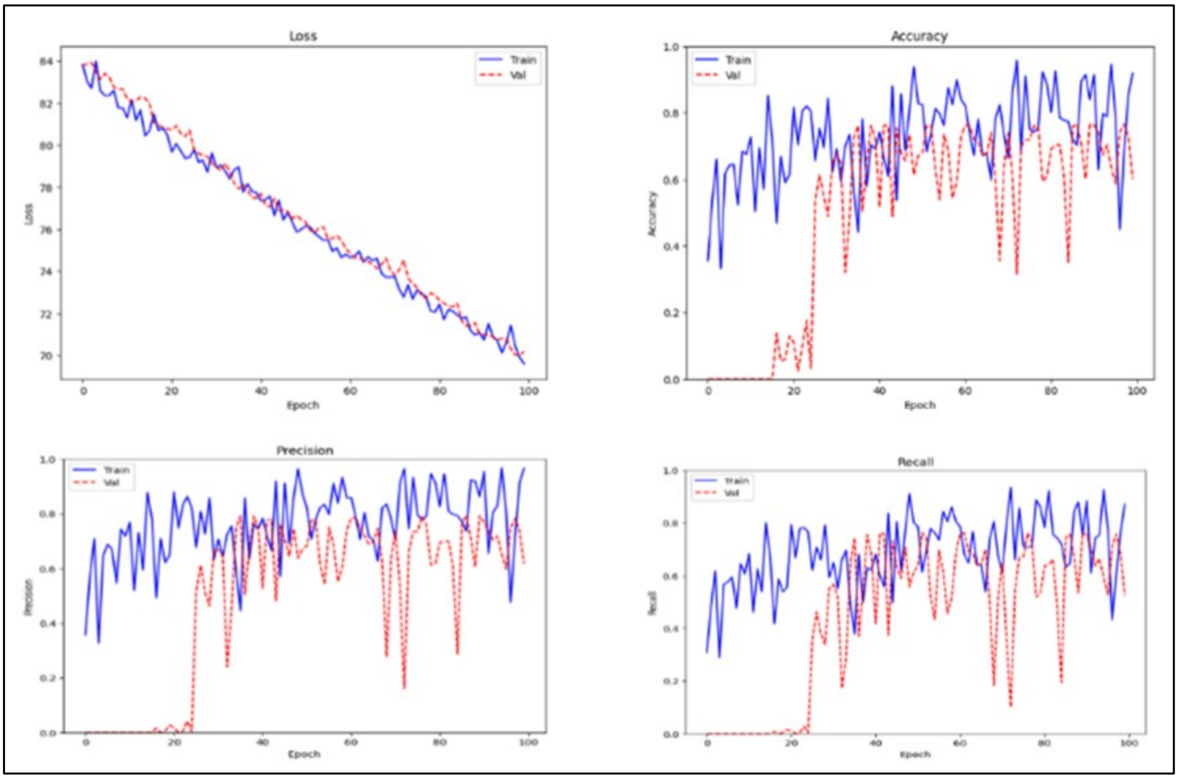


**Figure 8.** Graphs Plotted for Loss, Accuracy, Precision, and Recall

**Table 7.** Computational Requirements vs. Performance of Models

| Model | Accuracy (%) | GPU/Compute Requirement | Limitation |
|---|---|---|---|
| MobileNetV2 | 87.6 | Low (can run on CPU/GPU) | Misses complex features |
| ResNet50 | 98 | High-end GPU | High compute cost |
| DenseNet121 | 96 | High (multi-GPU recommended) | Overfitting on small data |
| U-Net | 88 | Moderate (GPU required) | Requires large annotations |

Table 7 compares the accuracy and processing demands of standard models. ResNet50 and DenseNet121 are deeper models that achieve higher accuracy at the expense of higher computational cost and a higher risk of overfitting, whereas lightweight networks like MobileNetV2 are efficient but compromise feature extraction.

## 5.1 Performance Evaluation

The results demonstrate that VGG19 performs significantly better on X-ray images than on CT scans for lung disease detection. This can be visualised in the following chart. Table 7 clearly shows that VGG19 achieves an accuracy of 90% on X-ray images, while the DCNN value drops to 85% for CT scans.

**Table 8.** Comparison of the Model with Accuracy, Precision, Recall and F1-Score

| S.No | Models | Precision (%) | Recall (%) | F1-Score (%) | Accuracy (%) |
|---|---|---|---|---|---|
| 1 | VGG19 [38] | 96 | 93 | 94 | 90 |
| 2 | Reviewed DCNN CT-Scan | 83 | 78 | 80 | 85 |

## 6. Conclusion

The ongoing COVID-19 pandemic has put millions of people's health at risk. During this survey, we aim to assess all the possible AI-supportive technologies that are designed to fight the pandemic through medical imaging. We suggest declaring the dominant and available literature on approaches so that new researchers are sufficiently knowledgeable regarding the prevailing knowledge and can help establish a cost-effective and quick model for tackling challenges related to the unique diagnosis of COVID-19. The majority of researchers carried out binary discrimination of X-ray images, i.e., CXR. For the task of feature extraction, the most notable technique is CNN, whereas bio-inspired techniques are the most commonly used algorithms for feature selection. Classification tasks are routinely carried out using DL techniques, which are widely utilized for performing these tasks. Finally, we point out some of the gaps in classification regarding the images of chronic diseases, which could be the target of future research. Some possible directions for future research include augmenting image datasets that involve the COVID-19 pandemic, reducing the computational cost of deep learning solutions, and enhancing parameter optimization methods. Among the hurdles that impede their clinical translation are the incorporation of deep learning systems into PACS and electronic health records, black-box interpretability issues, the cost of computational infrastructure, and the duration of regulatory approval. Hospital implementation is also limited by clinicians' lack of trust and concerns over dataset privacy.

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