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Deep learning-based COVID-19 detection: State-of-the-art in research

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Abstract

In the last two years, the coronavirus (COVID-19) pandemic put healthcare systems around the world under tremendous pressure. Imaging techniques (like Chest X-rays) play an essential role in diagnosing many diseases (such as COVID-19). There have been intelligent systems (Machine Learning (ML) and Deep Learning (DL)) able to identify COVID-19 from similar normal diseases. In this paper, we start by overviewing the status of COVID-19 from a historical standpoint and diagnosis updates. Moving on, provide an overview of the convolutional neural networks. Then, we elaborate Transfer learning method and its main approaches. Next, we provide a critical literature review on implementing Deep learning techniques: 1) Novel deep learning architecture; 2) Direct use of deep learning; 3) Transfer learning fine-tuning technique, and 4) Transfer learning feature extraction technique. For each of these, we evaluate and compare very recent studies published in highly ranked journals. The experiments show that all techniques achieve closer accuracy, ranging from (98-100 %). Along with all, the direct use of the deep learning technique records the highest accuracy and is less time-consuming and resource spending. Therefore, establishing such a technique is useful to predict the outbreak early, which in turn can aid in controlling the pandemic effectively.

Keywords: COVID-19, Deep learning, Machine learning, X-rays
2020 MSC: 68T07

1 Introduction

1.1 What is Covid-19

Ranging from the common cold to more severe diseases, coronaviruses (CoV) are a large family of viruses that cause illnesses, such as severe acute respiratory syndrome (SARS-CoV) and Middle East Respiratory Syndrome (MERS-CoV). As a new strain, a novel coronavirus (nCoV) has not been previously identified in humans (see Figure 1) [19].

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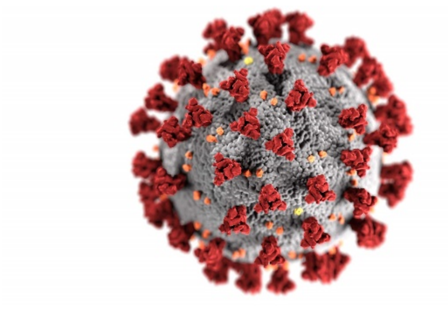

Figure 1: Coronavirus cell.

Since CoV are zoonotic, it can be spread between humans and animals. The studies found that MERS-CoV was transmitted from dromedary camels and SARS-CoV from civet cats. Yet, many coronavirus types are circulating in animals and not infected humans [93]. Figure 2 shows typical signs of infection, including respiratory symptoms, breathing difficulties, shortness of breath, cough, and fever. The infection can cause Pneumonia, kidney failure, severe acute respiratory syndrome, and even death [18].

Figure 2: Common signs of infection by Covid 19

As depicted in Figure 3, routine hand cleaning, covering the mouth and nose when sneezing and coughing, and adequately cooking meat and eggs are all typical advice to stop the transmission of illnesses. Stay away from someone who is coughing or sneezing and displaying signs of respiratory infection [60].

Figure 3: Standard recommendations to prevent infection by Covid 19

1.2 History of Covid 19

An unknown disease called Pneumonia occurred in Wuhan, Hubei province, China, in late December 2019. The outbreak had spread to 31 January 2020, and the infections around 20 countries were about ten thousand and more than 200 deaths [94].

After a couple of days, many independent laboratories announced that the causative agent of this Pneumonia is a novel coronavirus (nCoV). Then, the virus is called SARS-CoV-2 (severe acute respiratory syndrome coronavirus 2). Then, the World Health Organization (WHO) stated that the infected disease is called coronavirus disease 2019 (COVID-19). By the end of February 2020, in China, WHO stated that the SARS-CoV-2 had caused 2747 deaths and 78630. Furthermore, it spread to about 50 countries with 3664 cases. The COVID-19 epidemic has become a global health threat (see Figure 4) [92].

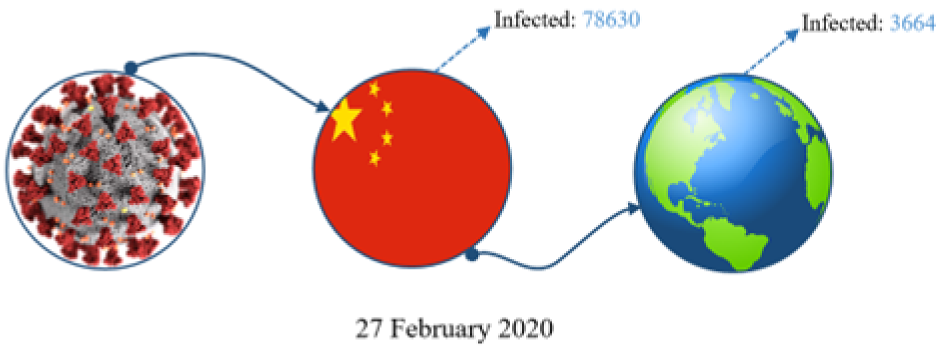

Figure 4: Statues of Covid -19 infections around the world

1.3 Diagnosis of Covid-19

To stop the virus from spreading and to prepare treatment to avoid consequences, early detection of COVID-19 is crucial. There are difficulties in recognizing and controlling the pandemic due to the daily increases in COVID-19 cases globally and the limits of the available diagnostic methods [28]. Researchers all around the world are actively looking for efficient diagnostic techniques and hastening vaccination and therapy development. As of the time this article was written, three diagnostic techniques are often employed: medical imaging, viral tests, and blood tests [39].

In blood, SARS-CoV-2 antibodies' presence can be detected using blood tests. Nevertheless, in diagnosing COVID-19, 2% or 3% is the reliability of blood tests [95]. From 10 January to 28 February 2020, 82 patients were received to a Wuhan hospital where COVID-19 and non-COVID-19 cases were 34 and 48, respectively. As shown in Figure 5, the experiments revealed that the sensitivity of suggesting COVID-19 using medical imaging, viral tests, and blood tests are 3%, 79%, and 97%, respectively [31], [5].

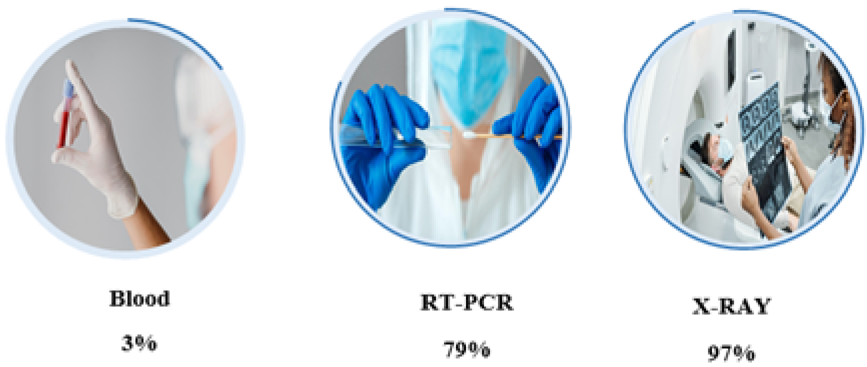

Figure 5: Sensitivity of Diagnostic Covid-19

As an essential tool, chest radiology scans are used for o diagnosing and managing COVID-19 early (since the respiratory system targets COVID-19). Using radiological scans, it is possible to accurately identify the state of the lungs and the various phases of disease or recovery. [27]. chest x-rays are considered a first-line COVID-19 diagnostic tool in different countries. Usually, a chest x-ray is available in most clinical settings because it is a low-time-consuming method for patient diagnosis. Accordingly, via chest x-rays, the degree of infection can be identified, the priority of treatment, and medical resources utilization[90].

This survey paper is organized as follows: Section 2 briefly defines the concept of artificial intelligence and presents its necessary implementations in medicine. Section 3 explains the Convolutional neural networks in detail and describes some important models. The concept of Transfer learning and its approaches are elaborated in Section 4. Section 5 defines datasets and their use in training, testing, and validation procedures. Section 6 provides a critical literature review on implementing Deep learning techniques in COVID-19 identification published in highly ranked journals, such as IEEE, Scopus, and Springer. Section 7 Compares all deep learning techniques used to detect COVID-19. Finally, we conclude the paper in Section 8. Figure 6 highlights the road map of this paper.

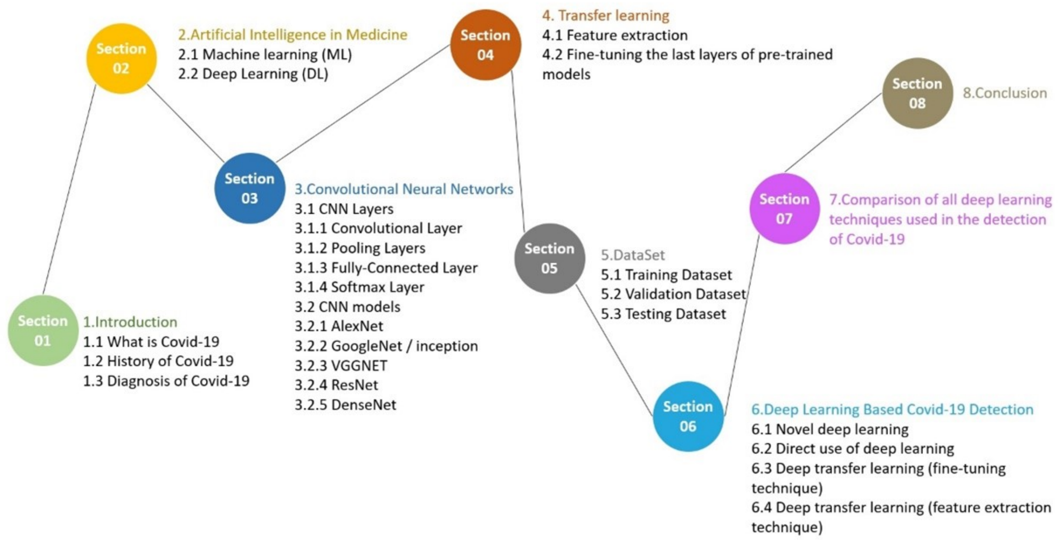

Figure 6: Organization of the paper

2 Artificial Intelligence in Medicine

Artificial intelligence (AI) is the study of how to make computers act in ways that are similar to how we would define intelligence in humans. Among scientists, AI is the general phrase used to define the inquiry field. For the foreseeable future, despite some people's concerns about developing an AI that could mimic every aspect of human behavior, AI systems will be "narrow," typically created to help humans with a specific task, such as interpreting a mammogram, adverting, or car driving. [52, 46].

The use of AI in medical imaging, including but not limited to image processing and interpretation, is one of the most promising areas of health innovation. AI has a wide range of potential applications, from image acquisition and processing to aided reporting, data mining, data storage, and follow-up planning. AI. AI is anticipated to significantly influence the everyday life of radiologists to its wide variety of applications [66, 23].

2.1 Machine learning

As a branch of AI, machine learning (ML) plays an essential role in many fields of computer sciences and engineering fields. It makes it possible to extract useful patterns from samples, which is a function of human intelligence. Usually, a computer can perform any task tirelessly and consistently in contrast to a human [33]. Nowadays, ML algorithms play potential components in enabling many systems to diagnose and make decisions. Accordingly, the ML-empowered systems showed the capability to learn and perform tasks that were thought too complex for systems [25].

Basically, ML trains a computer to use prior knowledge to address a specific problem. Because of the existence of inexpensive memory and cheaper computing power, ML is implemented in different topics to tackle issues faster than a human [51]. Therefore, to investigate the correlation among the data that are not clear to a human, ML gives the capability of processing and analyzing a large amount of data. To make judgments, ML is based on several algorithms that enable the system to perform abstractions based on their experiences [47].

2.2 Deep Learning (DL)

As a branch of ML, deep learning allows computational models composed of multiple processing layers. With multiple levels of abstraction, DL aims to learn data representations. Using DL methods, different state-of-art have been significantly improved, such as object detection, visual object recognition, speech recognition, and several medical fields, such as drug discovery and genomics [78]. Figure 7 defines and summarizes the historical development of AI, ML, and DL.

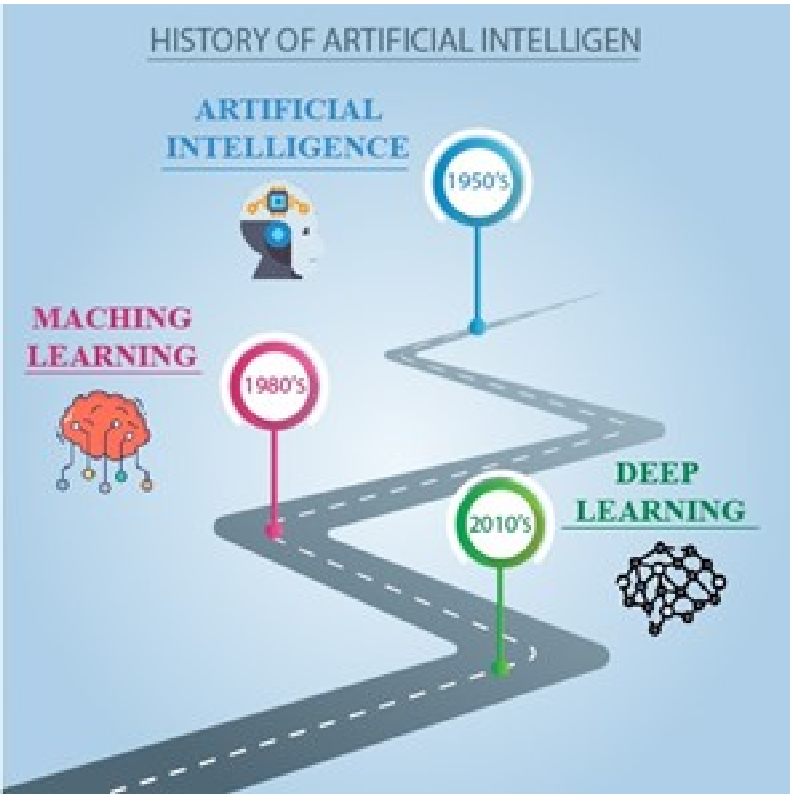

Figure 7: History of AI, ML, and DL developments

DL uses the backpropagation algorithm to explain how a machine should adjust its internal parameters to calculate each layer's representation from the previous layer's representation to uncover complicated structures in enormous data sets. Deep convolutional neural networks have advanced the processing of audio, speech, images, and video. On the other hand, recurrent nets process sequential data such as speech and text [53]. DL performed exceptionally in several applications in different domains, such as object segmentation, speech recognition, image recognition, pose estimation and object and key points detection. The development of deep learning libraries, high-speed computation resources and data availability are some of the main factors that played an essential role in DL success [8].

3 Convolutional Neural Networks

In the image processing field, Convolutional neural networks (CNNs) are considered the most successful model. CNN can automatically learn and extract image attributes and performs greatly in machine translation, semantic segmentation, recognition, and image classification [97]. Such as Handwritten digit recognition, many visual pattern recognition systems utilize CNN models. Furthermore, CNNs have been used successfully in image, eye and face identification [85].

3.1 CNN Layers

Crucial components of CNNs consist of the following layers: 1) convolutional layer, 2) pooling layer, 3) fully-connected, and 4) Softmax layers.

3.1.1 Convolutional Layer

Convolution is the main process for getting the features discovery in CNNs. A mathematical operation of matrices "dot product" is applied of weights across all content of every sample of the input data (such as videos and images). Accordingly, feature maps are then generated [56]. We also have a kernel or a filter (also known as a feature detector), which will explore the image's receptive fields to verify if the feature exists. This procedure is called convolution.

Figure 8 shows attributes detector is a two-dimensional (2-D) array of weights to represent the image's part. In the figure, typically, the filter size is represented as a 3x3 matrix, where the weights can change the size and calculate the size of the receptive field. Then, to an image area, the filter is applied, and a dot product is determined between the filter and the input pixels. Afterwards, the output array is fed by the dot product [7]. Then, repeating the process, the filter shifts by a stride until the kernel has completely covered the image. From the filter and input, the final output from the series of dot products is called an activation map, feature map, or convolved feature. To the feature map, the Rectified Linear Unit (ReLU) is applied by a CNN After each convolution operation, introducing nonlinearity to the model [37]. In CCN, nonlinearity is usually used to alter or cut off the generated output. Several nonlinear functions are used. Nevertheless, such as image processing, ReLU is the common function implemented in different domains. Finally, ReLU is written as ReLU = $\{0, \text{ if } x < 0 \; x, \text{ if } x \geq 0\ \}$ [9].

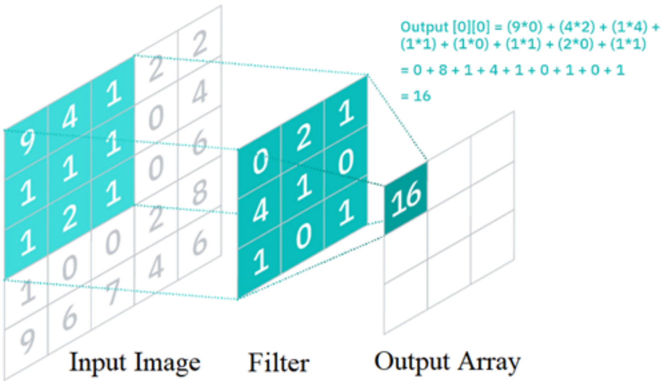

Figure 8: Convolutional layer.

3.1.2 Pooling layers

In this layer, the number of parameters and dimensionality is reduced in the input. Therefore, it is also called a down sampling layer. Across the entire input, the pooling operation sweeps a filter. Unlike the convolutional layer, no weights are available in the filter. Within the receptive field, an aggregation function is applied by the kernel to the values. The output array is populated [76]. Pooling layers have two main kinds:

- **Average pooling:** To send to the output array, it determines the average value within the receptive field as the filter moves across the input.
- **Max pooling:** Similarly, the pixel with the maximum value is selected to send to the output array. Usually, max pooling is used more than average pooling [10].

Additionally, in the pooling layer, while much information is lost, CNN gets several benefits from the pooling layers. Accordingly, they limit the risk of overfitting, improve efficiency, and decrease complexity [6].

3.1.3 Fully-Connected Layer

This layer directly connects each node in the output layer to a node in the previous layer. This layer's classification task is performed according to the last layers' attributes and their filters extracted. While ReLU functions are used in pooling and convolutional layers, fully-connected layers often leverage a softmax activation function to classify inputs correctly, introducing probabilities ranging from 0 to 1 [17].

3.1.4 Softmax Layer

The softmax layer is regarded as an effective method for demonstrating category distribution. It is usually utilized in the output layer. The output values exponent is normalized by the softmax function. A certain probability of the output is differentiable and represented by this function. Furthermore, the maximum value probability is increased by the exponential element.

$$O_i = \frac{e^{z_i}}{\sum_{i=1}^{M} e^{z_i}} \tag{3.1}$$

where M refers to the output nodes number, o_i denotes the number of softmax output I, and z_i defines the output i before the softmax [34].

To recap, as depicted in Figure 9, the main parts of CNNs (from the last to the first layer) are Softmax layers, fully-connected, pooling layer, and convolutional layer.

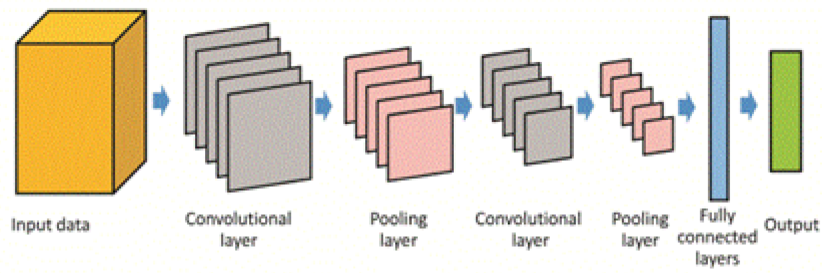

Figure 9: The structure of CNN layers

3.2 CNN models

Since 1998, when the first effective CNN was created, several CNN designs have been presented in the literature. For example, for handwritten digit recognition, Yann LeCun developed LeNet. In comparison to existed models, it is regarded as shallow architecture. LeNet consists of two fully connected layers, two average pooling, and three convolutional [99]. This subsection summarizes the main CNN models utilized for localization, detection, and classification tasks.

3.2.1 AlexNet

As a pre-trained CNN model, Alexnet was developed by the SuperVision group from the scholars Ilya Sutskever, Alex Krizhevsky, and Geoffrey Hinton. In each layer, Alexnet consists of several filters with stacked convolutional layers containing 11x11, 5x5,3x3 convolutions, ReLU activations, data augmentation, dropout, and SGD with momentum for face recognition [4, 63]. Alexnet significantly influences image classification and recognition tasks since its performance is exceptional. In 2012, Alexnet won ImageNet Large Scale Visual Recognition Challenge (ILSVRC); from (26 to 15.3%), it achieved a top-five error rate.

3.2.2 GoogleNet / inception

In 2014, GoogleNet won ILSVRC; at 6.67%, it achieved a top-five error rate. Compared to the existing CNNs, GoogleNet is significantly deeper and consists of an inception module (IM) in addition to pooling and convolutional layers. Along with spatial correlations, it can learn cross-channel correlations (depth-wise) and acts as a small network. GoogleNet comprises 6 convolutional layers: one concatenation layer, one max pooling layer, and four 1×1 convolutional layers. Several GoogleNet models with slightly modified inception components and improved performance have been suggested; for example, Inception-v4, Inception-V3, Inception-V2, and Inception-ResNet [80, 3].

3.2.3 VGGNET

At Oxford University, the Visual Geometry Group (VGG) developed VGGNet. In 2014, VGG got runner-up in the ILSVRC challenge. Similar to AlexNet and GoogleNet, it got a top-5 error rate of 7.3%. Using an architecture with very small (3×3) convolution filters, VGGNet has the advantage of architectural simplicity with 19 or 16 convolutional layers. The number of parameters in VGGNet is triple what is used in AlexNet [79, 96].

3.2.4 ResNet

IN 2015, ResNet won the ILSVRC challenge, and under 3.6%, it achieved a top-five error rate. A residual learning component is introduced by ResNet to the architecture of CNN. With a skip connection, a regular layer is existed in the residual unit (RU). The input signal of a layer is allowed by skip connection to cross the network by connecting it to the layer's output. The RUs of 152 layers enable the training of the extremely deep model. Finally, the rest of ResNet has 101, 50, and 34 layers [32, 91].

3.2.5 DenseNet

In the network, each layer in DenseNet is connected to every other forward. In the regular CNN architecture, L(LC1)=2 layer connections exist in DenseNet instead of L between L layers. In the network, the feature maps produced by any layer are used by all subsequent layers. This makes it possible to propagate and reuse features, including the final ones. At 6.12%, DenseNet achieved a top 5 error rate on ImageNet. Nevertheless, unlike other proposed CNN architectures, less computational cost and fewer parameters are required, such as ResNet [35].

4 Transfer learning

As a crucial tool in ML, Transfer learning seeks to tackle the fundamental problem of insufficient training data. This method transfers the knowledge from the source to the target domain. It is performed by relaxing the assumption that the training and test data need to be independent and identically distributed (i.i.d). Accordingly, a significant impact can be achieved in different domains, which are challenging to enhance due to insufficient training data [81].

Many ML techniques perform adequately with the fixed distribution when data for training and testing purposes is extracted from the same attribute space. Therefore, by collecting new data for training, most statistical models should be reassembled if any change happens to the distribution. When the system is needed, it is time-consuming and expensive to recollect the needed data for retraining the system. Additionally, we have access to insufficient labeled data in some cases. Transfer learning between task domains is a crucial solution to decrease the efforts of the model recalibration in such scenarios [82].

Usually, through the use of pre-trained models, the transfer learning method is expressed. Specifically, pre-trained models are used to tackle a particular problem and train on a large benchmark dataset. Therefore, the main aim of implementing Transfer learning is to reduce time and computational cost in training models [54, 30]. The differences between the transfer learning approach and learning from scratch are shown in Figure 10. The approaches of the transfer learning method are as follows:

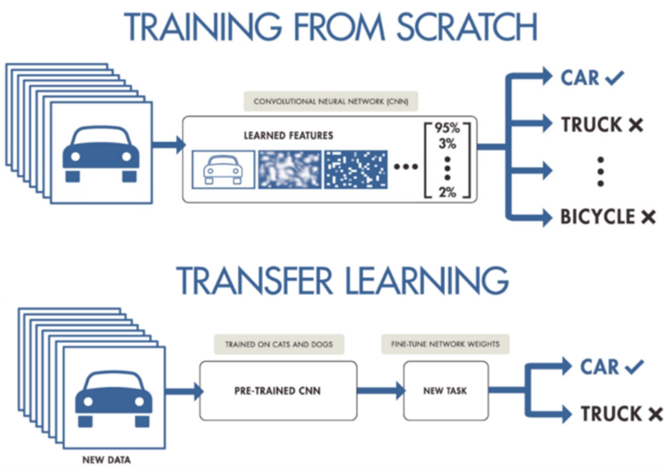

Figure 10: Transfer Learning

4.1 Feature extraction

Using a pre-trained CNN, a new network's weights can be initialized on a large-scale natural image dataset. The network is trained on the target data [75]. The main aim of feature extraction is to decrease the feature number of any dataset. Accordingly, original features are discarded from the existing ones, and a new set is created. It is important to mention that Most of the information of the original feature set must be summarized by the created (reduced) set. Therefore, combining the original set can create a summarized version of the original features [21].

4.1.1 Fine-tuning the last layers of pre-trained models

On a large-scale natural image dataset, some of the early layers of the pre-trained model were frozen. While the final layers were fine-tuned, the weights were kept unchanged [13]. It involves adding or replacing new structures to specific network parts. Some or entire networks part are kept and then transferred into the target domains. Accordingly, training the networks in the target domains from scratch does not always reduce the training duration. [69].

5 DataSet

Machine learning methods learn from examples. As illustrated in Figure 11, a dataset contains many separate pieces of data (infected and non-infected images) that can be used to train an algorithm to find predictable patterns [71, 20]. The quality of an AI solution is determined by the learning algorithm (such as a deep neural network model) and the datasets used to train and evaluate that algorithm. One of the most challenging tasks in implementing ML and DL approaches is obtaining suitable datasets for the training, testing and evaluating the proposed techniques [12].

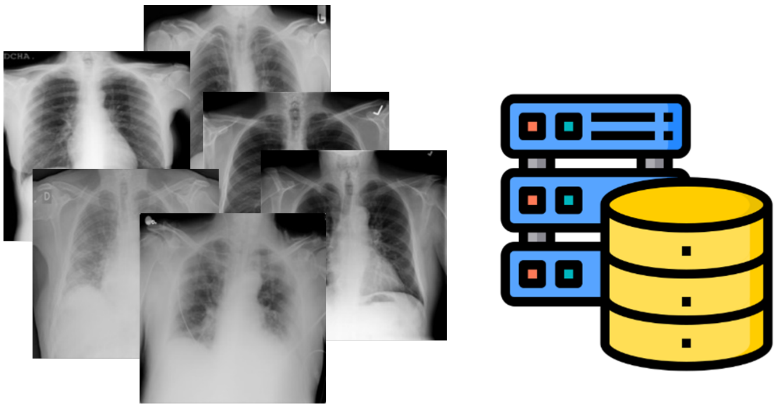

Figure 11: Chest x-ray dataset

5.1 Training Dataset

Usually, the dataset is fed into the deep learning algorithm to train the model. In the training set, the model is trained repeatedly on the same data during each epoch. Then, the process is continued to learn about data features. The aim is to implement the model to anticipate new data that has never been seen before. Accordingly, the predictions are based on the model's learning in the training data [29].

5.2 Validation Dataset

Separate from the training set, a validation set of the dataset is used to validate the model during the training. This process provides information that will help the developer to adjust the hyperparameters. In the training set, the model is trained on the data with each epoch during training. At the same time, the model is validated on the data in the validation set. A validation set is necessary to ensure that the model does not overfit the data in the training set. The concept of overfitting is that the model behaves well in classifying data in the training set. Nevertheless, it cannot accurately generalize and classify data that has not been trained on [62].

5.3 Testing Dataset

After the model has been trained, the test set is utilized to test the model. It is different than training and validation sets. The model will be used to predict the output of the unlabeled data in the test set once it has been trained and verified using our training and validation sets [49]. It is worth mentioning that the test set should not be labeled as the training set and validation set. Therefore, the two sets must be labeled so that it is possible to see the metrics given during training (such as accuracy and loss from each epoch) [77].

6 Deep Learning-Based COVID-19 detection

This research improves the understanding of deep learning-based COVID-19 detection techniques by looking over and reviewing previous research in the field. A total of 40 papers were analyzed to propose a comprehensive understanding of the existing studies of each technique. Relevant data were taken from papers published during the period 2020–2022. These supreme papers are taken from scientific databases. As illustrated in Figure 12, the deep learning techniques used in COVID-19 detection are as follows:

1. Novel deep learning architecture.
2. Direct use of deep learning.
3. Transfer learning fine-tuning technique.
4. Transfer learning feature extraction technique

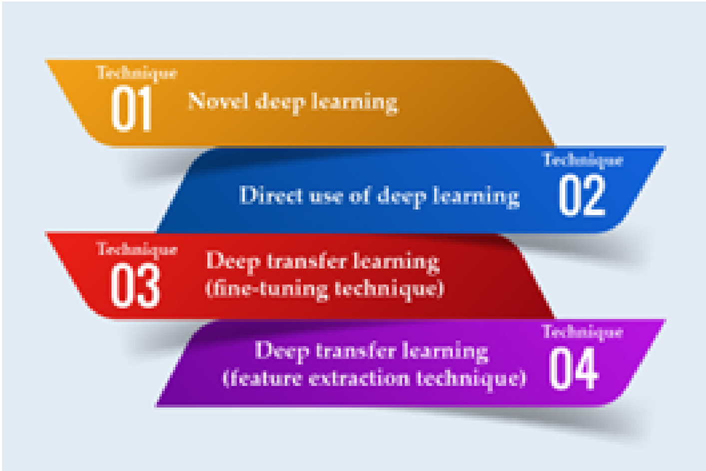

Figure 12: Deep learning techniques used in COVID-19 detection.

6.1 Novel deep learning

The author in [38] designed and proposed a novel and robust CNN model for detecting COVID-19 disease using publicly available datasets. This model was verified to determine whether the patient is infected with COVID-19 and achieved 99.20% accuracy. COVID-Net mode was proposed by the authors [89] as a deep CNN design tailored for detecting COVID-19 cases from chest x-rays images. It leveraged residual architecture design principles. To examine COVID-19, COVID-Net is considered the first open-source network design. The test demonstrated that its performance reached 93.3%. As an ensemble deep learning model, the authors in [83] developed the EDL-COVID model by employing deep learning and ensemble learning. Multiple snapshot models of COVID-Net have been combined in designing the EDL-COVID model. The findings indicated that EDL-COVID provides promising results for COVID-19 case identification with a 95 percent accuracy rate.

A novel artificial neural network (called Convolutional CapsNet) was developed in [86]. With capsule networks, chest X-ray images were used to propose the Convolutional CapsNet. The suggested model was intended to give rapid and accurate (with binary classification) diagnoses for COVID-19 diseases (COVID-19 and No-Findings) and multi-class classification (Pneumonia, No-Findings, and COVID-19). Accordingly, the tests demonstrated that the model's accuracy was 97.24%, while it was 84.22% for multi-class. In work in [48], two novel custom CNN architectures, namely COVID-RENet-1 and COVID-RENet-2, were developed. The proposed technique systematically employs Region and Edge-based operations along with convolution operations. The performance was a good result, with an accuracy of 98%.

In [2], as a novel model, Decompose, Transfer and Compose (DeTraC) has been proposed. In the DeTraC, the class decomposition mechanism is used to investigate image dataset class boundaries. Thus, any irregularities in the image dataset can be dealt with by DeTraC. The tests demonstrated DeTraC performance with a sensitivity of 100% and an accuracy of 93.1%. In another study, in [36], the CoroDet model was developed to achieve accurate diagnostics in three cases: 1) four classes classification (COVID-19, Normal, non-COVID-19 viral pneumonia, and non-COVID Bacterial Pneumonia), 2) three classes classification (COVID-19, Normal, and non-COVID-19 Pneumonia), and 3) two classes classification (COVID-19 and Normal). CoroDet revealed a high accuracy performance of 91.2%, 94.2%, and 99.1% in the 4, 3, and 2 classes classification cases, respectively. Similarly, the DarkCovidNet model was proposed in [65]. In the study, the authors proposed a 17-layer CNN model to achieve accurate diagnostics in two cases: 1) three classes classification and 2) two classes classification. The accuracy of the cases reached 87.02% in the three classes classification, whereas it was 98.08% in the two classes classification.

Based on the residual neural network, The CVDNet model was developed in [64] as a seep CNN model architecture. To capture local and global features of the inputs, the model was designed using two parallel levels with different kernel sizes. To classify COVID-19, normal and viral pneumonia infection, detection accuracy reached 97.20%, 96.73% and 96.58%, respectively. Based on depth-wise dilated convolutions, a novel deep neural network architecture was developed [55]. The model recorded an accuracy of 97.4% for the binary class. Finally, the main points of the studies are summarized in Table 1, and Figure 13 compares their achieved accuracy

Table 1: Summary of studies that used the novel deep learning technique.

Study	Dataset	No of Classes	Samples				Portion %			Model	Accuracy %
			Total	Normal	Covid 19	Viral Pneumonia	Training	Validation	Testing		
[38]	Joseph Paul et al., COVID-19 Radiography Database	2	1250	625	625	-	60	20	20	-	99.2
[89]	COVIDx(COVID-19 Image Data Collection, COVID-19 Chest X-Ray Dataset Initiative, RSNA Pneumonia Detection challenge dataset, actualMed COVID-19 Chest X-Ray Dataset Initiative, and COVID-19 radiography database	3	13962	8066	358	5538	90	-	10	COVID-Net	93.3
[83]	COVIDx(ActualMed COVID-19 dataset, COVID-19 image data collection, COVID-19 radiography database, and RSNA pneumonia detection challenge	3	15477	8851	573	6053	90	-	10	DL-COVID	95
[86]	Joseph Paul et al, Wang et al	2	3150	1050	1050	1050	90	-	10	CapsNet	97.24
[48]	Pneumonia	2	644	3224	3224	-	80	-	20	COVID-RENet-1, COVID-RENet-2	98
[2]	Japanese Society of Radiological Technology, Joseph Paul et al		1764	-	-	-	70	-	30	DeTraC	93.1
[36]	COVID-R	2	7390	3108	2843	1439	80	-	20	CoroDet	99.1
[65]	Cohen JP developed the COVID-19 X-ray image database. The ChestX-ray8 database was provided by Wang et al	2	1500	500	500	500	80	-	20	Dark Covid-Net	98.08
[64]	COVID-19 Radiography Database	2	2905	1341	219	1345	70	10	20	CVDNet	97.20
[55]	Guangzhou Medical Center, China, and Sylhet Medical College, Bangladesh	2	5856	1583	2780	2780	80	-	20	CovX Net	97.4

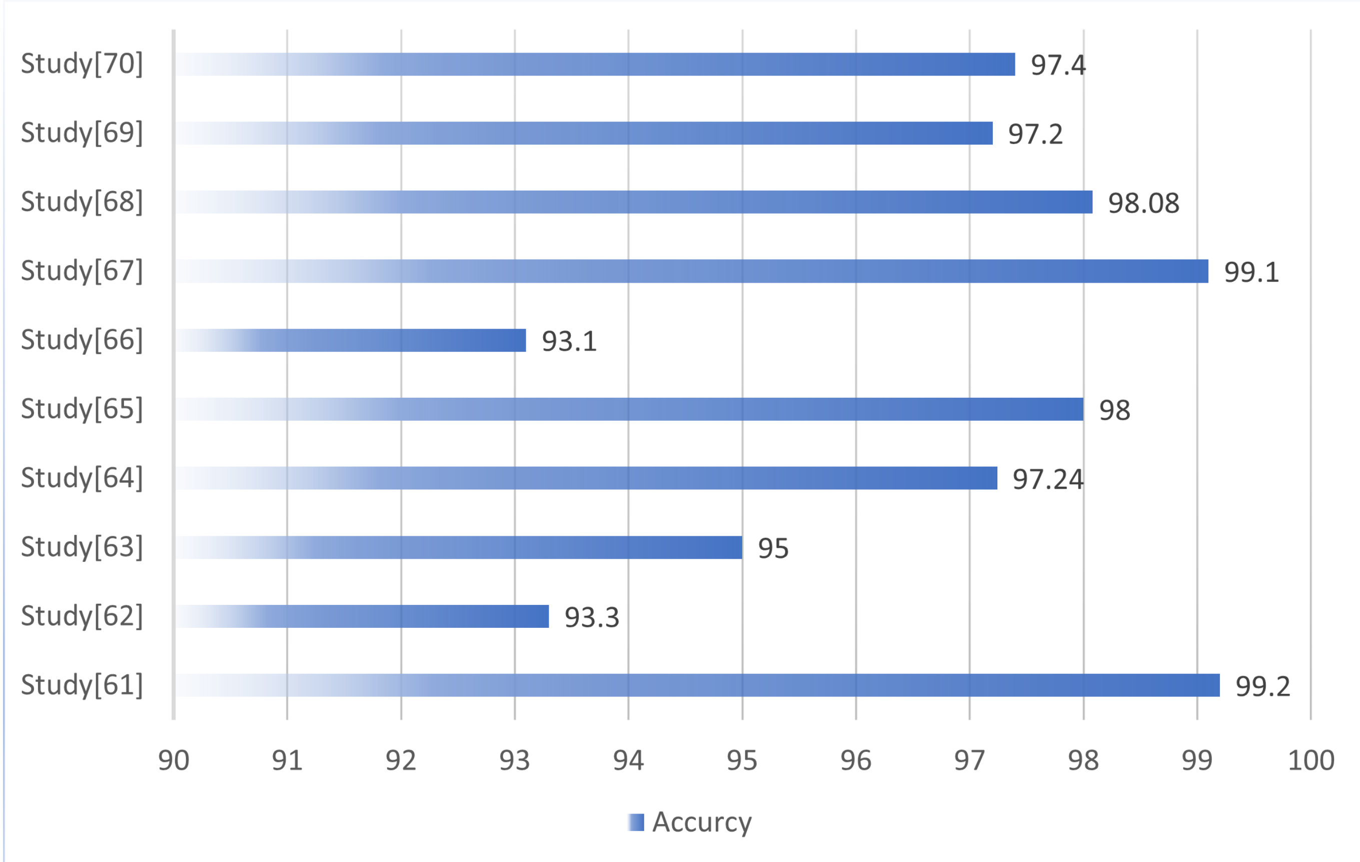

Figure 13: The achieved accuracy of studies that used the novel deep learning technique

6.2 Direct use of deep learning

The investigated studies that utilized CNN architecture in a directed way are as follows. The authors in [74] applied Deep learning methods: CNN, VGG16, VGG19, and InceptionV3 to the chest x-ray dataset. Adam has been used as an optimizer. Relu and softmax were used as activation functions. The CNN model's accuracy rate was 93%, 95% and 48% for VGG16, VGG19 and InceptionV3. Three phases model were applied in [45]. In the first stage, the datasets were collected from four sources. Then, they used image augmentation techniques to improve the training process efficiency. Lastly, the authors applied the pre-trained ResNet50 model of CNN to extract deep features on chest x-ray images (to distinguish between Covid-19 and nonCovid-19 patients). The results proved the performance of the model with an accuracy of 99.5%

As pre-trained on Image Dataset, the authors [41] utilized the architectures of the four models ResNet50, Xception, Inception V3, and MobileNet. The four models' accuracy indicated that CNN architectures are more dependable for Covid-19 patients. The results MobileNet achieved the maximum performance in terms of F score, with the highest accuracy of 98.6%. The accuracy of the rest models reached: 98.1%, 97.4%, and 82.5% in Inception V3, Xception, and ResNet50, respectively.

In [1], the authors developed a model to diagnose COVID-19 by analyzing computed tomography images. The test of the model revealed a promising accuracy in the following: 1) 96.90% in the ResNet network structure, 2) 95.87% in the VGG-16 network structure, and 3) 95.18% in the GoogleNet network structure. A comparison was conducted in [42] among three models ResNeXt, Xception, and Inception V3. From the Kaggle repository, the authors collected 6432 chest x-ray scan samples divided into 5467 (965) for training (validation). After comparing the models, the tests demonstrated that the Xception model achieved the highest accuracy (97.97%).

In [59], the performance of the following pre-trained models was investigated: VGG19, Mobilenet, Xception, ResNet50, NasNet Large, Inception v3, Inception ResNet v2, and VGG16. Before feeding the data to the models, the authors applied different augmentation and preprocessing functions to the training data. The highest accuracy (94%) was achieved by the models: Mobilenet, Xception, and VGG16.

The authors in [22] utilized the extracted DL features technique to predict patient progress as "improve" or "worse". The tests revealed that the accuracy was about 83%. In [68], the following pretrained CNN models were evaluated: NasNet-mobile, DenseNet-121, Xception, Inception-V3, VGG-16, and viz. Pre-trained models were instantiated with the weights of their ImageNet pretrained. Then, the models are truncated at fully-connected layers. The resultant feature maps are averaged globally and input to a final dense layer using Softmax activations to provide prediction probabilities. Superior accuracy performance of (93%) was achieved via the VGG-16 model. Three different CNN models, ResNet-50, Inception- ResNetV2, and InceptionV3, were evaluated in [58] to classify COVID-19 from the chest X-ray images. ResNet50 provided better classification accuracy of 98% than the other models. The authors in [15] trained 201 layers DenseNet after downloading the pre-trained model on ImageNet. Then they trained the model on the COVID-19 dataset. After using the transfer learning approach, the accuracy was raised to about 99.3%. Accordingly, we summarized the studies in Table 2 and compared the achieved accuracy in Figure 14.

Table 2: Summary of studies that utilized direct use of the deep learning technique.

Study	Dataset	No of Classes	Samples				Portion %			Model	Accuracy %
			Total	Normal	Covid 19	Viral Pneumonia	Training	Validation	Testing		
[74]	Chest x-ray dataset.	3	657	219	219	219	-	-	-	VGG19	95
[45]	Chest x-ray images data set, Italian Society of Medical Radiology (SIRM), Corona Virus open-source shared data set. Data set created by compiling diagnosed images from articles.	2	1200	100	200		-	-	-	ResNet-50	99.5
[41]	Collection of the public datasets	2	6500	600	500		80	-	20	Mobile Net	98.6
[1]	A research team from the University of Qatar, Doha, Qatar, Bangladesh and Dhaka University, collaborating with their collaborators in Pakistan and Malaysia, medical doctors created a database of chest X-ray images COVID-19 Chest X-ray Database.	3	3150	1341	219	1341	90	-	10	ResNet	96.90
[42]	Samples have been collected from the Kaggle repository	3	6432	1345	490	3632	85	-	15	Xception	97.97
[59]	Algerian private COVID-19 chest X-rays dataset, dubbed COVID Chest X-Ray Dataset Master, COVID-19 Radiography Database, Mendeley Chest X-Ray Images (Pneumonia).	3	6280	2924	518	2838	70	10	20	Xception	94
[22]	Chexpert	2	4547	3108	1439	-	80	-	20	Dense Net121	82.7
[68]	Pediatric chest x-rays dataset, RSNA chest x-rays dataset, CheXpert chest x-rays dataset, NIH chest x-rays -14 dataset, Twitter COVID-19 chest x-rays dataset, Montreal COVID-19 chest x-rays dataset	2	-	-	-	-	80	-	20	VGG-16	93
[58]	Dr. Joseph Cohen et al., chest x-rays Images (Pneumonia)	2	3041	2800	341	-	80		20	ResNet 50	98
[15]	NIH ChestX-ray14, COVID-19 database	3	25560	8640	8280	8640	80		20	Dense Net	99.3

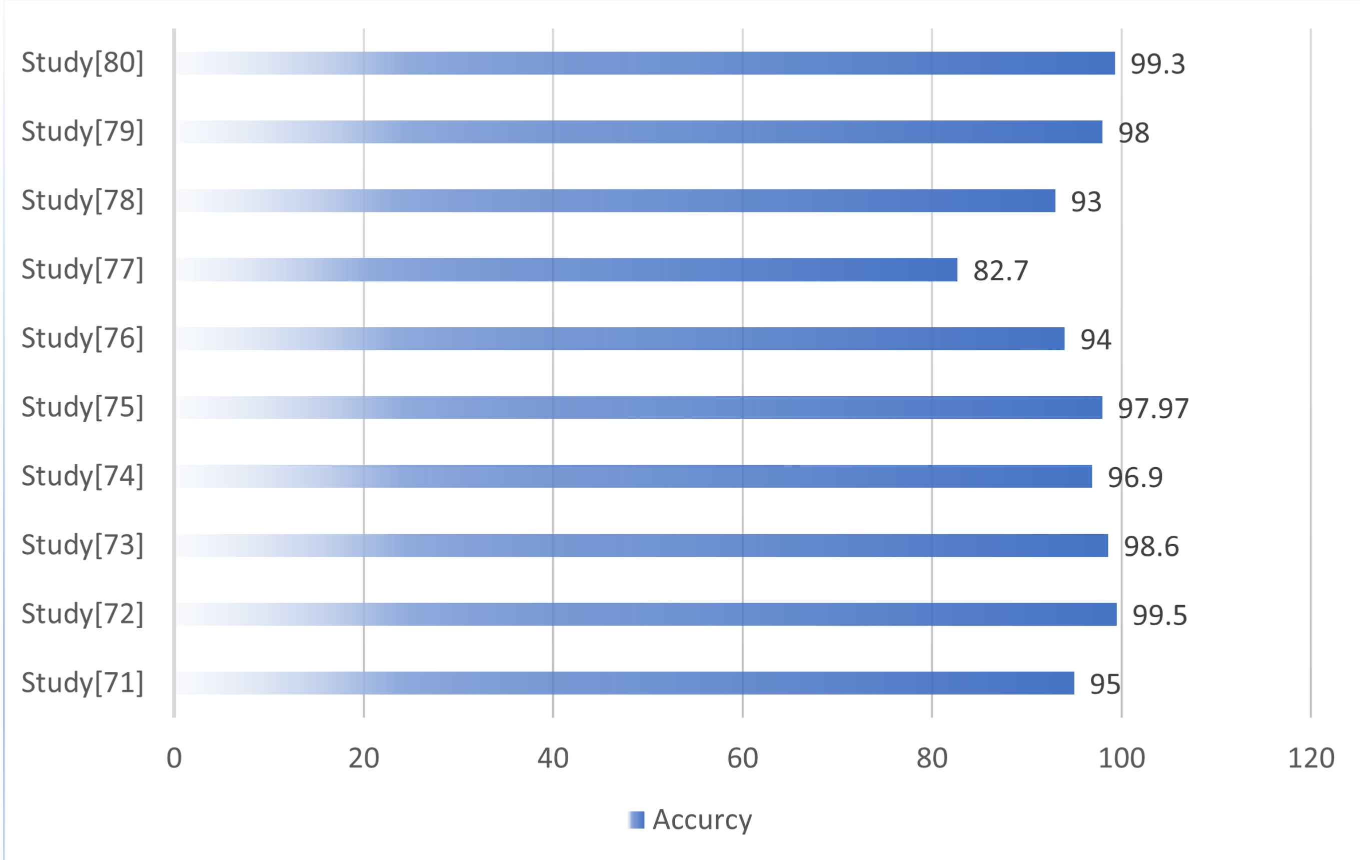

Figure 14: The achieved accuracy of the studies that utilized direct use of the deep learning technique

6.3 Deep transfer learning (fine-tuning technique)

Similar to other techniques, in this section, we investigated ten recent studies that utilized the transfer Learning fine-tuning technique. To classify chest X-ray images of COVID-19 and normal cases, the authors in [40] used a deep-learning-based approach to fine-tuning pretrained CNN (fine-tuned ResNet50 model). The tests revealed that the accuracy of the model reached 92.8%. Extensive tests were conducted in [87] to prove the superiority of AI-based structures over several models. With a Bayesian optimization additive, SqueezeNet has been utilized to diagnose COVID-19. The critical success led to outperforming the suggested model, fine-tuned hyperparameters, and augmented datasets. The study determined a higher COVID-19 diagnosis accuracy of 98.26%. In [26], a pre-trained ResNet50 model (used fine-tuned technique) was proposed. The model aimed to classify chest x-ray images into four cases: viral Pneumonia, bacterial Pneumonia, COVID-19, and normal. The authors reported better results when compared with the COVID-net, where sensitivity was 100%, and the achieved accuracy was 96.23%.

The work published in [61] utilized the architectures EfficientNet, NASNet, Xception, DenseNet121, and VGG16. They were pre-trained models using ImageNet weights, also used for fine-tuning the model. The performance of EfficientNet, in terms of accuracy, outperformed other models as follows: EfficientNet (93.48%), DenseNet121 (89.96%), Xception (88.03%), NASNet (85.03%), and VGG16 (79.01%). The fused-DenseNet-Tiny model was developed in [57]. The lightweight DCNN model was based on a densely connected neural network (DenseNet) truncated and concatenated. The model utilized transfer learning, feature fusion, and partial layer freezing to train and learn chest x-ray features. The study in [72] demonstrated that the pre-trained VGG16 model could detect COVID-19 from non-COVID-19 cases with an accuracy of 80%. The authors in [84] evaluated the effectiveness of AI in the rapid and precise identification of COVID-19 from chest x-ray images. Fine-tuned and -trained deep learning algorithms were used to improve the accuracy of the algorithms. The test demonstrated that VGG16 and MobileNet obtained the highest accuracy of 98.28%.

To classify COVID-19 patients, using a transfer learning approach, the authors in [43] designed an efficient hybrid algorithm that integrates the robustness of MobileNet to extract features and support vector machine (SVM). The tests showed that the classification accuracy reached 95%. To maximize the accuracy, in [88], the authors developed a model using a transfer learning approach and pre-trained customized models. ResNet50, MobileNetV2, InceptionV3, and VGG16 extracted deep features. The model showed the train and test accuracies as 93% and 98%, respectively. Additionally, the pre-trained customized models showed very high classification accuracy: VGG16 (98%), InceptionV3 (97%), and MobileNetV2 (97%). The procedure transfer learning was adopted in the model proposed in [13] for two types (two and three classes). The model behaved better in two classes type (98,75%), while it was 93.48% in three classes. Finally, Table 3 and Figure 15 summarize studies based on the deep transfer learning fine-tuning technique.

Table 3: Summary of studies that utilized the deep transfer learning fine-tuning technique

Study	Dataset	No of Classes	Samples				Portion %			Model	Accuracy %
			Total	Normal	Covid 19	Viral Pneumonia	Training	Validation	Testing		
[40]	GitHub, 2020; Kaggle, 2020b, Radiology Assistant, 2020	2	380	200	180	-	75	-	25	ResNet 50	92.6
[87]	COVID chest X-ray dataset, Kaggle chest X-ray pneumonia dataset	3	13962	1536	1536	4290	80	10	10	Squeeze Net	98.2
[26]	COVIDx	3	2862	931	68	1863	-	-	-	ResNet-50	96.23
[61]	(COVID-19 X-rays) chest X-ray images were collected from various private hospitals in Maharashtra and Indore regions from India	3	16634	6000	5634	5000	70	20	10	Efficient Net	93.48
[57]	Curated Dataset for COVID-19 Posterior-Anterior Chest Radiography Images (X-Rays).	3	9208	3270	1281	4657	80	20	-	Dense Net	97.99
[72]	chest X-ray and CT images of COVID-19 patients	2	140	70	70		75		25	VGG16	80
[84]	covid19-radiography-database	3	3886	1341	1200	1345	90	-	10	Mobile Net	98.28
[43]	COVID-19 radiography images from Kaggle	2	535	316	219	-	100	-	-	Mobile Net	95
[88]	COVID-19 Radiography Database	2	2541	-	-	-	75	-	25	Inception V3, VGG16	98
[?]	Cohen JP (2020) COVID-19 image data collection, Radiological Society of North America (RSNA), Radiopaedia, Italian Society of Medical and Interventional Radiology (SIRM), and COVID-19 X rays from Kaggle	2	1428	700	224	504	-	-	-	VGG19	98.75

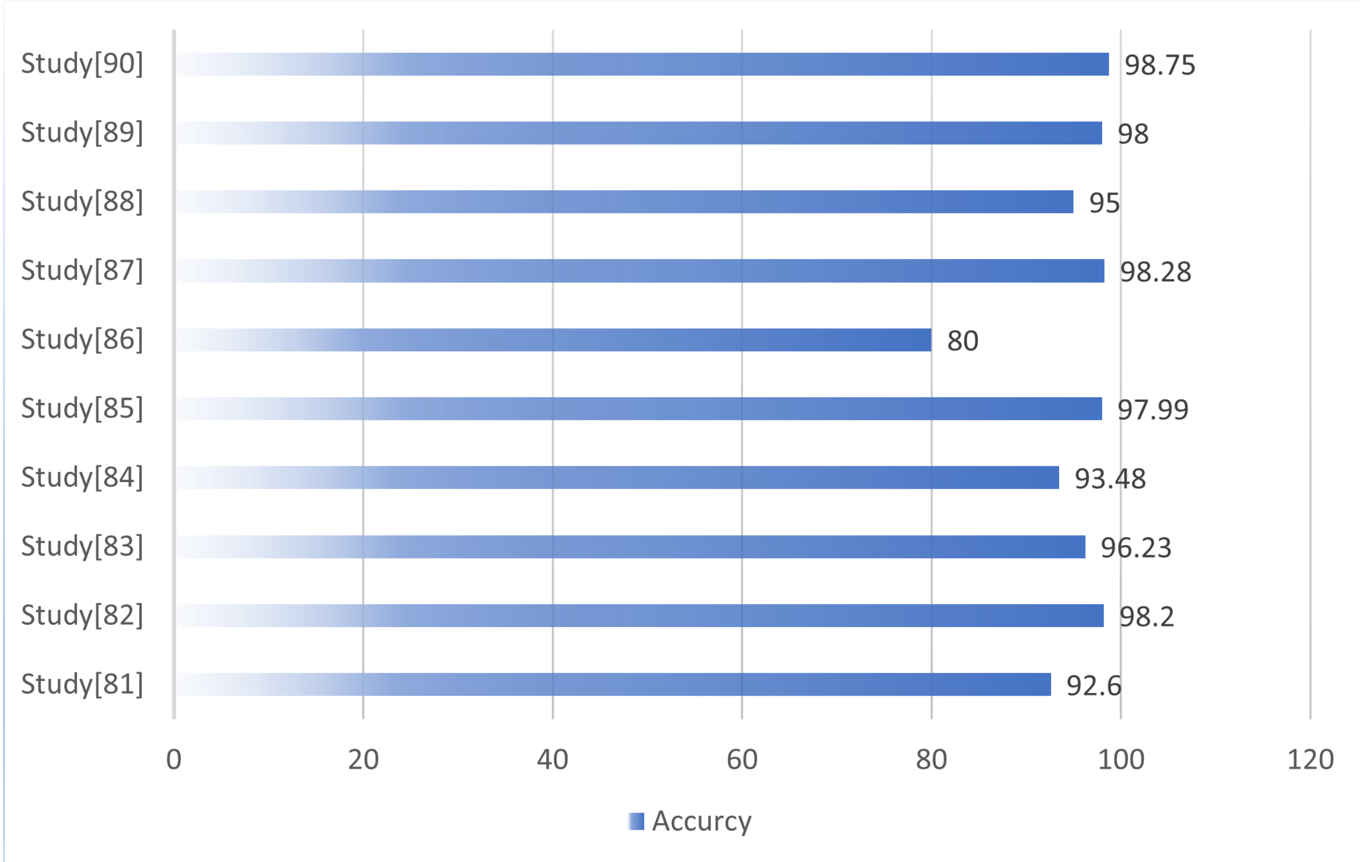

Figure 15: The achieved accuracy of the studies that utilized the deep transfer learning fine-tuning technique.

6.4 Deep transfer learning (feature extraction technique)

To improve the diagnostic performance, the authors in [70] used pre-trained knowledge using transfer learning techniques and compared different CNN architectures' performance. The proposed model, DenseNet201, provided an excellent classification accuracy of about 98.75%. To classify COVID-19 chest x-ray images, a transfer learning pipeline from two publicly available datasets was implemented in [98]. The classifier aimed to identify lung inflammation caused by COVID-19, Pneumonia and normal (no infection). They utilized multiple pre-trained convolutional backbones as a feature extractor to improve detection accuracy. The tests showed that the accuracy of each model is: EfficientNetB0 (96.8%), ResNet50 (94.3%), and VGG16 (90%).

ML classifier and ResNet152 were utilized in [50] to identify COVID-19 correctly. The authors encompassed the SMOTE algorithm to balance the intra-class variation among the datasets. The tests demonstrated the performance in terms of Accuracy, Sensitivity, Specificity, F1-score and AUC as follows: 1) XGBoost: 97.7%, 97.7%, 98.8%, 97.7%, and 99.8%,2) Random Forest: 97.3%, 97.4%, 98.6%, 97.3%, and 99.7%. In [67], the authors examined 15 different pre-trained CNN models. A total of 860 images (260 COVID-19 cases, 300 healthy and 300 pneumonia cases) have been employed to investigate the performance of the proposed algorithm. The utilization of the images was categorized as follows: 1) 70% of the images of each class used training, 2) 15% were utilized for validation, and 3) the rest were used for testing. The tests showed that VGG19 achieved the highest detection accuracy at 89.3%. Additionally, other performance evaluation metrics are as follows: 1) precision (90%), 2) Recall (89%), F1-score (90%).

A pre-trained deep convolutional neural network with Domain extension transfer learning (DETL), as a new concept, was proposed in [16]. A large chest x-ray dataset tuned to classify for classes: Covid-19, Pneumonia, viz., and normal. The model revealed a promising classification accuracy of 90.13% (± 0.14 error). ShuffleNet for the automatic extraction of features was used in [11]. Then, four classifiers were fed by the features: KNN, SVM, Softmax, and Random Forest. Via ShuffleNet features, different accuracies have been achieved. Bot Random Forest and SVM obtained the highest at 99.35%, whereas Softmax was 95.81%, and KNN was 80%. In [44], the transfer learning from the Residual Network (RESNET-50) was leveraged for model development on chest x-rat images from healthy individuals, bacterial and viral Pneumonia, and COVID-19 positives patients. For COVID-19 inference, the performance metrics were revealed as follows: accuracy (99%), recall (99.8%), precision (99%), and F1 score (99.8%).

The authors in [14] used Inception V3 with transfer learning (a deep CNN-based model). In the model, chest X-ray radiographs have been used to classify COVID-19 and Pneumonia patients. The tests showed that the accuracy of the model is 96%. A comparative study has been conducted in [24] to evaluate recent deep learning models: 1) VGG16, 2) VGG19, 3) DenseNet201, 3) Inception_ResNet_V2, 4) Inception_V3, 5) Resnet50, and 6) MobileNet_V2. The experiments were conducted using a chest X-ray and CT dataset comprising 6087 images. The images are categorized as follows: 2780 images of bacterial Pneumonia, 1493 of coronavirus, 231 of Covid19, and 1583 normal. Results found that the highest accuracy was achieved at 92.18% by Inception-ResNetV2. Lastly, in [73], the SVM was evaluated for detecting COVID-19 using the deep features of 13 CNN models. The model produced the best outcomes using the deep feature of ResNet50. The highest accuracy achieved by ResNet50 plus SVM is 98.66%. Finally, Table 4 summarizes studies that utilized the deep transfer learning fine-tuning technique, and Figure 16 draws the achieved accuracy of the studies. e.

Table 4: Summary of studies that utilized the deep transfer learning feature technique.

Study	Dataset	No of Classes	Samples				Portion %			Model	Accuracy %
			Total	Normal	Covid 19	Viral Pneumonia	Training	Validation	Testing		
[70]	Covid2019chestXray dataset of GitHub repository	2	480	240	240	-	80	20	20	ResNet 101	98.75
[98]	COVID-19 Image Data Collection	3	802	300	202	300	80	-	20	Efficient NetB0	96.8
[50]	Chest X-Ray Images (Pneumonia) and COVID-19 public dataset from Italy	3	9991	2916	62	7013	70	-	30	ResNet 152	97.7
[67]	COVID-19 image data collection, Chest X-Ray Images (Pneumonia)	3	860	300	260	300	70	15	15	VGG19	89.3
[16]	Italian Society of MedicalRadiology and Interventional, Radiopaedia.org (provided by Dr. Fabio Macori), COVID-19 image data collection, a hospital in Spain, NIHChest X-ray Dataset.	3	977	350	305	322	80	20	-	VGGNet	90.13
[11]	Cohen dataset on GitHub, Italian Society of Medical and Interventional Radiology, Radiopaedia and Radiological Society of North America, chest X-ray pneumonia from Kaggle,	3	930	310	310	310	-	-	-	Mobile Net	99.46
[44]	Labeled Optical Coherence Tomography (OCT) and Chest X-Ray Images for Classification, COVID Chest X-ray dataset	3	5155	2487	161	2507	75	25	-	RESNET -50	99
[14]	COVID-19 image data collection, Italian Society of Medical and Interventional Radiology, COVID-19 Radiography Database	3	3550	1341	864	1345	85	5	10	Inception V3	96

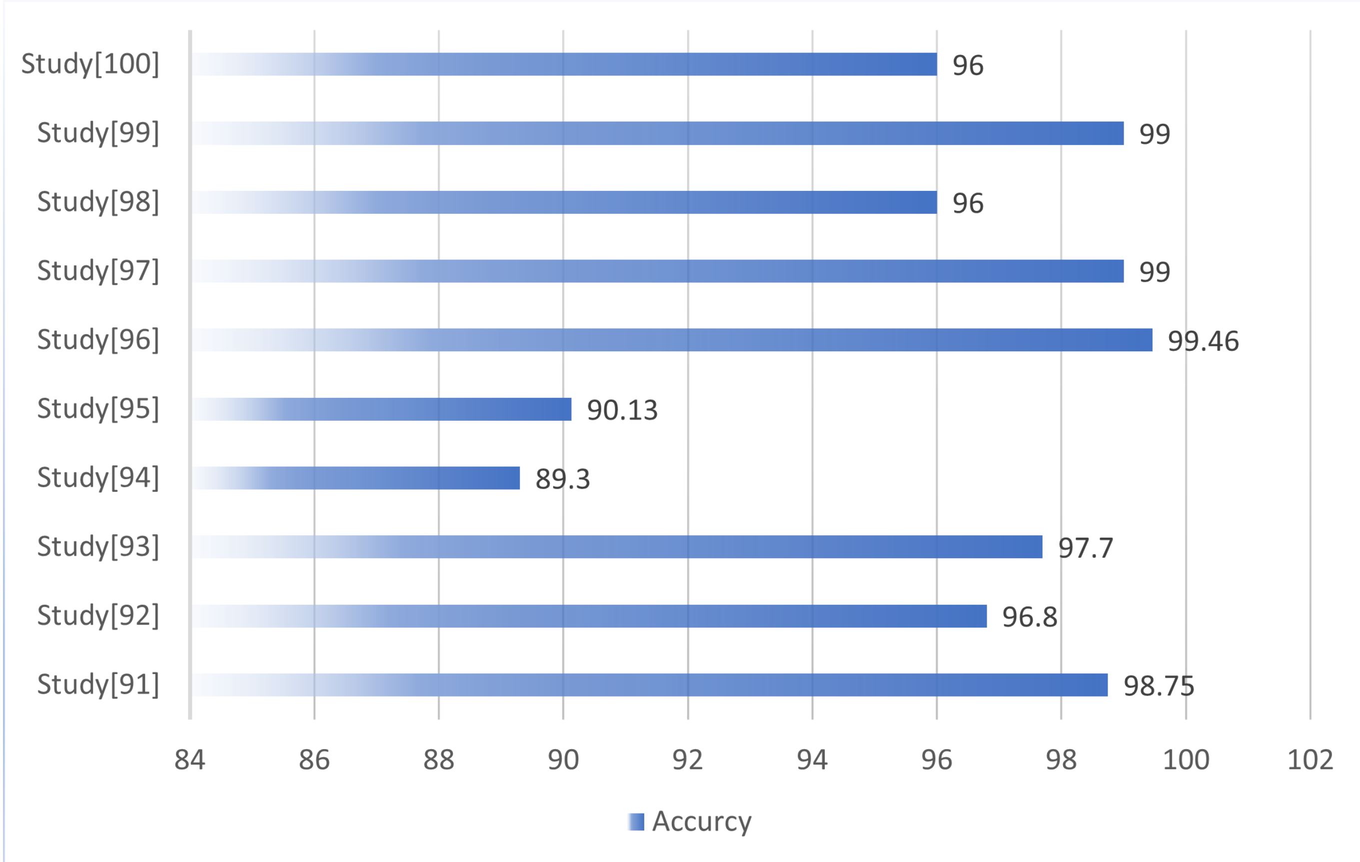

Figure 16: The achieved accuracy of the studies that utilized the deep transfer learning fine-tuning technique

7 Comparison of the studies of all deep learning techniques used in the detection of Covid-19

This state of the art evaluated 40 studies to assist researchers in exploring and developing knowledge-based systems based on artificial intelligence in detecting and diagnosing COVID-19. These papers have been categorized based on techniques used to detect COVID-19 (Novel deep learning architecture, direct use of deep learning, transfer learning fine-tuning technique, and transfer learning feature extraction technique). The following chart shows the best accuracy performance achieved by studies using those four techniques. The chart demonstrates that direct use of the deep learning technique and transfer learning feature extractions achieved the best accuracy among the techniques (about 99.5%). Figure 17 summarizes the highest accuracy of the technique in COVID-19 detection.

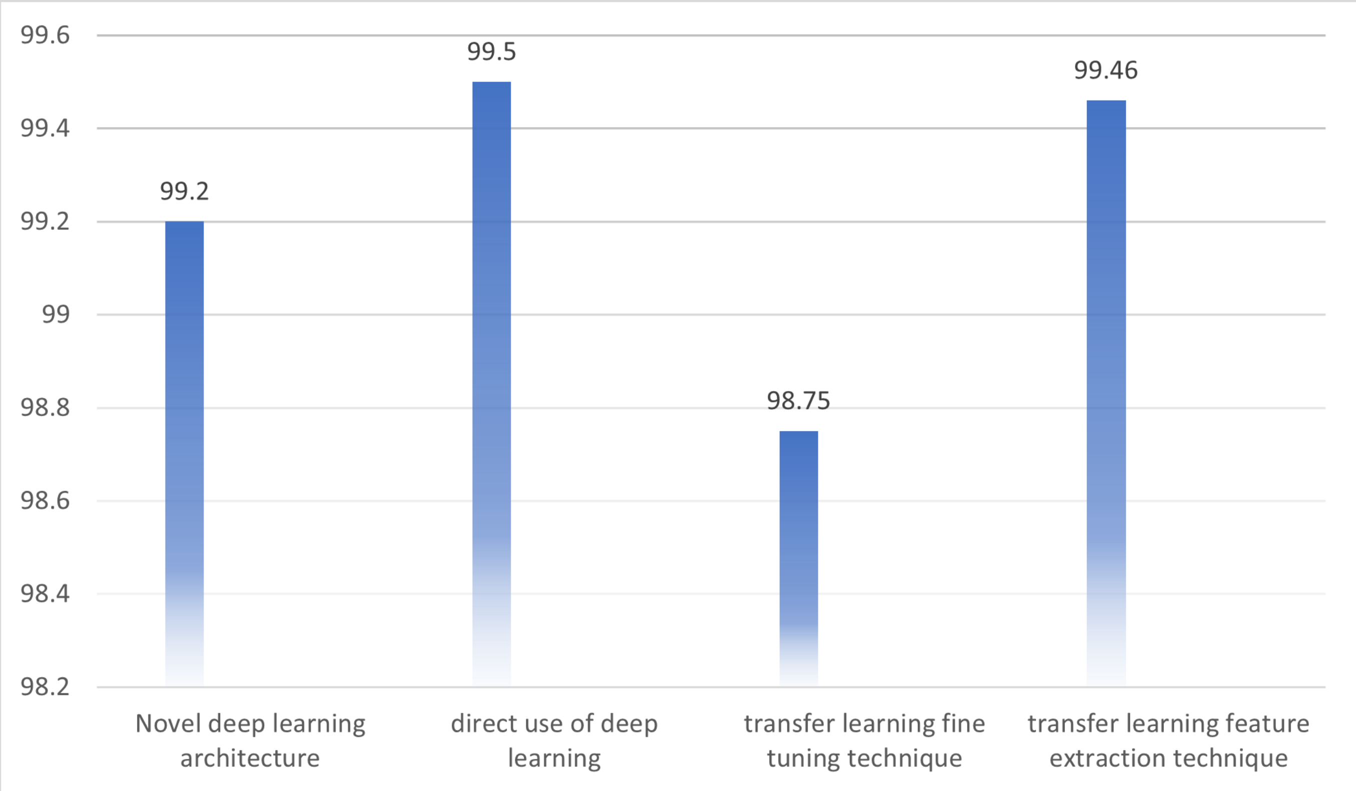

Figure 17: The accuracy performance of deep learning techniques

8 Conclusion

Every day, the Covid-19 epidemic spreads further. Therefore, this research aimed to improve the understanding of deep learning-based COVID-19 detection techniques by looking over and reviewing previous research in the field. A total of 40 papers were analyzed to propose a comprehensive understanding of the existing studies of each technique. These supreme papers are taken from scientific databases. Deep learning-based COVID-19 detection techniques: 1) Novel deep learning architecture; 2) Direct use of deep learning; 3) Transfer learning fine-tuning technique; and 4) Transfer learning feature extraction technique. For each of these, we evaluated and compared many very recent studies published in highly ranked journals. The studies recorded a closer accuracy performance metric ranged 98% to 100%.

Using a Novel deep learning technique, the study [38] recorded the highest accuracy performance metrics, about 99.20%. The proposed CNN architecture consists of twelve weighted layers, in which there are two convolutional layers and one fully connected layer. The study [45] also achieved the best accuracy (99.5%) using direct use of the deep learning technique. The model used image augmentation techniques to improve the training process efficiency. Then, to extract deep features on the chest x-rays image, the pre-trained ResNet50 model of CNN was applied. Also, using the deep transfer learning fine-tuning technique, the study [13] showed the best accuracy metric performance of 98.75%. The study used the VGG19 pretrained model and transfer learning to learn the model to classify COVID-9 and normal cases. The rest of the layers, which are closer to the output features, are made trainable to allow more information extraction from the late convolutional layers. Among studies that used the deep transfer learning feature extraction technique, the study [11] achieved the highest accuracy (99.46%). The authors used CNN architecture for automated feature extraction. The suggested method was implemented in three classes of chest x-ray image datasets. To avoid overfitting during the training and testing stages of CNN, the training dataset has been augmented, and the system tested using tenfold cross-validation.

Finally, before finalizing our article, two crucial points are noted while preparing this survey: the datasets and the methodologies.

- The first and most crucial issue is that researchers have studied a limited volume of Covid-19 data in their studies. Increasing the data with many clusters will empower stable systems. Data augmentation is a simple method that enhances CNN performance and avoids over-fitting. Nevertheless, using data augmentation methods, dataset inflating adds more invariant cases; hence, it avoids over-fitting. Due to the over-fitting issue, Training a CNN on limited data shows its capabilities to generalize outcomes to unseen data.

- The second crucial point is the methodology used, which required a lot of time and resources to build and train. If a novel architecture is created, less time and resources will be required when the direct use of a deep learning model or transfer learning technique is used.

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