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Recent Machine Learning and Deep Learning Theories and Methods for COVID-19 Diagnosis

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Review

Recent Machine Learning and Deep Learning Theories and Methods for COVID-19 Diagnosis

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Abstract: A long time has passed since COVID-19 was discovered and widely disseminated. Both machine learning and deep learning have moved towards the research of diagnosing COVID-19. Compared to deep learning, traditional machine learning-based methods can also achieve good diagnostic results if they are improved based on innovative points. And deep learning remains a more popular research object. Based on the deep neural network in the field of deep learning, the convolutional neural network, recurrent neural network, long and short-term memory network, and Transformer model have been extended. These models improve the performance and processing power of neural networks by introducing new structures and algorithms. This paper will introduce the basic concepts of machine learning and deep learning, as well as the details of using the relevant methods of both to help diagnose COVID-19.

Keywords: COVID-19; machine learning; deep learning; convolutional neural network

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1. Introduction

COVID-19, short for "Coronavirus Disease 2019," is a highly contagious respiratory illness caused by the novel coronavirus SARS-CoV-2 [1]. It was first identified in Wuhan, China, in late 2019 and has since evolved into a global pandemic. COVID-19 primarily spreads through respiratory droplets and can lead to a wide range of symptoms [2], from mild flu-like symptoms to severe respiratory distress and death, particularly in older adults and individuals with underlying health conditions. Efforts to control the spread of the virus have included vaccination campaigns, public health measures like mask-wearing and social distancing, and quarantine protocols to limit transmission.

According to clinical observations, most patients with COVID-19 infection have typical features such as loss or alteration of smell and taste [3], fever, dry cough, and weakness of limbs. Some findings have shown that the novel coronavirus has an incubation period of 3-14 days [4], even up to 24 days in some cases. During the incubation period of the virus, some cases have no typical clinical symptoms [5]; after the incubation period of the virus has passed, most of the cases will show relevant typical symptoms, while a few have not yet appeared. From the above analysis, it can be seen that COVID-19 is highly infectious, highly pathogenic, and has a long incubation period [6].

COVID-19 causes potentially serious consequences of respiratory distress, pneumonia, acute respiratory distress syndrome (ARDS), organ failure, and death. These consequences are more likely to be severe in the elderly and people with underlying health problems. The epidemic is not only a direct health hazard but also leads to serious social, economic [3], and psychological consequences such as work stoppages, unemployment, disruption of education, and increased mental health problems. In addition, the COVID-19 virus causes long-term effects. It causes symptoms such as fatigue, brain fog, and respiratory problems to persist regardless of whether the patient's initial condition was mild or severe. The multifaceted global impact of COVID-19 highlights the importance of prevention, vaccination, and early diagnosis in mitigating these deleterious consequences.

Diagnosing COVID-19 is crucial for several reasons. This is because, firstly, diagnosis allows for the timely isolation [7] and treatment of infected individuals, reducing the spread of the virus to

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others; secondly, public health authorities tracking the prevalence and trends of the disease need to rely on an accurate diagnosis, enabling them to make informed decisions when developing measures related to limiting the spread of the epidemic; and thirdly, the quality of patient care increases with an accurate diagnosis, especially in severe cases where early intervention can be life-saving. In addition, tracking the products of viral evolution, and thus their identification is essential for vaccine development and adaptation to ensure adequate preparedness against COVID-19. Finally, diagnosing COVID-19 can give individuals the information they need to help them prepare for community preparedness and personal protection.

In Section 2, we will introduce the basic concepts of artificial intelligence, machine learning, deep learning, and some related applications in some research areas. In Section 3, we will summarize some machine learning-based methods for diagnosing COVID-19 and analyze their advantages. Then, in Section 4, some deep learning methods for diagnosing COVID-19 are introduced into the narrative and we similarly analyze their merits. We outline the basic concepts of transfer learning in Section 5 and discuss how it can help with COVID-19 diagnosis. In Section 6, we propose solutions to the reality that evolving COVID-19 strains can make models trained on previous datasets unable to accurately determine other existing problems. Finally, Section 7 presents the conclusions we draw and suggestions for the development of future research directions.

2. Artificial Intelligence, Machine Learning, Deep Learning

In recent years, machine learning and deep learning have pioneered a new phase for disease detection and diagnosis using images [8]. As shown in Figure 1, machine learning (ML) is a subset of artificial intelligence (AI) that involves the development of algorithms and models that enable computers to learn from and make predictions [9] or decisions based on data. Instead of being explicitly programmed to perform specific tasks, ML systems use data to identify patterns, make inferences, and improve their performance over time [10]. This technology is widely used in various applications, from natural language processing and image recognition to recommendation systems [11] and autonomous vehicles [12]. It plays a pivotal role in automating complex tasks, extracting insights from large datasets, and enhancing decision-making processes across many industries. Nowadays, machine learning techniques generally include zero-shot learning, active learning, contrastive learning, self-supervised learning, life-long learning, semi-supervised learning, ensemble learning, sequential learning, and multi-view learning used in computer vision [13]. Machine learning also includes reinforcement learning. Reinforcement learning is the creation of an intelligence that effectively interprets perceptions of the environment and then takes relevant actions or decisions based on the perceptions [14]. Reinforcement learning differs from supervised and unsupervised learning in that it is not told what actions to take, but must discover on its own, by trial and error, which actions will yield the most lucrative benefits. Intelligentsia continuously learn and explore through self-reward.

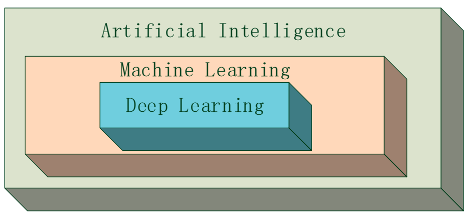

Figure 1. Relationship between AI, ML, and DL.

Cosgriff and Celi [15] pointed out that deep learning-based methods performed better in the postoperative mortality predictive modeling task. They also noted that deep learning (DL) applies connectionist principles to predictive modeling tasks, thus centering on the development and application of artificial neural networks (ANNs). DL is a subfield of machine learning that focuses on ANNs, particularly deep neural networks (DNN) with multiple layers (hence the term "deep"). It aims to mimic the human brain's structure and function by using interconnected layers of artificial

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neurons to process and learn from data. Neural networks are based on the extension of perceptual machines, while DNNs can be understood as neural networks with many hidden layers (Figure 2). Multilayer neural network and DNN are the same kind of network and DNN is also known as multilayer perceptual machine (MLP).

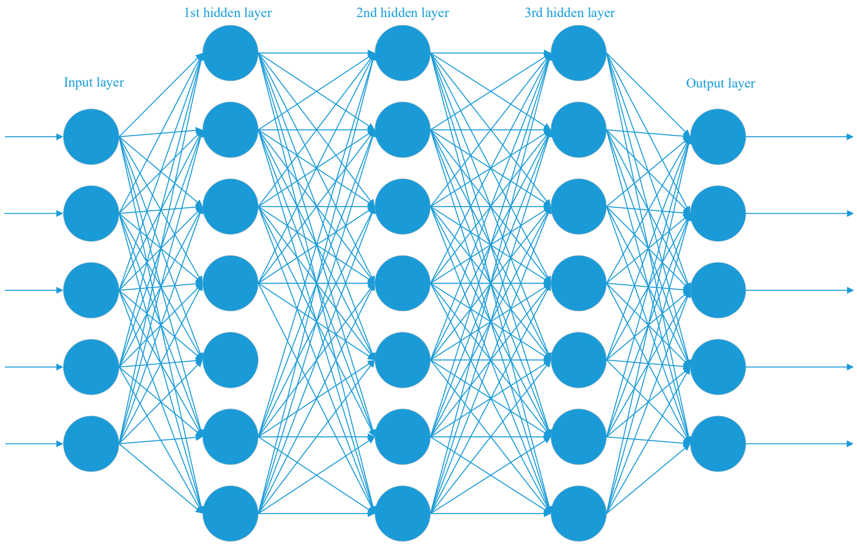

Figure 2. DNN with 5 layers.

Deep learning is a subset of machine learning because it shares the fundamental concept of using data to improve a system's performance. However, it distinguishes itself by its use of deep neural networks, which can automatically discover and represent complex patterns in data, making it particularly effective for tasks like image recognition [16], natural language understanding [16], and speech recognition. As shown in Figure 2, DNN consists of an input layer, a superimposed hidden layer, and an output layer. Each hidden layer consists of hidden units. Each unit in the layer represents a weighted linear combination of the units in the previous layer, which are usually obtained after a nonlinear transformation [15]. Each hidden layer has weights that represent the strength of the connections between the units. Deep learning has played a pivotal role in advancing the capabilities of machine learning in recent years and has been instrumental in numerous breakthroughs in AI research and applications.

3. Machine Learning for COVID-19

Scholars and researchers have employed machine learning techniques in various ways to aid in the diagnosis and management of COVID-19 [17]. One prominent application is the development of predictive models that use medical data, such as clinical symptoms [18,19], laboratory test results, and medical imaging, to identify and classify COVID-19 cases. Machine learning algorithms, including decision trees, support vector machines (SVM) [20], and deep learning neural networks, can analyze this data to distinguish between COVID-19 and other respiratory illnesses with high accuracy. Such SVM is a popular traditional classifier with high performance [21].

The basic principle of SVM is a method based on statistical learning theory applied to binary classification problems. As shown in Figure 3, the SVM algorithm aims to find the optimal hyperplane H to correctly separate the two types of data and maximize the classification interval $|H_1H_2|$, where H_1 and H_2 are the intervals of the closest samples in each type of class that are parallel to the optimal hyperplane (decision boundary), respectively.

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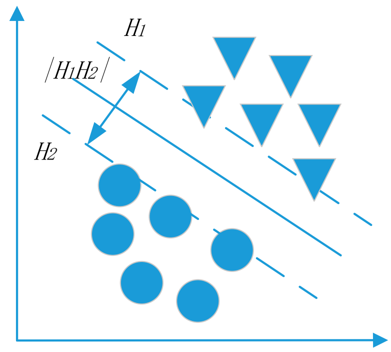

Figure 3. Support vector machines when data are linearly divisible.

SVM has better performance in solving practical problems such as small samples, nonlinear and high dimensional data, and local minima. For hyperplanes, as shown in Figure 4, SVM has linear hyperplanes and nonlinear hyperplanes. Moreover, for the former, there are two cases of linearly divisible and linearly indivisible; for the latter, there is only one case of linearly indivisible.

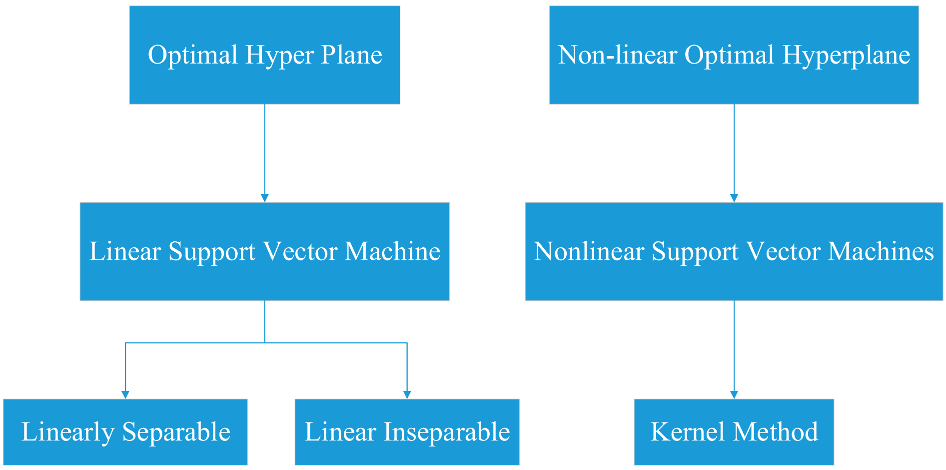

Figure 4. Illustrations related to SVM.

There exists a process of ascending linearization for SVMs. The process is based on the Mercer kernel expansion theorem, which maps the input space to the Hilbert space through a nonlinear transformation defined in terms of the inner product function, and searches for the relationship between the input variables and the output variables in this high-dimensional feature space. Chen [21] noted that standard linear SVM shows a good classification performance on a small dataset. These models help in early and accurate diagnosis, allowing for timely treatment and isolation of infected individuals, which is crucial in controlling the spread of the virus.

Another valuable use of machine learning in COVID-19 diagnosis is in medical imaging analysis, particularly in the interpretation of chest X-rays [22] and CT scans [22]. In the field of deep learning, radiologic examination using chest X-ray images is the effective screening method for COVID-19 case detection [23]; and chest computed tomography imaging is more conducive [24] to COVID-19 screening than RT-PCR testing [25]. Convolutional neural networks (CNNs), which are deep learning algorithms, are one of the hottest research areas in computer-aided diagnostic tasks [26]. Baghdadi, et al. [27] stated that CNNs play an important role in digital image processing and help in the development of medical systems. Such CNNs can be trained to detect characteristic patterns and features associated with COVID-19 lung abnormalities. This technology aids radiologists in quickly

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identifying potential cases and assessing disease severity, enabling more efficient and accurate diagnosis.

Furthermore, machine learning has been instrumental in the development of diagnostic tools based on non-invasive or less invasive data sources, such as voice, breath sounds [28] and cough analysis [29]. Researchers have used machine learning algorithms to analyze audio recordings of coughs and speech to detect subtle changes that may indicate COVID-19 infection. These tools offer a potential means for rapid and widespread screening, especially in resource-constrained settings. Overall, machine learning has been a valuable tool in enhancing the accuracy and efficiency of COVID-19 diagnosis across different domains of medical data analysis.

4. Deep Learning for COVID-19 Diagnosis

Scholars and researchers have leveraged deep learning techniques in several ways for COVID-19 diagnosis, offering a powerful tool for accurate and efficient identification of cases. One of the primary applications is in medical imaging [30], specifically chest X-ray [31] and CT scan analysis [32]. Deep learning models, particularly convolutional neural networks (CNNs), can automatically extract intricate patterns and features from these images, aiding in the detection of COVID-19-related lung abnormalities. Subramaniam, et al. [33] stated that Convolutional Neural Networks (CNNs) belong to the deep learning methods with good performance or are greatly favored in artificial intelligence methods for COVID-19 case diagnosis. By training these models on large datasets of radiological images, scholars have developed AI systems capable of identifying subtle lung changes indicative of COVID-19, assisting radiologists in diagnosis and assessment of disease severity. Subramaniam, et al. [33] also indicated that the generalization ability of these models can be enhanced by using techniques such as migration learning, cross-validation, and data augmentation.

Another key application is in the analysis of clinical data, including patient electronic health records (EHRs). Deep learning models can process diverse patient information, such as clinical symptoms, laboratory test results, and demographics, to predict the likelihood of COVID-19 infection. These models use recurrent neural networks (RNNs) and transformers to capture temporal and contextual information, improving diagnostic accuracy and helping healthcare providers make informed decisions about testing and treatment. RNNs are used in data analysis tasks because RNNs are the better-performing type of artificial neural networks. RNNs predict future data for a specified duration based on existing time series data [34]. RNNs have a promising future. Because their internal memory remembers the important features of the input sequential data, it produces an accurate prediction of the future [34].

Deep learning has also been instrumental in the development of diagnostic tools based on non-imaging data, such as voice and cough analysis [29]. Scholars have used deep learning algorithms to analyze audio recordings of coughs, speech, and even smartphone-recorded respiratory sounds [35] to identify distinct acoustic patterns associated with COVID-19 infection. These tools offer a non-invasive and potentially widespread means of screening for the virus, particularly in situations where traditional testing methods are limited. The implementation process of using deep learning to accomplish the above tasks can be summarized as data collection and preprocessing, deep feature extraction, pattern recognition, model training and optimization, and application. This process can also be described in detail as follows: first, a large amount of labeled audio data, including coughs, speech samples, and breath sounds, need to be collected. These data should be divided into three parts: training set, validation set, and test set. For speech and cough audio, preprocessing, such as noise removal and normalization, is needed to improve the recognition accuracy of the model; then, feature extraction is performed using deep learning models (e.g., CNN; RNN; or Transformer, etc.). These models can automatically learn features in the audio, such as the frequency of the cough, the pitch of the voice, the intensity of the sound, etc.; furthermore, the extracted features can be further used for pattern recognition (e.g., by using a deep learning model, it is possible to determine whether a piece of coughing audio displays a pattern specific to COVID-19 infection. This process can be regarded as a sound classification task); after that, the model is trained by using a large amount of labeled data, and a validation set is used to tune the parameters and select the best model. Once the

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model performs well on the validation set, a test set can be used to evaluate the generalization ability of the model; finally, the trained model can be used to analyze audio data in real-time to detect possible COVID-19 infections. For example, it can be integrated into a mobile app or online tool where the user uploads audio and the model returns a risk assessment for COVID-19 infection.

Additionally, deep learning has found applications in the development of predictive models [36–38] that forecast COVID-19 trends and outbreaks. These models analyze a range of data sources, including epidemiological data, population mobility, and social interactions, to predict the spread of the virus. They can help public health authorities make data-driven decisions regarding resource allocation, vaccination campaigns, and the implementation of preventive measures. In summary, deep learning has been a valuable asset in the fight against COVID-19 by enhancing diagnostic accuracy, enabling non-invasive screening methods, and aiding in predictive modeling for effective pandemic management.

5. Transfer Learning for COVID-19 Diagnosis

Transfer learning is very effective in the COVID-19 diagnostic domain, mainly because it retains and applies knowledge from one or more tasks, domains, or distributions to develop valid hypotheses for new hypotheses [39]. As shown in Figure 5, this reason can also be explained by the ability of transfer learning to utilize pre-trained models and adapt them to new tasks [40].

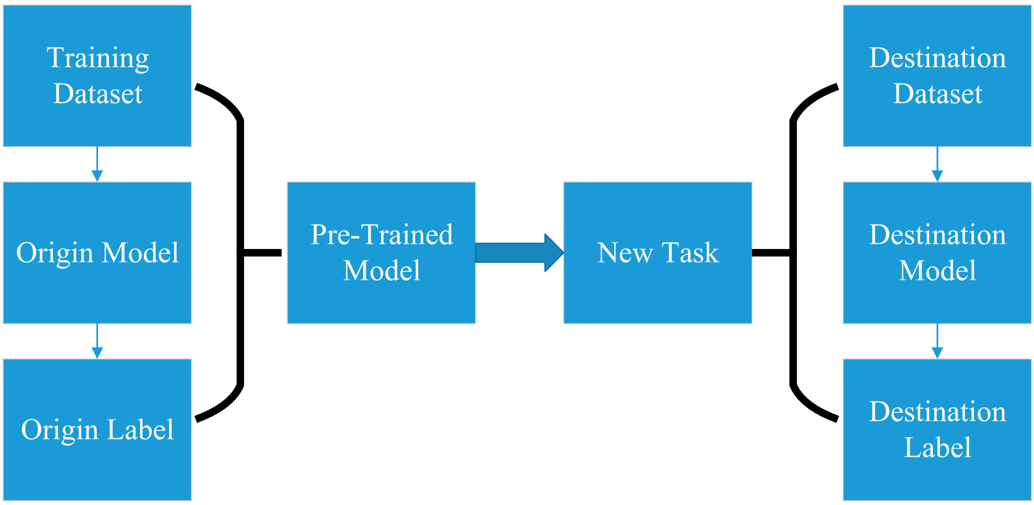

Figure 5. The concept of transfer learning.

Transfer learning allows the use of deep neural networks pre-trained on vast datasets for tasks like image analysis, which is essential in COVID-19 diagnosis, especially in radiology. Models like Convolutional Neural Networks (CNNs) pre-trained on diverse image datasets can be fine-tuned on X-ray or CT scan images of COVID-19 patients [41]. By doing so, these models can efficiently extract relevant features from medical images, such as lung opacities and ground-glass opacities, which are characteristic signs of COVID-19 pneumonia. This significantly reduces the need for manually engineered features and speeds up the development of diagnostic tools.

One of the significant challenges in COVID-19 diagnosis is the limited availability of labeled data [8], especially in the early stages of the pandemic. Transfer learning allows for the transfer of knowledge learned from larger, more diverse datasets to the task of COVID-19 detection. This transfer of knowledge enables models to generalize better even with limited COVID-19-specific data, leading to more robust and accurate diagnostic systems. Researchers can thus overcome data scarcity issues, which is crucial for timely and accurate diagnosis.

Transfer learning techniques offer built-in mechanisms for regularization [42] and adaptation [42]. Pre-trained models have already learned general features from extensive datasets, which makes them less prone to overfitting on smaller medical datasets. By fine-tuning these models on COVID-19 data, they can adapt their learned representations to the specific characteristics of COVID-19 cases,

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such as subtle radiological patterns and variations in patient demographics. This ensures that diagnostic models are more robust and reliable when applied to real-world medical data.

As the understanding of COVID-19 evolves and more data becomes available, transfer learning allows for continuous model improvement. Models can be updated and fine-tuned with the latest data, ensuring that they remain up-to-date with the changing landscape of the pandemic. This adaptability is crucial for the long-term effectiveness of COVID-19 diagnostic tools, as it allows them to better capture emerging trends, new variants, and evolving clinical practices.

In conclusion, as shown in Figure 6, transfer learning plays a pivotal role in COVID-19 diagnosis by enabling efficient feature extraction, overcoming data limitations [43], providing regularization, and facilitating continuous improvement.

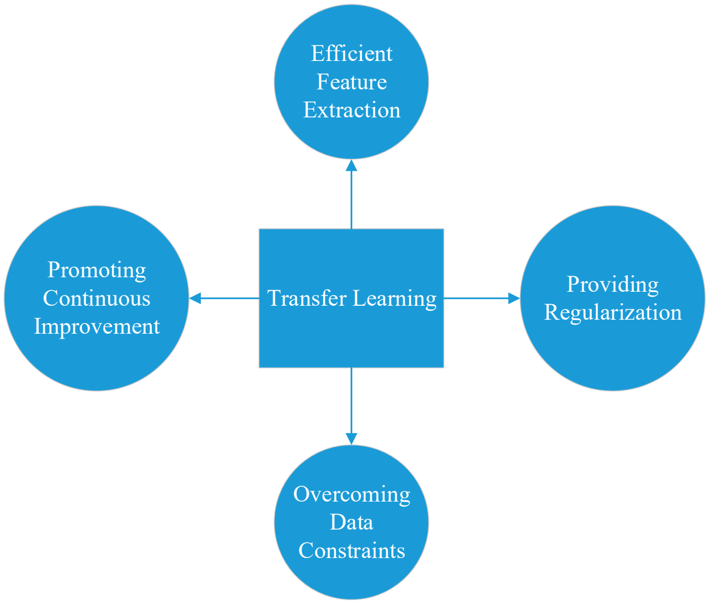

Figure 6. Advantages of transfer learning.

By leveraging pre-trained models, the medical community can develop more accurate and adaptable diagnostic tools, ultimately aiding in the early detection and management of COVID-19 cases. This not only assists healthcare professionals in providing timely care but also contributes to the overall effort to control the spread of the virus.

6. Challenges

Although AI tools like machine learning and deep learning can make quick decisions for the diagnosis of the infection of COVID-19 using medical images [44], using machine learning and deep learning in COVID-19 diagnosis presents several challenges. Firstly, obtaining high-quality labeled data for training these models can be difficult [45]. Building robust datasets that include diverse patient populations, different disease stages, and reliable ground truth labels can be time-consuming and resource-intensive. Additionally, data quality and consistency across healthcare institutions can vary, leading to potential biases in the models. Further, the raw data of the dataset provided by the healthcare organization can easily lead the machine learning algorithms to make wrong judgments with a high probability when perturbations imperceptible to the human eye are added [11].

Secondly, there is a challenge related to model interpretability. Deep learning models, particularly neural networks with numerous layers, are often considered "black boxes" [46] because it can be challenging to understand how they arrive at their decisions. Another reason why it is called a "black box" is that deep neural networks have the disadvantage that the internal logic to achieve the desired output or result is not understandable and explainable [47]. Panwar, et al. [48] used VGG-

19 as a transfer learning model and Gradient Weighted Class Activation Mapping (Grad-CAM) for interpretable deep learning. Grad-CAM will be applied to any of the convolutional layers of VGG-19 after the model has predicted the label.

In the context of COVID-19 diagnosis, where medical professionals need to trust and interpret the model's results, this lack of transparency can be a significant hurdle. The problem of interpreting the very difficult output of current deep learning models is compounded by the lack of reliable measures of uncertainty [49]. Interpretability is key to medical diagnosis, and understanding the reasons for decisions is viewed as important as the need for decisions [50]. Interpretable machine learning and deep learning techniques are actively being researched to address this issue [51–53], but they remain a challenge in many applications.

Moreover, the rapid evolution of the virus and the emergence of new variants pose a challenge in maintaining the accuracy and generalizability of machine learning and deep learning models. For example, SARS-CoV-2 is a virus that causes COVID-19, which is characterized by rapid transmission, constant change, and a higher probability of fatality [54]. These models are trained on historical data and may not perform as well when faced with novel variations of the virus [55]. Continuous model retraining and adaptation to evolving data are necessary to ensure their effectiveness in diagnosing new strains of COVID-19. Finally, the deployment of AI-driven diagnostic tools in clinical practice requires rigorous validation, regulatory approval, and adherence to ethical and privacy [56] considerations, adding another layer of complexity to their integration into healthcare systems.

7. Conclusion and Future Directions

Deep learning has proven invaluable in COVID-19 diagnosis, particularly in medical imaging analysis and clinical data interpretation. Convolutional neural networks (CNNs) enable the automatic detection of lung abnormalities on chest X-rays and CT scans, aiding radiologists in identifying COVID-19 cases. Recurrent neural networks (RNNs) and transformers process clinical data to predict infection likelihood. Voice and cough analysis using deep learning offer non-invasive screening methods.

Future research directions in this field include enhancing model interpretability to build trust with healthcare professionals, addressing data quality and diversity issues, adapting models to evolving virus strains, and navigating the regulatory and ethical considerations necessary for deploying deep learning-based diagnostic tools in clinical practice.

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