Automated Detection of Covid-19 Waves with Computerized Tomography Scan Using Deep Learning

D. Suganya and R. Kalpana

1 Introduction

Corona viruses are a large group of viruses; they cause various illnesses, ranging from the normal cold to more complicated diseases like Middle-East-Respiratory-Syndrome (MERS) and Severe-Acute-Respiratory-Syndrome (SARS). In 2019, a new virus was found that had never been seen in humans before [1]. It has been proven to be a communicable airborne infectious disease transmitted not only through human droplets, but also through the air. An accurate diagnosis remains the main challenge to alleviate this pandemic situation. The Covid-19 spread conferred a major problem to the diagnostic community; however, the courageous efforts of medical professionals have created an incredible effect on improving the identification and management of infected people as well as lowering the disease spread [2].

This paper discusses the techniques and the tests available to diagnose corona virus, like RT-PCR, swab test, and antigen test, with their challenges and comparatively analyze how CT scan image provides good result in diagnosis or screening of Covid pneumonia from common pneumonia with the help of references from numerous articles. Final study shows how DMIL and Mask R-CNN techniques can screen the Covid accurately. In addition, it needs to spotlight the fast improvement and implementations of diagnostic assays are vital to save you the spread of destiny novel infectious diseases.

D. Suganya (✉) · R. Kalpana
Puducherry Technological University, Puducherry, India
e-mail: suganyajagathguru@pec.edu; rkalpana@pec.edu

S. Awasthi et al. (eds.), *Sustainable Computing*,
https://doi.org/10.1007/978-3-031-13577-4_3

The remainder of the paper is organized in this way. Section 2 discusses several methods of diagnosis with its challenges. Section 3 addresses a summary of key publications for screening of Covid-19 with CT scan images. Section 4 gives the experimental findings and analyses of various datasets, whereas Sect. 5 presents the conclusions.

2 Related Studies

Several techniques have been used for rapid screening of Covid-19 accurately. Here we discuss the preeminent testing methods along with their merits and demerits.

2.1 Molecular RT-PCR Test

Molecular test is a majorly used testing method to diagnose sequences of DNA and RNA. Various molecular detection methods were used such as PCR, RT-PCR, qPCR, and RT-qPCR. Polymerase chain reaction (PCR) is a highly sensitive method for detection of sequences of DNA. RT-PCR is a method of reverse transcription-polymerase chain reaction used to find the presence of specific genetic material in pathogens [3]. Quantitative polymerase chain reaction (qPCR) and reverse transcription-polymerase chain reaction (RT-qPCR) are to identify, categorize, and quantify the nucleic acids for clinical relevant target.

Challenges RT-PCR testing for Covid-19 detection is accurate when the sample has active viral infection. But if the test is taken later, i.e., at the abortion stage of corona virus (day 11–14), it fails to predict whether you have been infected with the virus in the past [2].

2.2 RAT Tests

Antigen test is popularly known as RAT (Rapid Antigen Test). A sample from respiratory track is taken to detect the viral proteins and identifies the antigen connected with corona virus. Antigen test is used for speedy screening of Covid-19, which is comparatively faster than all other testing methods [4].

Challenges RAT is used for direct detection of viral (SARS-CoV-2) protein, i.e., antigen from the respiratory track, where the result is accurate and rapid with active corona viruses. But it fails to provide accurate results for negative cases. The negative result needs to be validated by some other tests.

2.3 Serological Tests

The test which is used to detect or identify the antibodies against the corona viruses is diagnosed with the help of serum or blood test is known as serological test. It is also known as serum test or antibody test. This test clearly tells how your immune system reacted to the virus in the past.

Challenges The serum blood test can determine whether your body has an antibody against the virus. But it fails to reveal about the active corona virus present in your body.

3 ML Algorithm Focused on Diagnosis Using CT Scan Images

ML algorithm focuses on applications that learn from experience and improve the accuracy of decisions and prediction accuracy time [5]. As shown in Fig. 1, algorithms in ML are very well trained to identify patterns and huge amounts of various features of data is being extracted to get more effective output from medical images for accurate prediction or diagnosis. The accuracy of output in a machine learning algorithm is entirely dependent on the amount of data that is trained; as we train or process more data, the accuracy increases.

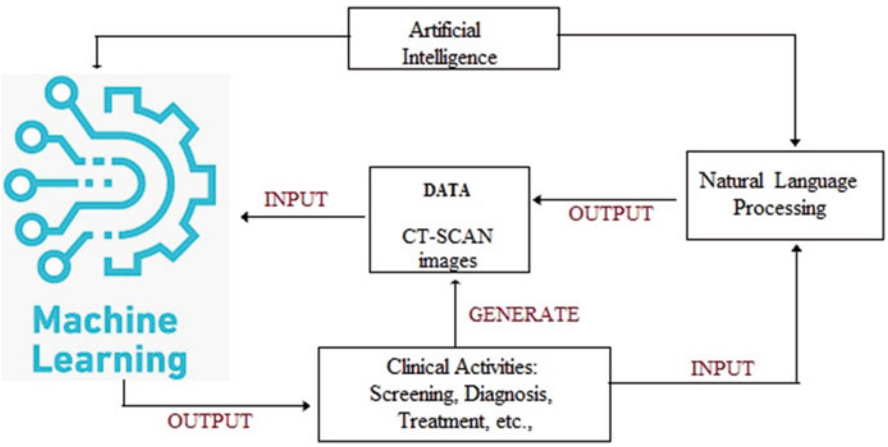

Fig. 1 Working of machine learning technique for clinical activities

3.1 Multiple Instance Learning (MIL)

MIL is a supervised ML algorithm. In general, each item is labeled individually whereas in Multiple Instance Learning, it receives a collection of multiple items in labeled bags. The bags can be labeled with positive and negative. If all the instances from the segmented image are negative the bag is marked as negative. If the sample with any one instance in a sample is positive, the bag is marked as positive. This algorithm effectively labels the individual object from a set of tagged bags.

A study has been recently published for Covid detection using chest CT images by Zhongyi Han et al. [6]. It impulsively detects the corona virus with attenuation-based multiple-instance learning algorithm. This algorithm facilitates large screening of corona virus effectively with labeled instances. It uses binary classification to classify whether the sample is labeled or tagged with positive or negative.

3.2 Why Deep Learning over Machine Learning

Machine Learning focuses on applications that learn through experiences, thereby improving prediction and making a right decision [7]. Several traditional ML algorithms are used for analysis and detection of Covid-19, but mainly focused in two ways, i.e., feature reduction techniques and model validation techniques.

Figure 2 depicts the relationship between AI, conventional ML techniques, and DL models [8]. Deep learning significantly reduces process time and human intervention [9]. The DL algorithm itself preprocesses, trains, and tests the datasets. Finally, it produces an accuracy based on the algorithm. Table 1 explains why we switch from machine learning to deep learning for detection when we have an image as input.

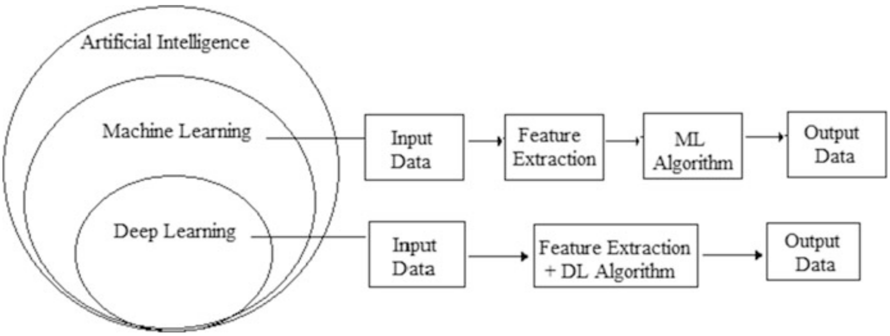

Fig. 2 Relationship among the subset of AI, ML, and DL

Table 1 shows how DL differs from traditional ML

Machine learning	Deep learning
In the problem-solving approach, the problem statement is first divided into several parts, then each part is solved, and finally, all of the parts are combined to yield a result	It will not break the problem; instead, it will attempt to solve the problem from start to the end
Multiple object detection problem	
In ML, we first use a support vector machine as an object detection algorithm to identify all objects, and then we use a histogram of oriented gradients as input for recognizing relevant objects. It takes a long time to complete the process	We use an image as input directly in DL techniques, such as Yolo net, which directly detect and provide the location as output. It solves problems directly with less amount of time

4 DL Algorithm Focused on Diagnosis Using CT Scan Images

The two most important sub-divisions of AI are ML and DL. Deep learning is necessarily a more progressive model compared to the traditional machine learning models. In ML algorithm, we take raw data as input and extract features from the preprocessed data. Then apply an algorithm to train the models for obtaining an accurate output or results. Deep Neural Learning or Deep Neural Network or Deep Learning algorithm, combine the process of feature extraction as well as training models or algorithms to achieve high accuracy of results effectively, as shown in Fig. 2. Several COVID cases can be detected accurately using chest CT scan than through RT-PCR tests. M. Chung et al. [10] recently published the features of individuals affected by novel corona virus detected using CT scan images. This method uses CT images effectively to find the how harm the virus is infected in the lungs. This paper also shows the high accuracy for prognosis of lung problems from the chest CT images.

4.1 Deep Neural Network (DNN)

DNN will create new patterns which contain multiple hidden layers. They have several types, where multiple neurons are processed like how our human brain neurons work. As shown in Fig. 3, the entire process took place in the hidden layer between an input and output layers. For example, if a DNN is trained to recognize a chest CT image, it will go over the image and calculate the likelihood that the virus is present [11, 12]. The user can examine the results and select the probabilities with which the network should display and return the tags [13, 14].

Hybrid 3D Deep Neural Network (H3DNN) paper explores the detection of novel corona virus from chest 3D CT scan images using a hybrid deep learning model

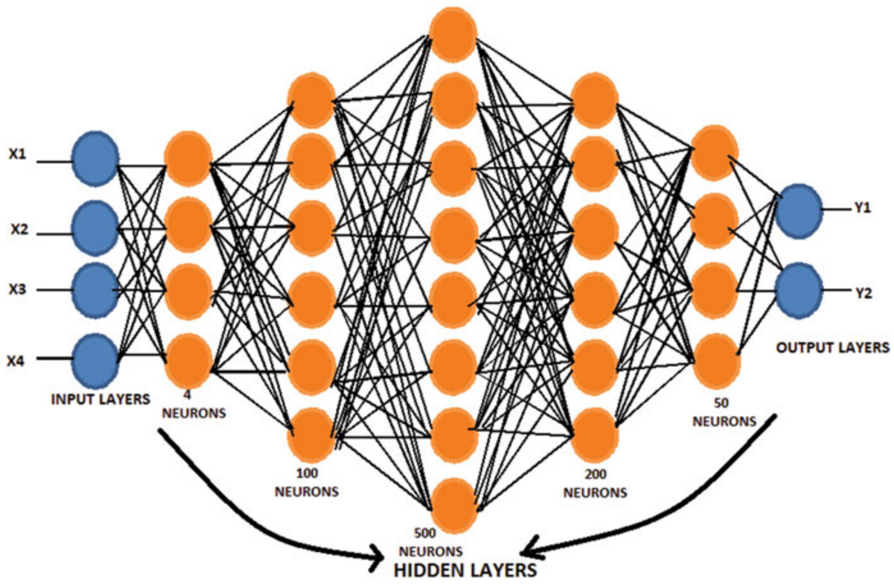

Fig. 3 Deep neural network with multiple hidden layers

which was recently published by Abdullah Aman Khan et al. [15]. It uses various datasets like CTC19 and COVIDCT, with ensemble of several transfer learning models like ResNet, DenseNet, and GoogleNet. This hybrid model works well in the diagnosis of Covid-19 with 3D-based deep learning models and acts as an effective tool in assisting the medical practitioner for large screening of novel corona virus.

4.2 Convolutional Neural Network

Convolutional Neural Network (CNN) generally analyzes, identifies, and categorizes the object in an image. ConvNet is composed of multiple layers of artificial neurons. It contains two basic operations such as convolution and pooling. CNN is a class of DNN; it contains one input layer, which combines convolution nonlinearity with pooling layers. The features are then extracted using vectors in the fully connected layers and normalization layers, as shown in Fig. 4.

O. Gozes et al. [16] recently published the corona virus detection and analysis using deep learning model with the help of chest CT. Several studies have focused on Covid-19 analysis and detection using ConvNet and medical images such as chest X-rays, computed tomographic scans, and so on. It can classify the process into distinct groups, such as Covid-19 or normal and viral pneumonia or common pneumonia or else normal/negative. With the help of various image dimensionalities and different ConvNet architecture, the output or result with minimized fully connected layers can identify Covid-19 from various medical images.

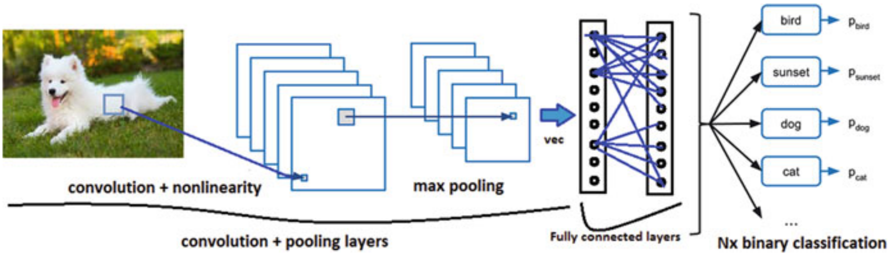

Fig. 4 Convolutional neural network working process

4.3 *Deep Convolutional Neural Network (DCNN)*

DCNN plays an essential role in image segmentation and classification. It is very effective in minimizing the number of frameworks without compromising the quality of models [17, 18]. It has the highest accuracy and is the more powerful among all the DNN algorithms such as ANN and RNN for predicting the images. Easy implementations and understand process which uses transfer learning techniques focus on gathering information for solving one problem and solve many problems related to that from the gained knowledge to get accurate output rapidly with less efforts [19–21].

Longxi Zhou et al. [22] discussed how to train the model using an accurate, rapid, and machine-agnostic segmentation and quantification method effectively. A new simulation model was created to dynamically represent the changes made for the Covid-19 infected area, and the dynamic model was used to expand additional data, which can improve the outstanding accomplishment of our segmentation model using DCNN. Through the development of a unified learning platform and heterogeneous data collection and development of preprocessing methods, the size of the data set is still limited.

Figure 5 here shows how DCNN preprocesses, extracts, and classifies the images [23, 24]. Initially, we take several chest CT images as input, then preprocess those raw input images and send for feature extraction. Here parallel deep feature extractors are used to extract the images using ResNet50V2 network and Xpection network which is much faster than the inception or GoogleNet. From the extracted features, Softmax classifier is added to classify the images into three different forms, whether it is normal or it has coon pneumonia or Covid pneumonia [25, 26].

Zhao Wang, Qi Dou, et al. [27] recently discussed about the correlative learning of redesigned Net such as COVID-Net for classification of corona viruses using CT images. It explains about the systematic study of various transfer learning models used for the classification of Covid-19. It creates a framework to work with various datasets for providing higher accuracy.

Chest CT images are used from screening and detecting Covid-19 based on Deep Learning networks and were discussed by Talha anwar et al. [28]. It clarifies the key differences between the normal CT image and viral CT image. To solve complex

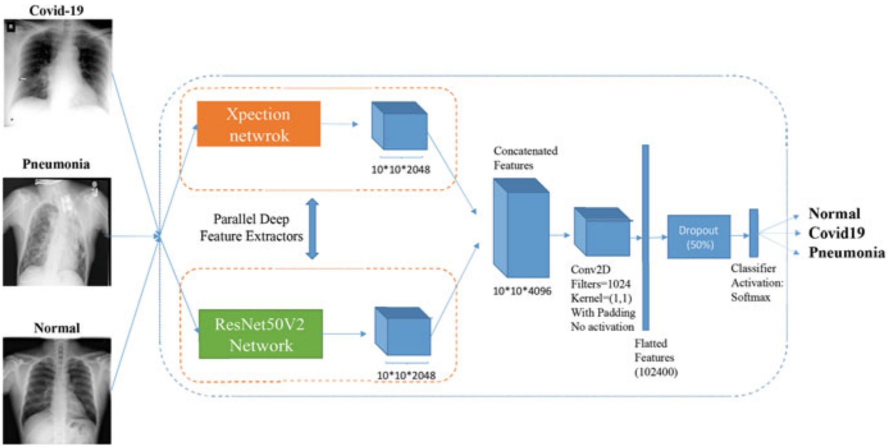

Fig. 5 Working of deep CNN to predict Covid-19

problems, various rates of learning strategies such as reducing plateau, recurring rate of learning, etc., have been used.

4.4 Transfer Learning Techniques in Deep Learning

Transfer Learning Techniques are widely used in DL for automatic detection. TL is a technique that focuses on gaining information (pre-trained models) by solving a specific problem and can be applied to a variety of related problems. The most commonly used Transfer Learning techniques for image segmentation and classification are (i) Fast R-CNN generate regions of interest with the help of selective search. (ii) Faster R-CNN is a variant of Fast R-CNN that employs the "Region Proposal Network" (iii) Mask R-CNN, a Faster R-CNN extension used for object detection and instance segmentation that is simple to train and adds little overhead to FR-CNN.

In general, CNN is used for the classifications and recognition of images, because of its high accuracy. VGG-16, ResNet50, and Inceptionv3 are a few examples of pre-trained image classification models. The process of classifying each pixel in an image as belonging to a specific category is known as image segmentation. Though there are several types of image segmentation methods, the two most commonly used are Semantic Segmentation and Instance Segmentation. Some of the Pre-Trained Models for Image Segmentation are U-Net, VB-Net, Inf-Net, or Semi Inf-Net, etc.

The related studies of Deep Learning methods used for Covid-19 diagnosis using chest CT images, as well as the datasets, transfer learning or pre-trained classifiers used by each technique, as well as its challenges and performance criteria, as shown in Table 2.

Table 2 Related studies of deep learning techniques for detection of Covid-19 using chest X-ray and chest CT scan images

References	Dataset used	DNN (TL) algorithms	Classifiers	Performance criteria (%)	Challenges
U. Ozkaya et al. [29]	Italian society of medical and interventional radiology dataset	Visual Geometric Group-19, GoogleNet, ResNet	Support vector machine	Accuracy is ~99.38 Sensitivity is ~93 Specificity is ~97.5 Precision is ~97.5	For covid-19 diagnoses, it employs a classification method. However, all deep learning models are insufficient to ensure success with the proposed method; new DL methods must be explored to ensure success
A. Ardakani et al. [30]	Clinical dataset	ResNet-101, Xception	Soft-Max classifier	Accuracy is ~99 Sensitivity is ~98.04 Specificity is ~100	Used to categorize and diagnose Covid-19 using Computer Aided Design (CAD) approach with the help of CT, whereas CAD system is not compared with radiologist
T. Ozturk, et al. [31]	Combination of different datasets	AlexNet or Image-Net	Dark Covid-Net classifier for YOLO	Accuracy is ~98 Sensitivity is ~100 Specificity is ~96	Covid-net model helps us to identify the covid-19 effectively but the dataset needs to be updated regularly in order to find an automatic detection

(continued)

References	Dataset used	DNN (TL) algorithms	Classifiers	Performance criteria (%)	Challenges
X. Wu, H. Hui et al. [32]	Clinical dataset	ResNet-50	Dense-Net-121	Accuracy is ~76 Sensitivity is ~81 Specificity is ~62	Rapid identification of Covid-19. Due to the limited data set, CT sliced pixels were used as samples for the DL model, which show fusion of inter-slice and tie-cost issues
H.S. Maghdid et al. [33]	Diagnostic imaging dataset	AlexNet, ResNet-34	Soft-max	Accuracy is ~94 Area under Curve (AUC) is ~96.35 Specificity is ~92	A large dataset of X-rays and CT image were used from various sources to provide a simple but effective detection result, but is not suitable for large data sources
L. Sun, et al. [34]	Clinical dataset	AFS-DF	Aggregation or cross-site learning approaches	Accuracy is ~91 Sensitivity is ~93 Area under Curve (AUC) is ~96 Specificity is ~89	This model is used to train a forest to reduce redundancy. It is mostly focused on feature which specifies the location whereas it is limited to validate only Covid-19 and CAP classification task

Y. Song, et al. [35]	Combination of different datasets	ResNet-101 DenseNet	Soft-max	Accuracy is ~98.5 AUC is ~99 Recall is ~93 Precision is ~96.43	Rapid and accurate identification of deep pneumonia to identify covid-19, implemented in super computer which enables parallel execution of 1000 tasks simultaneously
I. Razzak, et al. [36]	Cohens GitHub	Stacked Auto-Encoder used for Feature Reduction	Support Vector Machine	Accuracy is ~98 Sensitivity is ~69 Precision is ~70 F1-Score is ~69.5	It has a high level of accuracy for automatic diagnosis when using quantitative evaluation, but it is only useful for early screening and not for the complete screening procedure
S. Ozturk, et al. [37]	Clinical dataset	Covid-CTNet-112	Combined Decision Tree and Ada-Boost	Accuracy is ~83 Sensitivity is ~81 Specificity is ~84 Area under Curve (AUC) is ~90 F1-Score is ~77	The SMOTE method is used to eliminate unbalanced data, resulting in great accuracy in a short amount of time. It only works when we have previously trained datasets

(continued)

References	Dataset used	DNN (TL) algorithms	Classifiers	Performance criteria (%)	Challenges
S. Wang, et al. [38]	Diagnostic imaging dataset	M-Inception	Soft-max	Accuracy is ~89.5 Sensitivity is ~87 Specificity is ~88	With the pathogen images of conformed COVID cases, it employs modified Inception TL techniques. It is not appropriate for all data sources
T. Javaheri, et al. [39]	Aggregating multiple datasets	CovidCTNet open source	Soft-max	Accuracy is ~90 Sensitivity is ~80 Area under curve (AUC) is ~94	High accuracy and the model works with heterogeneous open source data, but uses very small sample sizes
X. He. et al. [40]	Clinical dataset	ResNet-V2 models, VGG-16, VGG-19	Ensemble learning approach	Accuracy is ~87.5 Sensitivity is ~87 F1-Score is ~85.0	The Self-Trans approach is used, which combines several learning techniques to produce unbiased results by reducing the over fitting problem. It has only been trained on publicly available datasets

X. Ouyang, et al. [41]	Combination of different datasets	3D ResNet-34 models	Multi-layer perceptron	Accuracy is ~87 Sensitivity is ~86.9 Specificity is ~90.1 Area under curve(AUC) is ~94.4 F1-Score ~ 82	The proposed model is being tested for tracking its consistency only when longitudinal data is ready
K. Elasnaoui and Y. Chawki [42]	Combination of different datasets	ResNet-50 models, VGG-16, VGG-19 Inception-V3 MobileNetV2	COVIDX-Net	Accuracy is ~99.5 Sensitivity is ~93	It uses automatic classification of Covid-19 with deep convolution neural networks, it uses transfer learning techniques which is not applicable for all data sets
K. Yang, et al. [43]	UCSD-AI4H datasets	CXR dataset, Inception-V1 And MobileNetV2	Softmax classifier	Accuracy is ~96 Area under curve(AUC) is ~99.4	It resizes an image during training phase, whereas the last hidden layer is learned by using t-SNE method. Quality becomes the biggest challenge while resizing the images

(continued)

References	Dataset used	DNN (TL) algorithms	Classifiers	Performance criteria (%)	Challenges
S. Rajaraman and S. Antani, [44]	Public datasets	DenseNet-121	Support vector machine	Accuracy is ~91 Recall is ~90.8 Precision is ~89.5 F1-Score is ~90	It uses datasets which represent pneumonia-related opacities; we train CNN using only DenseNet and get positive detection of Covid-19
R. Hu. et al. [19]	Combination of different datasets	CovXNet-V2	Linear layer	Accuracy is ~91 Sensitivity is ~91 Specificity is ~92 AUC is ~92	Insufficient samples also developed using augmentation of data for correct diagnosis. Misdiagnoses may occur when the necessary data is missing

Table 3 Comparison of various existing work for Covid-19 detection

Models	Accuracy	F1-Score	Specificity
Shallow CNN	95.9%	90.52%	92.9%
COVIDX-Net	93.4%	89.5%	94.3%
DenseNet-121	94.8%	92.3%	93.5%
VGG-19	95.5%	91.1%	97.5%
Mask R-CNN	96.98%	85%	**98.36%**
DMIL	**97%**	**91.3%**	96.5%

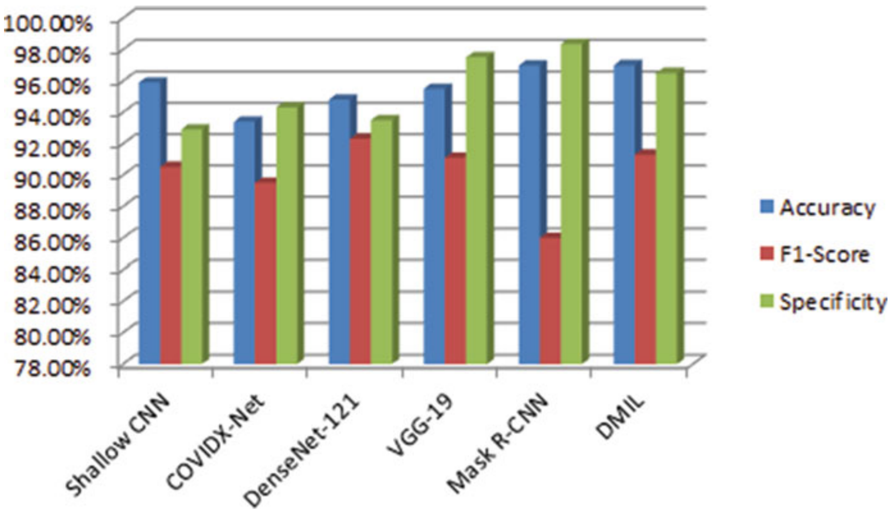

Fig. 6 Performance chart of various DL models

The performance parameters of all the six models were calculated, and the results of the parameter are given in Table 3. From this table, we came to know that among the six models, DMIL and mask R-CNN show an eminent performance for Covid-19 detection. Here, the parameters evaluated and compared are accuracy, specificity, and F1-score. By comparing these parameters with various algorithms, DMIL achieves maximum accuracy of 97%, F1-score of 91.3% and Mask R-CNN achieves the maximum specificity of 97.36%. The below chart shows the performance of various deep learning models as shown in (Fig. 6), which clearly exhibits the accuracy, specificity, and F1-score.

Table 4 shows the comparative analysis of various ensemble models with the proposed work. The performance parameters were calculated, and Mask R-CNN with DMIL technique shows an excellent performance with an accuracy of 98.96%, specificity of 97.83% and F1-score of 91.3%. These parameters are also explained clearly in the chart shown in (Fig. 7). By comparing all other existing ensemble models, the proposed DMIL with Mask R-CNN gives better accuracy for predicting Covid-19 using CT scan images.

Table 4 Comparison of various ensemble methods

Ensemble methods	Accuracy	Specificity	F1-Score
Xception65+VGG16	96.77%	97.48%	91.2%
DenseNet+ResNet-50	95.6%	97.5%	90.4%
MobileNetV2+CapsNet50	95.87%	96.13%	89%
MaskR-CNN+DMIL	**98.96%**	**97.83%**	**91.3%**

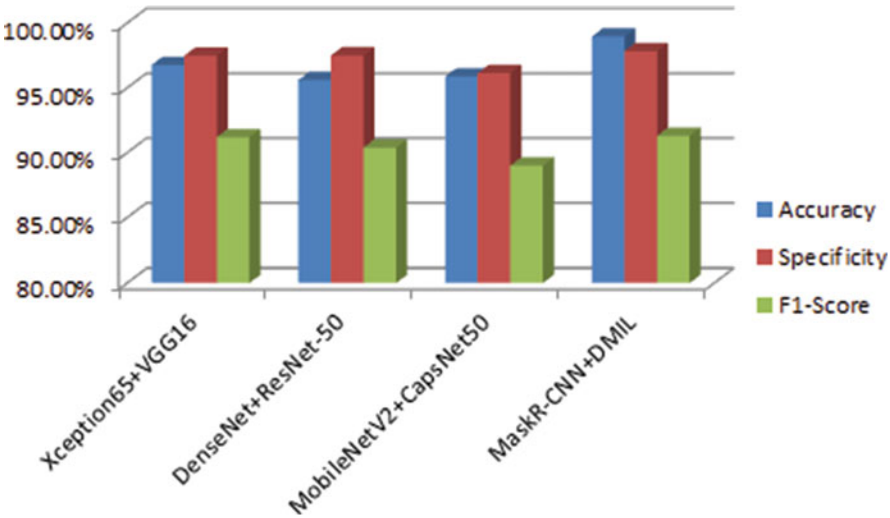

Fig. 7 Performance chart of various ensemble methods

5 Conclusion

An extensive review of research on diagnosis and prognosis using ML and DL networks was presented. A comparison of automated screening of Covid-19 from CT scanned images using various DL algorithms, including profound differential models such as MIL, DNN, Deep CNN, and Transfer Learning techniques, was discussed. Several tests were investigated for the detection of Covid-19 with its challenges, whereas the specialist can detect accurately using CT images. Various datasets were analyzed using pre-trained DNN, classifiers, performance metrics, and challenges. Transfer learning is only applicable to data that is similar in nature. The proposed ensemble models of DMIL with Mask R-CNN show a better accuracy of 98.96%. In the future, we will improve and expand the capability of transfer learning into multi-site settings as well as from other large-scale datasets to improve prognosis accuracy.

References

1. A. Nadya, J. Fouad, Editor in Chief's introduction to essays on the impact of COVID-19 on work and workers. J Vocat. Behav. **119**, 103441 (2020). https://doi.org/10.1016/j.jvb.2020.103441. Published online 2020 May 8. PMCID: PMC7205668
2. D. Suganya, R. Kalpana, Automated COVID-19 diagnosis using Deep Multiple Instance Learning with CycleGAN. 2022 International Conference on Smart Technologies and Systems for Next Generation Computing (ICSTSN), 2022
3. M. Eisenstadt, M. Ramachandran, N. Chowdhury, A. Third, J. Domingue, COVID-19 antibody test/vaccination certification: There's an app for that. IEEE Open J. Eng. Med. Biol. **1**, 148–155 (2020). https://doi.org/10.1109/OJEMB.2020.2999214
4. A. Crozier, S. Rajan, I. Buchan, M. McKee, Put to the test: Use of rapid testing technologies for covid-19. BMJ **372**(n208) (2021). https://doi.org/10.1136/bmj.n208
5. O. Shahid, M. Nasajpour, S. Pouriyeh, R.M. Parizi, M. Han, M. Valero, F. Li, M. Aledhari, Q.Z. Sheng, Machine learning research towards combating COVID-19: Virus detection, spread prevention, and assistance. J. Biomed. Inform. **117**, 103751 (2021). https://doi.org/10.1016/j.jbi.2021.103751
6. Z. Han, B. Wei, Y. Hong, T. Li, J. Cong, X. Zhu, H. Wei, W. Zhang, Accurate screening of COVID-19 using attention-based deep 3D multiple instance learning. IEEE Trans. Med. Imaging **39**(8), 2584–2594 (2020)
7. M. Roberts, D. Driggs, M. Thorpe, et al., Common pitfalls and recommendations for using machine learning to detect and prognosticate for COVID-19 using chest radiographs and CT scans. Nat. Mach. Intell. **3**, 199–217 (2021). https://doi.org/10.1038/s42256-021-00307-0
8. Y. Song et al., Deep learning enables accurate diagnosis of novel coronavirus (COVID-19) with CT images (2020), *medRxiv*. [Online]. Available: https://www.medrxiv.org/content/early/2020/02/25/2020.02.23.20026930
9. O. Gozes et al., Rapid AI development cycle for the coronavirus (COVID-19) pandemic: Initial results for automated detection & patient monitoring using deep learning CT image analysis (2020), *arXiv:2003.05037*. [Online]. Available: http://arxiv.org/abs/2003.05037
10. M. Chung et al., CT imaging features of 2019 novel coronavirus (2019-nCoV). Radiology **295**(1), 202–207 (2020)
11. J. Zhao, Y. Zhang, X. He, P. Xie, Covid-ct-dataset: A CT scan dataset about covid-19 (2020), *arXiv* preprint arXiv:2003.13865
12. J. Born, G. Brandle, M. Cossio, M. Disdier, J. Goulet, J. Roulin, N. Wiedemann, Pocovid-net: Automatic detection of covid-19 from a new lung ultrasound imaging dataset (pocus) (2020), *arXiv* preprint arXiv:2004.12084
13. F. Shi et al., Large-scale screening of COVID-19 from community acquired pneumonia using infection size-aware classification (2020), *arXiv:2003.09860*. [Online]. Available: http://arxiv.org/abs/2003.09860
14. M. Rahimzadeh, A. Attar, A modified deep convolutional neural network for detecting COVID-19 and pneumonia from chest X-ray images based on the concatenation of Xception and ResNet50V2. Inform. Med. Unlocked **19**, 100360., ISSN 2352-9148 (2020). https://doi.org/10.1016/j.imu.2020.100360
15. A.A. Khan, S. Shafiq, R. Kumar, J. Kumar, A. Ul Haq, H3dnn: 3D deep learning based detection of Covid-19 virus using lungs computed tomography. 2020 17th International Computer Conference on Wavelet Active Media Technology and Information Processing (ICCWAMTIP) | 978-0-7381-4259-3/20/$31.00 ©2020 IEEE | https://doi.org/10.1109/ICCWAMTIP51612.2020.9317357
16. O. Gozes, M. Frid-Adar, N. Sagie, H. Zhang, W. Ji, H. Greenspan, Coronavirus detection and analysis on chest CT with deep learning (2020), *arXiv:2004.02640*. [Online]. Available: http://arxiv.org/abs/2004.02640
17. X. Xu et al., Deep learning system to screen coronavirus disease 2019 pneumonia (2020), *arXiv:2002.09334*. [Online]. Available: http://arxiv.org/abs/2002.09334

18. S. Jin et al., Ai-assisted CT imaging analysis for COVID-19 screening: Building and deploying a medical AI system in four weeks (2020) medRxiv. [Online]. Available: https://www.medrxiv.org/content/early/2020/03/23/2020.03.19.20039354
19. R. Hu, G. Ruan, S. Xiang, M. Huang, Q. Liang, and J. Li, Automated diagnosis of covid-19 using deep learning and data augmentation on chest CT (2020), medRxiv.
20. S. Khobahi, C. Agarwal, M. Soltanalian, Coronet: A deep network architecture for semi-supervised task-based identification of covid-19 from chest x-ray images (2020), medRxiv
21. J.P. Cohen, P. Morrison, L. Dao, K. Roth, T. Q. Duong, M. Ghassemi, Covid-19 image data collection: Prospective predictions are the future (2020), *arXiv* 2006.11988. [Online]. Available: https://github.com/ieee8023/covid-chestxray-dataset
22. L. Zhou, Y. Hong, T.L.X. Zhu, H. Wei, A rapid, accurate and machine-agnostic segmentation and quantification method for CT-based COVID-19 diagnosis. IEEE Trans. Med. Imaging **39**(8), 2638–2652 (2020)
23. J. M. Banda, R. Tekumalla, G. Wang, J. Yu, T. Liu, Y. Ding, G. Chowell, A large-scale covid-19 twitter chatter dataset for open scientific research–an international collaboration (2020), *arXiv* preprint arXiv:2004.03688
24. J. Long, E. Shelhamer, T. Darrell, Fully convolutional networks for semantic segmentation, in Proceedings of the IEEE conference on computer vision and pattern recognition, 2015, pp. 3431–3440.
25. L. Zhang, M. Wang, M. Liu, D. Zhang, A survey on deep learning for neuroimaging-based brain disorder analysis (2020), *arXiv* preprint arXiv:2005.04573
26. S. Wang et al., A deep learning algorithm using CT images to screen for Corona virus disease (COVID-19) (2020), *medRxiv*. [Online]. Available: https://www.medrxiv.org/content/early/2020/04/24/2020.02.14.20023028
27. Z. Wang, Q. Liu, Q. Dou, Member, IEEE, Contrastive cross-site learning with redesigned net for COVID-19 CT classification. IEEE J. Biomed. Health Inform. **24**(10), 2806–2813 (2020)
28. T. Anwar, S. Zakir, Deep learning based diagnosis of COVID-19 using chest CT-scan images. 2020 IEEE 23rd International Multitopic Conference (INMIC) | 978-1-7281-9893-4/20/$31.00 ©2020 IEEE | https://doi.org/10.1109/INMIC50486.2020.9318212
29. U. Ozkaya, S. Ozturk, M. Barstugan, Coronavirus (covid-19) classification using deep features fusion and ranking technique (2020), *arXiv* preprint arXiv:2004.03698
30. A.A. Ardakani, A.R. Kanafi, U.R. Acharya, N. Khadem, A. Mohammadi, Application of deep learning technique to manage covid-19 in routine clinical practice using CT images: Results of 10 convolutional neural networks. Comput. Biol. Med. **121**, 103795 (2020)
31. T. Ozturk, M. Talo, E.A. Yildirim, U.B. Baloglu, O. Yildirim, U.R. Acharya, Automated detection of covid-19 cases using deep neural networks with x-ray images. Comput. Biol. Med. **121**, 103792 (2020)
32. X. Wu, H. Hui, M. Niu, L. Li, L. Wang, B. He, X. Yang, L. Li, H. Li, J. Tian, et al., Deep learning-based multi-view fusion model for screening 2019 novel coronavirus pneumonia: A multicentre study. Eur. J. Radiol. **128**, 109041 (2020)
33. H.S. Maghdid, A.T. Asaad, K.Z. Ghafoor, A.S. Sadiq, M.K. Khan, Diagnosing covid-19 pneumonia from x-ray and CT images using deep learning and transfer learning algorithms (2020), *arXiv* preprint arXiv:2004.00038
34. L. Sun, Z. Mo, F. Yan, L. Xia, F. Shan, Z. Ding, W. Shao, F. Shi, H. Yuan, H. Jiang et al., Adaptive feature selection guided deep forest for covid-19 classification with chest CT (2020), *arXiv* preprint arXiv:2005.03264
35. Y. Song, S. Zheng, L. Li, X. Zhang, X. Zhang, Z. Huang, J. Chen, H. Zhao, Y. Jie, R. Wang et al., Deep learning enables accurate diagnosis of novel coronavirus (covid-19) with CT images (2020), medRxiv
36. I. Razzak, S. Naz, A. Rehman, A. Khan, A. Zaib, Improving coronavirus (covid-19) diagnosis using deep transfer learning (2020), medRxiv
37. S. Ozturk, U. Ozkaya, M. Barstugan, Classification of coronavirus images using shrunken features (2020), medRxiv

38. S. Wang, B. Kang, J. Ma, X. Zeng, M. Xiao, J. Guo, M. Cai, J. Yang, Y. Li, X. Meng et al., A deep learning algorithm using CT images to screen for corona virus disease (covid-19) (2020), MedRxiv
39. T. Javaheri, M. Homayounfar, Z. Amoozgar, R. Reiazi, F. Homayounieh, E. Abbas, A. Laali, A.R. Radmard, M.H. Gharib, S.A. J. Mousavi et al., Covidctnet: An open-source deep learning approach to identify covid-19 using CT image (2020), arXiv preprint arXiv:2005.03059
40. X. He, X. Yang, S. Zhang, J. Zhao, Y. Zhang, E. Xing, P. Xie, Sample-efficient deep learning for covid-19 diagnosis based on CT scans (2020), medRxiv
41. X. Ouyang, J. Huo, L. Xia, F. Shan, J. Liu, Z. Mo, F. Yan, Z. Ding, Q. Yang, B. Song, et al., Dual-sampling attention network for diagnosis of covid-19 from community acquired pneumonia. IEEE Trans. Med. Imaging (2020)
42. K. Elasnaoui, Y. Chawki, Using x-ray images and deep learning for automated detection of coronavirus disease. J. Biomol. Struct. Dyn.., no. just-accepted, 1–22 (2020)
43. K. Yang, X. Liu, Y. Yang, X. Liao, R. Wang, X. Zeng, Y. Wang, M. Zhang, T. Zhang, End-to-end covid-19 screening with 3d deep learning on chest computed tomography (2020)
44. S. Rajaraman, S. Antani, Training deep learning algorithms with weakly labeled pneumonia chest x-ray data for covid-19 detection (2020), medRxiv