Challenges of computational intelligence approaches as an alternative tool for diagnoses of covid-19 based on medical images

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Abstract— The coronavirus disease 2019 (COVID-19) pandemic is spreading all over the world, requires a crucial diagnosis of individuals to help reduce virus transmission. The current gold standard for covid-19 diagnosis using polymerase chain reaction (PCR) can take a few hours/days, which is problematic. The most promising and inspiring domain for the utilization of computational intelligence (CI) approaches is medication, and furthermore one of the most challenging domains to see an effective and successful adoption by clinician. However, CI approaches further strengthen the power of the imaging tools and help medical specialists in the global fight against COVID-19 with help of clinical imaging such as X-ray and computed tomography (CT). This paper presents a review of the developments issues on a diagnosis of covid-19 based on clinical image, and how computational intelligence (CI) methods applied for diagnosis of covid-19, that gives precise and effective imaging solutions for various Coronavirus diagnosis applications have been investigated. Nonetheless, the strength, weaknesses, and accuracy of various methods applied, the state-of-the-art datasets utilized, and various difficulties on the identification of abnormalities on diagnosis based on the clinical image have also been discussed. Lastly, this survey also gives new insight into future research requirements in the clinical image-based diagnosis of coronavirus disease 2019 (Covid-19).

Index Terms— Computational Intelligence, Medical Image, X-ray, Computed Tomography (CT), Covid-19 Diagnosis, Coronavirus Detection.

1 Introduction

IN this Covid-19 global health emergency, the clinical industry is looking for new computational intelligence approaches to screen and controls the spread of COVID- 19 (Coronavirus) pandemic. Computer-based intelligence is one such innovation that can effectively track the spread of this infection, recognizes the high-hazard patients, what's more, is valuable in controlling this contamination progressively. It can likewise predict mortality hazards by satisfactorily examining the past data of the patients. Computational intelligence can assist us with fighting this infection by populace screening, clinical assistance, warning, and recommendations about disease control [1][2]. This innovation can improve the treatment, planning, and revealed results of the COVID-19 patient, being a proof-based clinical device.

All these are realized because of the approach of the data age, additionally usually known as the digital age, has had a significant effect on health sciences. Tremendous amounts of datasets now move through the various phases of healthcare organizations, and there is a significant prerequisite to extract knowledge and utilize it to improve these sectors in all regards. Computational intelligence frameworks offer help to medical experts included both in the clinical doctors and administrative settings. Among these frameworks, computational intelligence techniques have increased expanding prevalence given their capacity to adapt to a lot of clinical information and uncertain data [3]. Besides, the doctor isn't just centered around the treatment of the patients, yet besides the control of illness with the computational intelligence application. Significant manifestations and test investigation are finished with the assistance of computational intelligence with the most elevated of precision. It additionally shows it diminishes the complete number of steps taken in the entire procedure, making progressively obtainable [4].

Computer-based intelligence can rapidly break down sporadic symptoms and other 'warnings' and in this manner caution the patients and the healthcare experts [5], [6]. It assists in giving quicker decision making, which is financially savvy. It assists with building up another diagnosis and the executive's framework for the COVID 19 cases, through valuable algorithms. Computational intelligence is useful in the diagnosis of tainted cases with the assistance of clinical imaging advancements like Computed tomography (CT), Magnetic resonance imaging (MRI) scan of the patient's body, and X-Ray images.

Besides, the majority of these processing instruments are generally new and as yet developing regarding the clinical field, and there are various related issues that despite everything should be valued and understood. Moreover, health experts and related partners have not completely grasped these advances, however. Therefore, perilous decisions are still intensely dependent upon human-based interpretations that are tedious and lack understanding of data assessments. This is valid despite numerous innovations being much slower when compared with decisions got from the utilization of traditional computing. Based on this, it is noticed that legitimate frameworks can assist with managing issues like data collection and sharing prompting greater receptivity by the health community. Besides, the absence of normalization of protocols additionally implies that the extent of data to be analyzed is restricted to explicit zones. In this manner, results got in particular clinical as well as topographical areas may not apply in others [7].

Even though real-time reverse transcriptase-polymerase chain reaction (RT-PCR) has been thought of as the best quality level for Covid-19 diagnosis, suspected patients delay accurate diagnostics due to very limited supply, severe prerequisites for laboratory facility and 4-6 Hours delays to obtained results, which would incredibly defer exact diagnosis of suspected patients, which has presented phenomenal difficulties to forestall the spread of the disease, especially at the center of the scourge zone. Conversely, with it, chest computed tomography (CT) is a quicker and simpler strategy for clinical diagnosis of COVID-19 by combining the patient's clinical symptoms and signs with their ongoing close contact, travel history, and laboratory discoveries, which can make it feasible for speedy diagnosis as right on time as conceivable in the clinical practice. Now, what is the key to a quick, fast, and less expensive diagnosis of Covid-19? The answer is chest CT and other medical image-based as a key part of the diagnostic strategy for suspected patients and its CT appearances have been emphasized in a few ongoing reports [8]–[10]. The inspiration for this survey is to introduce the bigger picture of the issues and developments in the clinical diagnosis of COVID-19 and to investigate the different computational intelligence (CI) methods applied for various clinical diagnostic tasks.

2 METHODOLOGY

In this investigation, the latest articles identified with various computational intelligence (CI) methods utilized in the clinical diagnosis of Covid-19 have been reviewed. The recent articles for the distinctive CI strategies were looked through thoroughly from credible sources, for example, ScienceDirect, IEEE Xplore, Springer, and PubMed named it. We have included just the articles distributed from the beginning of coronavirus disease, December 2019 to September 2020. The researchers have utilized both the nonexclusive and explicit hunt strings on the above databases to look through the articles. The given strings have been looked at on the above databases, both in parts and as an entirety. The following are the biggest conventional inquiry string with keywords used to look through the articles. ‘‘(‘Deep learning’, ‘Computational intelligence’, ‘Soft computing', 'Machine learning', 'Artificial intelligence' ‘Convolutional neural network’) based ('approaches' OR 'techniques' OR 'methods') in ('medical disease diagnosis) of (‘Coronavirus’ or ‘Covid-19') OR 'clinical decision support system of (‘Coronavirus’ or ‘Covid-19'), OR 'computer-aided medical diagnosis of Coronavirus or Covid-19')’’.

‘‘('Hybrid') computational ('approaches' OR 'techniques' OR' methods') in ('medical disease diagnosis' OR 'clinical decision support system' OR 'clinical medicine' OR 'computer-aided medical diagnosis' of (‘Coronavirus’ or ‘Covid-19’)’’.

‘‘(Uncertainty) handling ('approaches' OR 'techniques' OR 'methods') in ('medical disease diagnosis' OR 'clinical decision support system' OR 'clinical medicine' OR 'computer-aided medical diagnosis') of (‘Covid-19’ or ‘Coronavirus’)’’.

At first, the articles have been chosen by going through their abstract. Likewise, a few articles were chosen via looking through the reference of the articles. The chose articles have been evaluated in depth. Table 1 summarized the surveyed articles' references, methodology, diagnostic task, and database used. Also, Table 2 summarized the surveyed articles' references, strengths, weaknesses, and accuracy.

TABLE 1
SUMMARY OF THE SURVEYED METHODOLOGY, DIAGNOSTIC TASK, AND DATABASE USED.

References	Methodology	Diagnostic tasks	Database used
[11]	UNet++	Diagnosis	Datasets from Renmin Hospital of Wuhan University, 51 patients confirmed cases of Covid-19 and 55 of other diseases.
[12]	3D CNN Model	Classification	A total sum of 618 CT samples was collected, out of 219 patients, 110 are confirmed case of Covid-19. The remaining 399 was the control experiment group which constituted 224 CT samples of patients with Influenza viral pneumonia and 175 CT sample

			of Healthy folks.
[13]	DL-Based Segmentation Network: VB-Net	Segmentation	A Sum of 300 CT scans of Covid-19 patients collected from the Shanghai Public Health Clinical Center and other 249 covid-19 patients CT images were also collected outside Shanghai for training.
[14]	2D and 3D deep learning models	Detection, characterizing, and tracking.	157 multinational datasets comprise of China and USA.
[15]	Infection Size Aware Random Forest method(ISARF)	Classification	A total sum of 2685 CT images was collected from three different centers, which comprises (Tongji Hospital of Huazhong University of Science and Technology, Shanghai Public Health Clinical Center of Fudan University, and China-Japan Union Hospital of Jilin University). The datasets made-up of 1658 confirm the case of Covid-19 and 1027 community-acquired pneumonia.
[16]	Deep Convolutional Neural Networks (CNN)	Classification	Datasets utilized in the study was collected from two recently published article and the other two was gathered by the author.
[17]	CNN Model	Classification	A Sum of 99 CT images of patients was collected, among which are, 55 typical viral pneumonia cases and 44 confirmed cases of covid-19 from three different center as follows (Xi'an Jiaotong University First Affiliated Hospital, Nanchang University First Hospital, and Xi'an No.8 Hospital of Xi'an Medical College)
[18]	DeepPneumonia	Diagnosis	Datasets were collected from two different centers, Renmin Hospital of Wuhan University and Sun Yat-sen University in Guangzhou. The CT images obtained comprises 88 confirmed covid-19 patients, 101 other pneumonia patients, and 86 healthy people for diagnosis.
[19]	DeCoVNet	Detection	Datasets were collected in this study in Union Hospital, Tongji Medical College, Huazhong University of Science and Technology. 540 patients engaged in the study, which comprises 313 patients clinically diagnosed with covid-19 positive and 227 patients without covid-19.
[20]	CovNet	Detection	A total of 3,322 CT images of patients were obtained from 6 different clinical centers, which comprises of 30% confirmed covid-19, 40% community-acquired pneumonia, and %30 non-pneumonia.
[21]	Bayesian Convolutional Neural Networks (BCNN)	Diagnosis	The paper used available public datasets of 68 x-ray images of covid-19 confirmed cases from Dr. Joseph Co-

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			hen's Github repository and Kaggle's Chest X-Ray Images (Pneumonia) from healthy patients.
[22]	COVIDX-Net	Classification	5o X-ray images datasets from the public repository by Dr. Joseph Cohen and Dr. Adrian Rosebrock was used, which comprises 25 negative and 25 positive Covid-19 cases.
[23]	Deep CNN, Decompose, Transfer, and Compose (*DeTraC*)	Classification	Healthy folk datasets from the Japanese Society of Radiological Technology (*JSRT*) was collected, which contains 80 sample and another 105 covid-19 confirmed cases and 11 sample SARS was also utilized in the study.
[24]	Deep learning algorithm	Detection and quantification	The datasets use consist of 110 CT scan of confirmed COVID-19 patients from Zhejiang province, China.
[25]	CNN	Classification	The study used publicly available datasets by Dr. Joseph Cohen available from a GitHubrepository, which consists of 137 x-ray images of confirmed covid-19 cases, and 117 images of healthy people with pneumonic disease similar to covid-19 from the Kaggle repository.
[26]	Deep learning	Classification	The datasets used during the experiment in this study was collected from multiple sources such as the Radiological Society of North America (RSNA), U.S. national library of medicine (USNLM) collected Montgomery country - NLM(MC) and COVID-19 image dataset is a public database of pneumonia cases with CXR images related to COVID-19, MERS, SARS, and ARDS.
[27]	DenseNet201 model	Identification and diagnosis	Covid-19 datasets from Kaggle were utilized in the study, which comprises a sum of 2492 CT-scans out of which 1262 are positive for covid-19.
[28]	Deep learning algorithm	detection, segmentation, and location	A Sum of 96 datasets was collected, out of which 84 patients from Taihe Hospital, Shiyan, Hubei; 11 from Wuhan First Hospital,Wuhan, Hubei; 1 from Jinling Hospital, Nanjing, Jiangsu was used during testing of the algorithm.
[29]	Deep learning	Detection	The datasets used from GitHub, Kaggle, and Open-i.
[30]	deep transfer learning	Detection	Published available datasets by [31] were used in the study.
[32]	SVM	Classification	Datasets of 53 infected patients from Societa Italiana di Radiologia Medica e Interventistica was utilized.
[33]	convolutional neural net-	Detection	A total of 50 datasets of covid-19

	work		open-source GitHub repository shared by Dr. Joseph Cohen and another 50 x-ray images of pneumonia from Kaggle was obtained.
[34]	Multi-class Classification and Hierarchical Classification	Classification	The datasets used in the study were collected from three different sources such as Dr. Joseph Cohen GitHub repository, Radiopedia encyclopedia, and NIH dataset.
[35]	Fast Fourier Transform (FFT based)	Diagnosis	A total of 275 positive and 195 negative CT images of covid-19 patients were collected from the GitHub repository.
[36]	Case-based reasoning (CBR) method	Detection and diagnosis	The researchers curated new datasets of COVID-19 from some publicly available data from a standard source such as the Italian Society of Medical and Interventional Radiology (SIRM)
[37]	ML algorithms	Identification	A Sum of 6,512 patients from seven different provinces (Anhui, Guangdong, Henan, Jiangsu, Shandong, Shanxi, and Zhejiang) in China datasets of covid-19 downloaded from GitHub repository.
[38]	Transfer learning with CNNs	Classification	Several sources of X-rays datasets from the public domain were collected such as GitHub repository, Radiological Society of North America (RSNA), Radiopaedia, and Italian Society of Medical and Interventional Radiology (SIRM)
[39]	Artificial neural network and Convolutional CapsNet	Diagnosis	Datasets x-ray images of covid-19 and pneumonia from public domain such as GitHub and other web service used in this study.
[40]	2D curvelet transformation, chaotic salp swarm algorithm (CSSA) and EfficientNet-B0	Diagnosis	The researchers created a dataset in total, 2905 x-ray images used in the study, which comprises of 219 COVID-19 patients, 1341 normal, and 1345 viral pneumonia.

TABLE 2
SUMMARY OF THE SURVEYED STRENGTHS, WEAKNESSES, AND ACCURACY

References	Strengths	Weaknesses	Accuracy
[11]	The model has compared with experts Radiologists and shows a shorter time than experts. Also, the model was highly sensitive and stable, and would never be affected by work burden, subjective status, and outside pressure. Analysis by radiologists reduced by 65%.	The datasets used were very small and the model utilized was not compared with any other model.	The model shows a sensitivity of 100%, a specificity of 93.55%, accuracy58 of 95.24%, PPV of 84.62%, and NPV of 100%; a per-image sensitivity of 94.34%, a specificity of 59 99.16%, accuracy of 98.85%, PPV of 88.37%, and NPV of 99.61% in

			retrospective dataset.
[12]	The model classifies three different CT sample, which includes, Covid-19, Influenza pneumonia, and non-infection folks. Also, the model performed much better than RT-PCR testing.	Effective monitoring of patient progress over time not embedded in the model	The model indicated an AUC of 0.996 (95%CI: 0.989–1.00) for Coronavirus vs Non-coronavirus cases per thoracic CT studies. They calculated a sensitivity of 98.2% and a specificity of 92.2%.
[13]	The model quantifies the COVID-19 infection region, thus, provide the basis for evaluation of severity Covid-19 and tracking progressing changes over time during treatment. Also, the model provides a 3D rendering early stage, progressive stage, and severe stage of the infection.	The model quantifies covid-19 infections lesion only not includes other pneumonia. The validation datasets were also collected from one region, which may not be the same with a covid-19 patient in another zone. Furthermore, the model was not compared with another existing model.	The results show dice similarity coefficients of 91.6%±10.0% between automatic and manual segmentations. Validation datasets also show an estimation error of 0.3% and lastly eliminate manual delineation of 1-5 Hours to 4 minutes when the model loop 3 times.
[14]	The proposed system detects, characterize, and track the progression of COVID-19 over time.	The datasets were too small. The model was not applicable in detecting other pneumonia.	The model achieved 0.996 AUC (95%CI: 0.989-1.00); on datasets of Chinese control and infected patients. Possible working point: 98.2% sensitivity, 92.2% specificity.
[15]	The model proposed size-aware and location-specific of the disease and separated the cohorts into different sizes. The study compared the handcrafted features with Radiomics features extracted directly from infected lesions.	The tracking progression of Covid-19 and symptom severity was not included in the study. correlation between symptoms and radiologic findings were not compared with pneumonia-related clinical characteristics.	The proposed method is shown a screening of COVID-19 from CAP with 90.7% sensitivity, 83.3% specificity, and 87.9% accuracy.
[16]	The study compared four different CNN based deep learning algorithms on x-ray images, which shows that SqueezeNet outperforms the other three AlexNet, ResNet18, DenseNet201.	None of the models quantifies the infected region or shows the severity of the infection. The models only classify and not be able to monitor the progress of the ailments over time.	The research results show accuracy, sensitivity, specificity and precision for both the schemes were 98.3%, 96.7%, 100%, 100% and 98.3%, 96.7%, 99%, 100%, respectively
[17]	The algorithms tested with external data and achieved 73% accuracy.	The datasets utilized were very small and did not include healthy patients. The algorithm used is not compared with the existing one. Only one radiologist was involved in the study and features analyzed were from a patient with severe lung lesions.	The model achieved an accuracy of 82.9% with a specificity of 80.5% and a sensitivity of 84%. The external testing dataset showed a total accuracy of 73.1% with a specificity of 67% and sensitivity of 74%
[18]	One of the most important features of the model was its interpretability, and the model visualized the extracted details. Besides, the model provides convincing	The datasets used were very small. The model was not able to quantify infected lesions in the lung. Progression over time does not monitor by the model.	They show excellent results of AUC of 0.99 and a sensitivity of 0.93. Also, the model distinguished between Covid-19 patient

	clues on the factors for its decision making, and automatically to identify the lesions from CT images.		and pneumonia infected patients with an AUC of 0.95 and a sensitivity of 0.96.
[19]	Even without COVID-19 lesions annotation by experts, the model used a weakly-supervised deep learning algorithm, which shows high performance on COVID-19 detection.	Temporal information was not used for lung segmentation by the model which could be improved by a 3D segmentation network and an expert's radiologist. The datasets utilized by the study collected from a single center and expert radiologist not included in this study.	The results of this study shown 0.959 ROC AUC and 0.976 PR AUC. There was an operating point with 0.907sensitivity and 0.911 specificities in the ROC curve. When using a probability threshold of 0.5 toclassify COVID-positive and COVID-negative, the algorithm obtained an accuracy of 0.901, a positive predictive value of 0.840, and a very high negative predictive value of 0.982.
[20]	The model visualized the important region of the lung in other to improved interpretability of the framework without manual annotation that leads to decision making. Abnormal regions were paid attention to by the algorithm while ignored the normal-like region.	The performance of CovNet was not evaluated in distinguishing Covid-19 from another pneumonic virus. Heatmaps are used to visualized unique features from the image in decision making not enough. The algorithm was not able to classify covid-19 into different severity.	The model CovNet achieved sensitivity and specificity for identifying COVID-19 in the independent test set was 114 of 127 (90% [95% CI: 83%, 94%]) and 294 of 307 (96% [95% CI: 93%, 98%]), respectively, with an AUC of 0. (p-value<0.001).
[21]	Uncertainty estimation by the model adds insight to point prediction performance to improve the reliability of the automated framework, which can alert radiologists on false predictions, which will increase the acceptance of deep learning into clinical practice in covid-19 diagnoses.	The datasets utilized for covid-19 were too small, the model not test with external data, and collected from a single repository. The model does not quantify the region of the infections on the lungs. Treatment follow-up and responses overtime not provided by the model.	The model showed experienced radiologist (i.e. 80% accuracy), when joined the performance reaches 90% when rejecting either almost 40% of the most uncertain samples or samples with *Hnorm* >= 0.4. For less than 2% of decisions referred for further inspections, there is a 95% confidence interval of the two non-overlapping scenarios.
[22]	The COVIDX-Net framework, compared 7 various classifiers based on deep learning algorithms which shows the best performance among them are VGG19 and DenseNet201models.	Scanty datasets were used to test the models. The model cannot classify another pneumonic disease. The model was not able to classify whether the disease was severe or not. Also, the models were not able to quantify the region of the disease in the lungs.	The results of VGG19 and Dense Convolutional Network (DenseNet) models showed a reasonable and alike performance of automated COVID-19 classification with fn1-scores of 0.89 and 0.91 for normal and COVID-19, respectively. The worst classification perfor-

			mance was reached by the InceptionV3 model with f1-scores of 0.67 for normal cases and 0.00 for COVID-19 cases
[23]	The model DeTraC utilized class decomposition within the *CNN*s to overcome irregularities in annotated data that remains the biggest challenge and an insufficient number of training images.	The datasets utilized were not sufficient and no quantization of the infected region of the lungs. Also, no indication of whether the covid-19 is severe or not by the model.	*DeTraC* model attained an impressive accuracy of 95.12% (with a sensitivity of 97.91%, and a specificity of 91.87%).
[24]	The model creates a Corona score that enables estimating the disease severity grade and external datasets were used during testing of the model.	The datasets used were not sufficient enough. The model cannot classify another pneumonic disease that is similar to covid-19.	The model obtained results of an Area Under Curve (AUC) result of 0.994 with 94% sensitivity and 98% specificity (at threshold 0.5).
[25]	The algorithm does not need handcrafted features to work efficiently. The datasets used collected across multiple platforms. The proposed method compared different CNN algorithms, which showed DenseNet121 performed better.	The training datasets were not sufficient, extending additional data sources can enhance the efficiency of the model. The algorithm not calculates the corona score in the lungs and does not distinguish the severity of the disease.	The results have shown that the DenseNet121 classifier obtained the best performance with 99% classification accuracy. The second-best learner wasa hybrid of the ResNet50 feature extractor trained by LightGBM with an accuracy of 98%.
[26]	Datasets imbalanced were addressed using the Weighted class approach and Random oversampling approach. Also, classification was done using two different designs such as binary classification and multi-class classification.	The model was not able to measured lung infections lesion and classification of disease based on severity or early stage. The study does not include radiology experts.	The study examined and analyzes different algorithms utilizing benchmark performance metrics such as accuracy, precision, recall, an area under a curve, specificity, and F1 score under four different scenarios concerned with imbalanced learning and classification strategy. However, models obtained a different grade in different scenarios, among which NASNetLarge showed better performance especially in the binary classification of COVID-19 samples.
[27]	The proposed model DenseNet201 compared with other competitive models which showed a 1% improvement which when applied to larger size datasets can save a lot of lives.	the proposed model not quantifies the size of the lesion in the lung, and also, not be able to distinguish the initial stage and severity of covid-19 from CT images.	The model DenseNet201 showed a 1% improvement in accuracy which is 97% compared with the accuracies obtained from VGG-16 and Resnet152V2 are 96% and 95%, respectively.
[28]	Automatic detection of lesions by	The model is not compared	The model showed 96

	the model and compare performance between radiological experts and the algorithm, which the model outperforms the experts. Also, the model extracted the detailedvolume and density of each abnormality, a distance of lesion from pleura from chest CT scan.	with another existing deep learning algorithm. The datasets of other pneumonic diseases were not included in the study. Also, the datasets utilized was not sufficient, because small datasets results cannot be generalized well-unseen cases and external datasets were not utilized to validate the model.	patients, 88 had pneumonia lesions on CT images and 8 had no abnormities on CT images. For a per-patient basis, the algorithm showed superior sensitivity of 1.00 (95% confidence interval (CI) 0.95, 1.00) and an F1 score of 0.97 in detecting lesions from CT images of COVID-19 pneumonia patients.
[29]	A deep learning feature extraction model of nine pre-trained CNN models utilized and fed to SVM classifier individually when statistical analysis is carried out ResNet50 plus SVM achieved the highest performance compared to the other 8 models.	The models used were not trained with other similar pneumonic disease and scanty datasets used. The model is not validated with external datasets. Also, the models are not distinguished between initial stages and severity of covid-19.	The results of resnet50 and SVM show superior performance in accuracy, FPR, F1 score, MCC and Kappa are 95.38%,95.52%, 91.41%, and 90.76% respectively for detecting COVID-19
[30]	The proposed model gained superior performance of area under curve (AUC) values as compared to the competitive models. Also, to defeat the challenges of small datasets the model exploits transfer learning algorithms.	The proposed model not validated with external datasets, and the datasets used were very small.	The results obtained by the proposed model showed an AUC of 0.9864, which is the highest score among the competitive models.
[32]	The classification was done in two stages, first without the feature extraction process, and another with five different feature extraction techniques was utilized.	The proposed model needs to be tested in other external datasets, and the patient's sample CT image was collected from a single center and was not sufficient enough.	The results obtained from the study showed GLSZM feature extraction method achieved 99.68% with 10-fold cross-validation accuracy.
[33]	Three different models were compared in the study, and to defeat the limited number of datasets used, deep transfer learning models were utilized.	The datasets utilized were very scanty and collected from a single repository.	The study showed ResNet50 pre-trained model yielded a superior accuracy of 98% among the three models.
[34]	The proposed model classifies different pneumonic disease caused by different pathogens. An imbalanced data issue was solved with resampling methods, and eight different feature sets extraction from the image was used by the proposed model.	The datasets used were very small, and no cross-validation approached.	The proposed model obtained a macro-avg F1-Score of 0.65 using a multi-class approach with MLP classifier using the LBP feature set and resampled with ENN. The proposed also gainedan F1-Score of 0.89 for the COVID-19 identification in the hierarchical classification scenario using the earlyfusion combination of BSIF, EQP, and LPQ feature resampled with SMOTE+TL.

[35]	The proposed model FFT Gabor shows supporting the confirmation of the predicted decision by visually showing the final features upon which decision is made.	The datasets were collected from a single repository, and the proposed model was not tested with the external datasets.	The results of the study showed the FFT-Gabor scheme achieved superior performance to predict in almost real-time the state of the patient with an average accuracy of 95.37%, sensitivity 95.99%, and specificity 94.76%.
[36]	The proposed model utilized a semantic and ontology-based approach, which allows it to achieve superior performance more than previous work.	The datasets used were not sufficient, and other similar pneumonic diseases to covid-19 were not included. Also, the model was tested with external datasets.	The proposed model achieved an accuracy of 94.54%.
[37]	The proposed models test on different clinical features of patients with COVID-19 infections and utilized different classifiers to examine information criterion and assess performance.	The size of the datasets used was extensively small to prove predictive accuracy	XGBoost algorithm showed superior performance in accuracy (>85%) to predict and select features that correctly indicate COVID-19 status for all age groups. Statistical analyses unveil that the most frequentand significant predictive symptoms are fever (41.1%), cough (30.3%), lung infection (13.1%), and runny nose (8.43%).
[38]	Tenfold-cross-validation of training and evaluation of the algorithms was performed. An encourage results showed MobileNet v2 effectively distinguished the Covid-19 cases from viral and bacterial pneumonia cases from the particular dataset.	The model does not classify covid-19 based on mild or severe symptoms, and the datasets used are not enough.	The proposed models result revealed accuracy, sensitivity, and specificity as 96.78%, 98.66%, and 96.46% respectively.
[39]	A binary class algorithm and a multi-class algorithm were used by the proposed model during detection. 10-fold cross-validation was used during the evaluation of the performance of the model.	A lot of hardware resources are required to processed huge x-ray imaged by Capsule networks, therefore this increases processing time. Classification by capsule networks required the same input image size, therefore required serious processing before passing it to the model as input.	The proposed model achieved an accuracy of 97.24%, and 84.22% for binary class, and multiclass, respectively.
[40]	The proposed hybrid model when tested on 1596 chest X-ray images revealed a superior performance of COVID-19, normal and viral pneumonia with high accuracy, which indicates superior to the single deep learning model, due to its fast and low cal-	The proposed model not categorized patients of covid-19 based on early stages, intermediates, or severe. Secondly, not be able to quantify infected lesions from the x-ray images.	The study reveals three different results, which made-up of the EfficientNet-B0 model, which showed accuracy, specificity, precision, recall, and F-measure values of 95.24%, 96.05%, 92.22%,

	culation cost.		93.61%, and 92.91%, respectively. The second results belong to 2D curvelet transformation also achieved accuracy, specificity, precision, recall, and F-measure values of 96.87%, 97.46%, 94.96%, 95.68% and 95.32%, respectively. The last results which belong to the hybrid model revealed accuracy, specificity, precision, recall and F-measure values of 99.69%, 99.81%, 99.62%, 99.44% and 99.53%, respectively.

3 STATE-OF-THE-ART DATASETS UTILIZED ON THE DIAGNOSIS OF COVID-19 INFECTIONS BASED ON MEDICAL IMAGE: CHALLENGES AND RECOMMENDATIONS.

Coronavirus has spread worldwide and compromised human life. In like manner, a few investigations have been directed to create an intelligence clinical diagnosis framework utilizing computational intelligence methods to control the impacts of this infection. However, various difficulties and exploration constraints have been shown on datasets utilized in the scholastic writing and should be tended to later on [41]. Data collection is the initial step to create computational intelligence (CI) techniques for COVID-19 applications. Datasets are accessible for the majority of the exploration headings in biomedical imaging. Notwithstanding, these datasets are limited in size for the utilization of deep learning methods. Scientists have underscored that bigger datasets are required for deep learning algorithms to give better insight and accuracy in diagnosis [42]. Even though there exist enormous open-source CT or X-ray datasets for lung infections, diabetes, and cancer, etc. However, both X-ray, CT scans for COVID-19 applications are not broadly accessible at present, which extraordinarily thwarts the exploration and development of CI strategies. However, distinctive COVID-19 datasets can be found in the writing. Some depend on X-ray images [43], while others depend on CT scans images [44]. Each dataset has a few limitations. For instance, a small number of training samples, low-quality images provided and images size are not equivalent.

Moreover, a portion of these difficulties are identified with covid-19 nature and conduct since seeing how the infection spreads and how individuals can be tainted brought about by the unpredictability of this pandemic disease is very troublesome. The need for a huge dataset in the scholastic writing for covid-19 is considered a difficult undertaking for researchers since it impedes the comprehension of viral patterns and features [45], [46]. The interest to develop a dataset that can be perceived by CI algorithms has expanded because the current dataset includes infographic information [47]. Different difficulties are associated with individuals and government reactions to covid-19 that requires all the newer observing methodologies and extra endeavors contrasted and the customary methodology for controlling pandemic disease [48]. Other challenges with covid-19 are the enormous variety in symptoms that are generally like basic cold symptoms, with numerous different varieties of infections that may happen in cases yet not in others. A few patients have remarkable symptoms, and others have no manifestations by any stretch of the imagination. Activists have produced tremendous and complex volumes of information that render its investigation illogical and hard to foresee utilizing linear classifiers [49], [50].

It is obvious from [51] outline four (4) challenges of datasets as follows: utilized little dataset size, utilized early phase datasets, the greater part of the datasets utilized are Chinese datasets, and dismissing the validation of the dataset. The little dataset isn't sufficient to prepare CI strategies. This is because the presentation of the most CI procedures is improved on huge datasets. Albeit numerous CI methods have demonstrated its appropriateness to contain COVID-19 scourges, there are questions about the precision of its outcomes. This debilitates their materialness, all things considered, for offering concrete symptomatic and treatment choices, as depending on their outcomes can influence patients' lives. Along these lines. After painting all challenges, [51] also accompanying recommendations such as the critical need to grow enormous worldwide datasets about COVID-19 pandemic. It is suggested to sorted datasets under a specific setting. These datasets ought to be refreshed constantly. Also, to produce another and complete dataset about COVID-19, data mining research is prescribed to find the example of these datasets. Moreover, the approval of these datasets is important to guarantee their legitimacy and security for being utilized by CI procedures for control the COVID-19 pandemic. Maybe it is smarter to characterize these datasets by a nation in which it was gathered. This is essential to examine whether there is a distinction in the consequences of the use of these datasets starting with one nation then onto the next, which thus can help in a more profound comprehension of COVID-19 disease by nation and the

capacity of its occupants to react to this disease.
Also, a warning to researchers overusing open-source datasets by [52] and those readers ought to know about the accompanying:

a) Duplication and quality issues. Contributors have no restriction to add COVID-19 images to numerous of the opensource databank vaults, for example, [53]–[55]. There is a high probability of duplication of images over these sources and no affirmation that the cases remembered for these datasets are affirmed COVID-19 cases (creators take an incredible jump to accept this is valid). Additionally, the vast majority of the images have been pre-handled and compressed into non-DICOM formats prompting a misfortune in quality and an absence of consistency/similarity.
b) Source issues. Numerous research papers utilize the pneumonia dataset of Kermany et al. [56] as a benchmark group. They normally neglect to refer to that this comprises of pediatric patients aged somewhere in the range of one and five. Building up a model utilizing grown-up COVID-19 patients and very young pneumonia patients is probably going to overperform all things considered simply recognizing youngsters versus grown-ups. This dataset is likewise wrongly alluded to as the Mooney dataset in numerous papers (being the Kermany dataset conveyed on Kaggle [57]). It is likewise imperative to consider the sources of each image class, for instance, if images for various diagnoses are from various sources. It is exhibited in [58] that by excluding the lung region the creators could distinguish the source with an AUC between 0.9210 to 0.9997 and 'analyze' COVID-19 with an AUC=0·68.
c) Frankenstein datasets. The issues of duplication and source become intensified when open 'Frankenstein' datasets are utilized, that is, datasets amassed from different datasets and redistributed under a new name. For example, dataset 55 joins datasets 48–50 and dataset 53 consolidates 14,50,55, disregarding that dataset 50 is now remembered for dataset 55. This repackaging of datasets, albeit practical, unavoidably prompts issues with algorithms being trained and tested on indistinguishable or overlapping datasets while trusting them to be from different sources.
d) Implicit biases in the source data. Images added to an opensource datasets bank and those extracted from publications [59] are probably to have implicit biases because of the commitment source. For instance, additional intriguing, unusual, or severe cases of COVID-19 likely show up in publications.

Also, a concluding remark by [60] revealed that they recognized genuine impediments in most, if not all, as of now accessible datasets. It is desperately required that more images from bigger and better datasets are made freely accessible. Dataset proprietors should put forth an attempt to improve the documentation about the entire datasets building cycle to increment fundamentally the dataset esteem and the nature of models prepared on them. For instance: there ought to be an away to categorically state clear statement of the proposed dataset to use, and express warning of regular misused cases; label definition and producing technique ought to be accounted for in detail, so different analysts can confirm the exactness of label assignments and assess the utility and sufficiency to the current issue; at long last, datasets ought to contain cohort attributes and subject determination models data, to assess the danger of choice inclination and to check if the training furthermore, target populace has a comparative characteristic. Finally, the joint effort of clinical associations over the globe is vital for extending existing datasets. Besides, the exactness of augmentation methods in expanding the size of the datasets should be evaluated. MRI gives high-resolution images and delicate tissue contrast at a greater expense. MRI based Coronavirus diagnosis and datasets are requested to contrast their accuracy with CT-scans and X-ray based strategies.

4 State-of-The-Art Approaches Utilized Based on Clinical Images

There is a lot of developing enthusiasm for other diagnostic techniques that utilize clinical imaging for the screening and diagnosis of COVID-19 cases [61]. This is outstanding because of the way that COVID-19 displays specific radiological signatures and image patterns which can be seen in clinical imager [5], [62] yet the analysis and identification of these patterns remain tedious and time-consuming, for experts' radiologists. This makes image examination from lung CT and X-Ray images of COVID-19 patients a prime possibility for computational intelligence-based methodologies, which could help quicken the investigation of these images, although the degree to which imaging can be utilized for diagnosis is as yet under development [63], [64].
Regardless, there are a few methodologies that plan to use computational intelligence for diagnosing COVID-19 from CT scan, through binary (for example normal versus Coronavirus positive) [17], [24] or multi-class (normal patients versus Coronavirus versus different kinds of pneumonia) classification tasks utilizing neural network trained without any preparation [18], [65][20]. These methodologies/approaches utilize various models, for example, Inception [66], UNet++ [67], and ResNet [68], which can be trained straightforwardly either on CT scan, or x-ray marked with areas of interest distinguished by radiologists. A few investigations additionally receive a hybrid approach, consolidating off-the-shelf software with customized computational intelligence approaches to accomplish higher accuracy. For instance, in Gozes et al. [14], a marketable clinical imaging program is utilized for starting image processing and afterward joined with a computational intelligence pipeline. The two-advance computational approach comprises of U-Net engineering [69] prepared on the clinical image of lung irregularities to pinpoint lung regions of interest and a Resnet-50 [68] prepared on ImagetNet [70] and calibrated on COVID-19 cases to classify the images as COVID-

positive or normal. The subsequent architecture can separate pertinent features from the images and distinguish COVID-19 pneumonia even in situations where there are a few contending expected diagnosis and can be sent both at emergency clinics to help radiologists quicken the investigation of new cases and shared on the Internet to empower fast survey of new images.

The recently computational article has shown that X-Ray images, and explicitly chest radiographs, likewise can be utilized for COVID-19 diagnosis and detection. Given the openness and possible convenience of the imaging gear required, they can be an option in settings where admittance to cutting-edge clinical hardware, for example, CT scanners is limited. As appeared in [23], [71], [72], there is potential in the utilization of Deep Learning approaches on X-Ray imagery, utilizing models like the ones utilized for CT examines (e.g., ResNet [68] and Convolutional Neural Networks (CNNs) [73]). Further work means to make prediction interpretable [74][21] and guarantee that the models can be applied in mobile and low-resources settings [75].

Deployment operation of detection and diagnosis framework which report in recent studies, for example, [13], have picked human-in-the-loop ways to deal with diminish the investigation time required while using computational models. The researchers utilize little manually-labeled clumps of data for training an underlying model given the V-Net engineering [76]. This model at that point proposes the segmentation of new CT scans, which would then be able to be adjusted by radiologists and took back into the model, in an iterative cycle. This methodology has empowered the advancement of a Deep Learning-based framework for both automatic segmentation and the checking of the disease-infected region in the lungs, just as surveying the severity of COVID-19, for example, the level of disease in the entire lung. The researchers show not just that the model improved its performance steadily, yet also that the human time required for examination of new images dropped from more than 30 minutes at first to under 5 minutes after 200 annotated sample was utilized to train the model, minimized the effort required by radiologists to survey other scans. This is a promising heading that saddles the intensity of computational intelligence alongside human annotation and expertise, which can be corresponding and commonly advantageous.

While promising results have been accomplished by numerous clinical imagery-based computational intelligence diagnostics techniques, all together for these strategies to be utilized as clinical decision support frameworks, they ought to go through clinical investigation and consent of quality control and regulations requirements. Specifically, their performance ought to be validated on an applicable and differing set of training, validation, and test datasets, and they ought to show adequacy in the clinical work process [77]. We note that the majority of the papers investigated needed to provision for these measures, depending on little and inadequately balanced datasets with defective evaluation approaches and no arrangement for incorporation in clinical work processes.

5 DISCUSSION

This section presents general issues of clinical diagnosis of covid-19 based on medical images. Numerous issues that emerged in the clinical diagnostic process such as fundamental difficulties on the identification of abnormalities on diagnosis based on clinical image, uncertainty in the clinical domain, knowledge acquisition and representation, and fingerprints of good computational intelligence (CI) approaches in clinical diagnosis.

5.1 Fundamental Difficulties on The Identification Of abnormalities on Diagnosis Based on Clinical Image.

Clinical assessment of imaging findings ordinarily requires investigation of various features, requiring a few degrees of examination beyond object recognition and classification (past the exemplary visual task of distinguishing "Cat versus Dog)". Except if these learning algorithms can be trained with hundreds or thousands of extra computational algorithms to recognize fluctuating features of a perceived object, it won't yield any helpful information about such inquiries. In the clinical imaging domain, numerous sorts of imaging pathology require detailed analysis and investigation of a mix of features, likely requiring a more prominent level of testing and validation, just as a gathering of different narrow computational algorithms. In any case, many studies that engaged uses of deep learning on some explicit clinical imaging issues have just been conceived and evaluated, particularly in the fields of cardiothoracic imaging and bosom imaging [78], [79].

For computational intelligence framework to recreate completely the multi-factorial nature of the radiologist's analysis of an image, for instance, a chest radiograph, it will probably be trained not by only one hug dataset (containing different divergent sorts of radiographic abnormalities), yet by the introduction of different datasets that explicitly strengthen the learning related with each class of imaging anomalies, (for example, cardiovascular, mediastinal, pneumonic, and rigid) just as extra datasets with different significant subclasses of imaging variations from the norm (for instance, innate coronary disease). The last total of the various datasets for chest radiographic images should be very hugged and extensively annotated, to guarantee that the computational intelligence experience matches both the depth and broadness of the radiologist's experience and knowledge. A less aggressive training approach could be devised to find out whether a radiograph is normal or abnormal for triage and emergency purposes, yet this methodology would not replicate the capacity and detailed accuracy of expert performance.

Another serious issue is the establishment of the best quality level. For instance, inside a huge dataset of chest radiographs in patients suspected to have covid-19, there might be differences among a few clinical radiologists in image interpretation. In clinical practice, one individual radiologist may need to not miss an instance of covid-19 because of its high clinical effect and accordingly would annotate on cases as confirmed covid-19 positive with subtle/non-specific findings Covid-19, while another radiologist may not have any desire to overcall covid-19 and may rather search for the more classical signs explicit to the disease. Along these lines, while making a predictive model of computational intelligence, does one endeavor to make diverse radiologist "personas" (e.g., high sensitivity versus high specificity profiles), or predict what a particular radiologist will report, or by one way or another make a balance middle way appealing report or " consensus " report? Finally, is the undertaking to predict how a particular radiologist performs or how an " average " radiologist acts in the interpretation of a radiograph or prediction of the clinical result? If the objective is to anticipate the clinical result, at that point issues, for example, the prevalence of the disease in a specific populace may weigh too vigorously on the performance of the framework. These inquiries raise significant, clinically relevant issues that have not yet been settled.

In computational intelligence, the computer's most prominent strength - its capacities to process data interminably and to repeat similar steps without tiring. However, the issue of overfitting-characterized as the function of a learning model (or prediction model) that fits so well with its training dataset to the degree that it models the statistical noise, variances, biases, and error inalienable in the dataset, contrarily affecting the performance on new data. This is bound to happen in clinical imaging than in other computer vision applications because of the generally enormous number of classes of normal and abnormal findings and limited quantities of annotated training datasets. More concisely, research has shown that overfitting occurred "when your learner yields a classifier that is 100% accuracy on the training data however just half exact on test data when in reality it could have yield one that is 75% accurate on both." [80] While the idea of accuracy in CI was generally straightforward in the detailed investigations of object recognition, we note that radiology has a rich scientific history of estimation of diagnostic accuracy, including the improvement of receiver-operating characteristic (ROC) analysis [81]–[83].

Performance of classifier is key to making a diagnostic decision about CI but then, the run of the utilization of a solitary measurement of diagnostic accuracy, while basic, is lacking for technical evaluation. Most articles on clinical computational intelligence (CI) studies are considerably more informative and thorough when they use ROC analysis since its measures of sensitivity and specificity are not reliant on the prevalence of disease (as is valid for accuracy). Likewise, the measure of diagnostic accuracy is ordinarily gotten from the utilization of a solitary subjective threshold, though ROC analysis shows the performance utilizing all realized or known threshold values. Nonetheless, since the prevalence of disease influences the performance of any diagnostic classifier, it would likewise be useful to know the prevalence of the disease in the test populace, so the false-positive and false-negative rates could be resolved. Precision, which generally deciphers as the probability that a positive test implies that the disease or find is genuinely present (also called the positive predictive value), can show the relative strength or weakness in a classifier for finding or ailments that are low predominance [84].

The issue of overfitting in clinical imaging is additionally amplified by the wide variety of "odd" states of normal structures, and the myriads of anatomic variations identified with extra or missing anatomical structures, (for example, embellishment ossicles or congenitally absent or hypoplastic structures). This issue is made generally apparent by considering the issues looked at by a radiology scientist who is gathering and classifying the numerous sorts of anatomic structures and abnormalities that are found on chest radiography. That specialist would need to get images and related data for the computer to show variations from the norm of the heart, mediastinum, lungs, bones, pleura, and different structures. Recognizing anatomic variations from pathologic elements has been a significant capacity of the practicing radiologist, with an entire atlas devoted to helping them abstain from making a false-positive diagnosis [85]. In some related scientific fields, for example, the field of genomics, there has been recognition of the inadmissibly " false-positive " rate related to different sorts of "wild-type" variations that mimic findings related to genetic mutations related to cancer [86]. In one investigation of computational algorithms dedicated to this issue, they described the types of false-positive error into six distinct groups and recommended that " feature-based analysis of 'negative' or wildtype positions can be helpful to guide future developments in software" [86]. This is similar to the issue with anatomic variations in diagnostic radiology. Since the deep learning approach is exceptionally complex, and because no strategy has been built up that permits a given algorithm to "explain" it is reasoning, computational intelligence specialists are commonly not able to tell completely the explanations behind the algorithms decisions, and not able to predict the occurrence and recurrence of failure or error in the performance of the algorithms [87]. Thusly, validation, and regulatory endorsement could take additional time due to the "Black box" nature of computational intelligence techniques. Luckily, significant advances have been made as of late in illuminating the contents of the CNN black box [88]. One such development, saliency maps, was initially proposed in 1998 and depends on the " feature-integration theory " of human visual consideration [89]. In 2013, two images of visualization strategies for representation inside deep convolutional networks were illustrated, one of which included saliency maps [90]. For a given output classification value (e.g., a sort of interstitial lung disease), saliency maps show the pixels of the image (e.g., CT of the chest) that were generally significant for image classification. Besides, other more advanced procedures have been built up that compose non-human interpretable convolution layers into an explanatory and potentially interactive intelligent graph or image that can be utilized to accelerate the learning cycle and distinguish errors or a significant area of an image disregarded by a CNN permitting refinement of the model and improving performance [88], [91].

Conversely, computational intelligence algorithms have been created more than quite a few years, a significant number of which are centered around explicit clinical imaging issues, and subsequently have moderately narrow imaging applications. Instances of these applications include 1) fracture detection, bone age determination, and bone mineral density quantitation in orthopedic radiology; 2) brain hemorrhage detection, multiple sclerosis detection and quantitation, and regional brain segmentation and volumetry in neuroradiology; and 3) coronary and/or carotid artery stenosis evaluation, and cardiac function assessment in cardiovascular radiology. All together for a CI framework to replicate the work of a radiologist, it would need to join a huge arrangement of narrow CI algorithms, every one of which has been devised to respond to a particular clinical question. The utilization of combinations of algorithms to tackle a solitary restricted CI issue or issues has been referring to as ensemble strategies in CI and has been effective in winning CI rivalries on the classification of complex datasets. In the field of computational intelligence, the "sacred goal" is to devise a type of "general computational intelligence," which could recreate normal human intelligence. Most computer science researchers don't accept that generalized computational intelligence will rise in the following 20 years to come, if at any point. Notwithstanding, different ways narrowed computational intelligence can assist with improving the radiology work process, besides diagnostic interpretation. There is a wide scope of chances to increment operational efficiency, improve the radiology workflow process, and give decision help to clinicians and radiologists.

5.2 Uncertainties in the Clinical Domain

Uncertainty is an unavoidable and significant issue that has pulled in increasing attention in healthcare, given the developing emphasis on evidence-based diagnosis, mutual decision making, and patient-focused consideration. Nonetheless, our comprehension of this issue is limited, due to the absence of a unified, intelligent concept of uncertainty. There are various implications and varieties of uncertainty in medical care, which are not regularly distinguished or acknowledged albeit each may have exceptional impacts or warrant various courses of action[92]. Osler [93] once referenced, medical practice as a science of uncertainty and craft of probability. Medical sociologist Fox [94] recognized that clinical uncertainty in medication originates from the limitation of clinical knowledge, restrictions of individual information, and trouble distinguishing the two. From that point forward, the terms described by [95] ‘uncertainty’ and ‘ambiguity' are utilized interchangeably. A few researchers, for example, Han et al. [96], accept ambiguity to be one of the sources of uncertainty. Han et al. [96] observed different studies in literature from assorted discipline, including psychology, communication, and health services, and proposed another scientific classification of clinical uncertainty comprising of three dimensions: sources, issues, and locus. The sources of uncertainty derived from 'probability, ambiguity, and complexity'. probability alludes to chance, and it originates from the indeterminacy of future results. Ambiguity alludes to indecisiveness, and it emerges from imprecision, clashing information, and an absence of proof. Complexity alludes to incomprehensibility, and it emerges from an assortment of causal factors or trouble on interpretation difficulty.

However, another research by [97] pointed out three different sources of clinical uncertainty depicted as: technical, individual, and conceptual. Insufficient or deficient scientific data emerges as a result of technical uncertainty and could be perceived as data related uncertainty. Individual uncertainty emerges from an uncertain doctor-patient relationship. Difficulty in applying data to genuine circumstances emerges as a result of conceptual uncertainty. First-order uncertainty could be viewed as technical uncertainty and second-order could be view as individual and conceptual uncertainty, or meta-uncertainty, as shown by [98]. First-order uncertainty is gotten from the unsure likelihood of future results and relates to scientific nature itself, while second-order uncertainty happens while applying data to patient care, and it incorporates not just uncertainty that emerges from genuine results of given probabilities yet additionally patients' desire or level of interest concerning the result [98].

However, we can recall one of the basic segments involving clinical decision is diagnostic thinking. Nonetheless, it has been accounted for that the precision of doctors' diagnosis, as evaluated by autopsies, has not improved since the mid-twentieth century [99], [100]. As uncertainty lies in diagnosis and treatment, which are the significant segments of clinical decision making [101], the impression of uncertainty by doctors during clinical reasoning would force a lot of significance on patient care.

The proposal has been made that building up and adjusting to clinical guidelines are productive methods of reacting to uncertainty in clinical diagnosis and treatment [102]. To be sure, doctors will in general react by sticking to guidelines when confronted with uncertainty. Notwithstanding, despite the utilization of guidelines, uncertainties in clinical practice are probably not going to be defeated [103]. Eddy [104] called attention to the that a few parts of clinical knowledge can never be confirmed by randomized controlled trial and uncertainty can't be disposed of because of the variance of human nature. Furthermore, clinical uncertainty, which can be settled by clinical knowledge and evidence-based research, is limited to first- order, or technical uncertainty [97], [102]. Doctors need to manage second-order or meta- uncertainty in clinical decision making, notwithstanding huge clinical evidence and profoundly refined technical data [102].

5.3 Knowledge Acquisition and Representation

In designing computational intelligence frameworks, the way toward eliciting information has been named knowledge acquisition. Also, the process that involves extracting problem-solving skills from knowledge sources, which are normally domain experts is termed Knowledge acquisition (elicitation) [105]. In investigation reviewed by [106] knowledge acquisition is defined as the way toward extracting, structuring, and organizing knowledge from a few sources, normally human area specialists, so it tends to be utilized in a program. It includes the acquisition of knowledge from human specialists, books, records, sensors, or PC documents. Knowledge acquisition is a significant and basic stage in the development of a computational intelligence framework. Knowledge acquisition is considered by numerous individuals to be the most troublesome and unstable stage in the knowledge engineering process. Knowledge acquisition has regularly been portrayed as the bottleneck in computational based frameworks development today, subsequently, much theoretical and applied research is as yet being directed in this domain. The achievement of any computational intelligence framework significantly relies upon the quality, fulfillment, and accuracy of the information stored in the experts-based system [107], [108].

While knowledge representation is the efficient method for encoding knowledge on the human specialists in a fitting medium. In computational frameworks development, a decent solution relies upon a decent representation. For computational frameworks applications, the underlying decision of a representation procedure/technique is especially significant. This is because the possible representation procedures/approaches are diverse and the forcing criterion for the decision is typically not satisfactory at the beginning of the project. The result of inadequate choice can be a serious issue in the later phases of a computational System development, on the off chance that it is found that critical data can't be encoded inside the picked representation technique or procedure [106].

5.4 Fingerprints of Good Computational Intelligence (CI) Approaches in Clinical Diagnosis

This subsection presents the fingerprint of decent CI approaches in clinical diagnosis. Among the different fingerprint describe below, the most noteworthy is the clarity of diagnostic knowledge, explanation, and reasoning capacity. These fingerprints or rather features give solid explanations behind the clinicians to embrace the computational intelligence (CI) diagnostic framework and to believe in its reliability.

5.4.1 Clarity of Diagnostic knowledge, Explanation, and Reasoning Capacity

The utilization of computational intelligence (CI) to predict diagnostic results depend on programs in which human specialists decided the features to search for and the rules by which these features were to be analyzed [109]. CI prediction abilities are frequently portrayed as a "black box." This is because data are processed through hidden layers of decision-making that are regularly seen as opaque, with just the results accessible to the interpreter [109]–[112].

Computational intelligence Application can't communicate reasons why a specific conclusion was made and clinicians can't determine what data input was utilized to go to a decision [109], [113]. Achieving knowledge on how a decision is reached is challenging, for clinicians as well as for the developer of the CI framework. Computational intelligence that utilizes mathematical algorithms based on artificial neural networks might be practically difficult to comprehend the extent that why or how algorithms arrive at conclusions. Algorithms like decision trees or Bayesian networks are more straightforward to inspect [114]. Within a medical care setting, CI tools must have the option to give proof concerning how they come to arrive at specific conclusions, permitting doctors to affirm that the conclusion makes sense and of course right if necessary [115]. Abstract, hidden layers may likewise make difficulties in looking at and evaluating the performance of various CI framework [116].

In Europe, the General Data Protection Regulation [117] furnishes people with the " right not to be subject to a decision based solely on automated means"[118]. The guideline additionally indicates that people ought to likewise be furnished with significant data about how computerized frameworks make their decisions [117]. Also, the results of the clinical diagnosis undertakings ought to be clear to the clinicians. The doctors must have the option to dissect and comprehend the results of the clinical diagnostic assignments. In a perfect world, the outcomes ought to give the new interrelations that are verifiable [119]. The clear diagnostic model can show how the results are derived from the input, where the input to the model is the patient's data and the results are the predicted diagnosis [120]. Clear or transparent models have the trademark property of white boxes which can clarify an official decision rather than non- transparent models which are “black box” [120].

Official decisions and recommendations are given by the framework. The framework ought to have the option to explain these decisions to the clinicians, especially if there should be an occurrence of an unexpected solution for the new issue [121]. Otherwise, the clinicians won't consider the framework's solution. The clinicians will in general grasp the decision support framework that has more similarity with the human reasoning style [122].

6 Conclusion and Future Research Directions

The coronavirus disease 2019 (COVID-19) has spread everywhere in the world. Computational intelligence (CI) clinical imaging has assumed a significant role in battling against COVID-19. Computational intelligence techniques anyway are not silver bullets however they have limitations and difficulties, for example, inadequate training and validation data or when datasets are abundantly accessible, they are typical of low quality. Gigantic endeavors are required for a CI framework to be powerful, effective, and useful. They may incorporate proper data processing pipelines, model determination, proficient algorithm improvement, remodeling and retraining, constant performance monitoring, and validation to encourage consistent deployment, etc. There are CI ethics standards and rules [88], [89] that each period of the CI framework lifecycle, for example, design, development, implementation, and ongoing maintenance, may need to cling to, particularly when most CI applications against COVID-19 involve or affect human beings. The more CI applications are proposed, the more these applications need to guarantee fairness, security, logic, accountability, privacy protection, and data security, be aligned with human values, and have positive impacts on societal and environmental wellbeing.

Also, it is important that imaging just gives fractional data about patients with COVID-19. Accordingly, it is critical to combine imaging data with both clinical manifestations and laboratory assessment results to help better screening, detection, and diagnosis of COVID-19. For this situation, we trust CI will exhibit its normal ability infusing information from these multi-source data, for performing accurate and effective diagnosis, analysis, and follow-up. The use of CI methods on COVID-19 research is only the start. As presented above, endeavors have been made to apply CI to the whole pipeline of the imaging-based diagnosis of COVID-19. In any case, there are as yet numerous attempts to be directed later on, in the future as clarified in the accompanying paragraphs.

Clinical images ordinarily give negative radiological indications in the early stage of the disease, and along these lines, the investigation of this stage is imperative to help with the clinical diagnosis uncertainty. In the interim, numerous current CI studies for segmentation and diagnosis are based on small and inefficient datasets, which may prompt the overfitting of results. To make the outcomes clinically helpful, the quality and number of datasets should be additionally improved. Additionally, existing studies by and large use U-Net for image segmentation and CNN models (i.e., ResNet) for diagnosis. Interpretability must be a central issue for CI application in medical care services. Also, explainable CI is significant to comprehend the efficiency of the deep learning algorithms, as well as image features that contribute to the distinction between COVID-19 and other forms of pneumonia.

Deep learning has become the predominant technique in battling against COVID-19. In any case, the imaging data in COVID-19 applications may have incomplete, inexact, and inaccurate labels, which provides a challenge for training an accurate segmentation and diagnostic network. Along these lines, weakly supervised deep learning techniques could be utilized. Further, manually labeling imaging data is costly and tedious, which likewise empowers the investigation of self-supervised deep learning [123], [124], and deep transfer learning strategies [125]. Likewise, as deep learning for both segmentation and abnormality classification has been demonstrated to be promising in studies with noisy labels [126], they will be additionally included for possible application for COVID-19 diagnosis.

Follow-up is critical in diagnosing COVID-19 and assessing treatment. Even though there are limited studies, we accept that the strategies from other related studies could be obtained such as the prognosis of other pneumonia infections, CI-based technique could rouse the follow-up study of COVID-19 [127]–[129], the follow-up inside and outside of medical clinics could be combined as a long period tracking for the COVID patients, and multidisciplinary integration, i.e., clinical imaging [130], natural language processing [131], and oncology and fusion [131]], could benefit the overall follow-up procedure of measurement for COVID-19.

Nonetheless, the most important requirements of the clinical diagnostic models are good and acceptable performance and explanation ability. In any case, these requirements are clashing and, in this manner, difficult to meet in all cases. The simplest models which perform better with fewer attributes have great explanation capacity, for instance, decision trees. However, the performance degrades if there should arise an occurrence of huge multi-dimensional datasets. In this case, the black-box models (for example ANN and DL) performance is great yet it lacks the explanation capacity. Lastly, from the current information on the clinical diagnosis, it is clear that any single CI method is not competent to efficiently deal with the clinical diagnostic tasks. The hybrid methodologies are the most promising strategies that improve the performance of clinical diagnostic tasks.

LIMITATIONS

This paper systematically reviews searched articles gathered from selected published major databases. As indicated, the review was based development challenges approaches of computational intelligence for clinical diagnosis of ('Covid-19' or 'Coronavirus') based on clinical imaged. Also, by preset inclusion and avoidance criteria, only English articles were included in this review, and along these lines, relevant studies published in other languages may have been missed.

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DECLARATION OF COMPETING INTERESTS

The authors declare no competing interests.

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