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TOPICAL REVIEW

A Comprehensive Review on COVID-19 Detection Based on Cough Sounds, Symptoms, CXR, and CT Images

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ABSTRACT The worldwide spread of the coronavirus illness has led to the requirement of creating machine-based technologies to identify the diseases. The worldwide pandemic caused by new coronaviruses has resulted in a significant loss of life and necessitates the development of several affordable diagnostic methods to detect the presence of COVID-19 infection. Thankfully, the current era of advanced technology, including transfer learning (TL) approaches, has improved several areas of human health and enabled the identification of chronic and communicable diseases. There is a need for thorough investigation in order to combat the transmission of this alarming virus via the use of evidence-based intelligence models and implementation of preventive measures. The present systematic review focuses on the examination of TL and fuzzy ensemble techniques that have been described in the literature pertaining to strategies for detecting COVID-19. Multiple studies have used cough sounds, CT scans, X-ray images, and symptoms information to identify cases of COVID-19. The application of DL/ML, TL, fuzzy ensemble, and fuzzy inference approaches for COVID-19 identification is discussed in this paper.

INDEX TERMS Prediction, COVID-19, cough sounds, CXR images, CT images, symptoms, ensemble.

I. INTRODUCTION

The COVID-19 virus quickly spread throughout the globe, and the WHO classified it as a pandemic [1]. COVID-19 requires early detection to stop the pathogen from spreading. It spreads by touch, inhalation, or coughing from a coronavirus individual, which accounts for its exponential development [2]. Coronavirus spreads most easily via the air and also through personal contact with someone who is already sick. It infects the lungs after invading the human body via the respiratory system. Fever, coughing, and shortness of breath are basically considered coronavirus symptoms [3], [4]. Researchers are aiming to leverage clinical data such as Chest X-ray (CXR) and CT images to diagnose this medical condition with the support of AI enabled models to help in automating the scanning operation since RT-PCR procedures are unprofitable and time-consuming [5].

We analyzed some of the recently developing AI driven algorithms that can identify coronavirus from CXR/ CT pictures in this work. The primary purpose of this article is to comprehensively summarize the workflow of previous studies, collect all the images from various sources, and

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summarize the commonly used techniques to automatically identify coronavirus utilizing clinical data so that a newbie researcher can examine prior work and develop a more accurate solution. Early identification of COVID patients is a crucial problem for healthcare professionals and government organizations to combat the fatal virus's fast dissemination. The prior pandemic evidence on ML and DL approaches inspired the researchers to play a significant role in recognizing COVID-19 in this case. Similarly, the expanding range of ML/DL methods in the medical area supports their importance in COVID-19 identification [6], [7]. This comprehensive review includes ML and DL methods, transfer learning, fuzzy ensemble, and fuzzy inference methodologies used to predict, diagnose, categorize, and identify the coronavirus.

Researchers have recently proposed utilizing cough sounds to identify COVID-19 early on. However, there are some difficulties since coughing is also a sign of 30 other illnesses [8]. DL models have proven to be very effective in a range of recognition tasks, especially in the fields of image and audio processing. In terms of identifying respiratory patterns, the Convolutional Neural Network (CNN) identified deepbreathing [9]. As a result, labelling of respiratory signals

derived by non-contract measuring methods using a deep learning methodology is increasingly important. Each database required for the procedure is obtained by analyzing the respiratory events of test subjects using deep learning algorithms [10]. Furthermore, a conversation is held to assist the new researcher in locating future efforts in the identification of COVID-19.

The flow of this article is stated as follows. COVID-19 identification based on coughing and breathing sounds are presented in section II. COVID-19 identification using CXR and CT scan images is represented in sections III and IV, respectively. COVID-19 detection based on symptoms is illustrated in section V. Section VI contains the discussions. conclusions, future prospects and limitations are presented in section VII.

II. COVID-19 DETECTION BASED ON COUGHING AND BREATHING SOUNDS

In this work, we primarily concentrate on literature studies of how COVID-19 spreads and an in-depth examination of coronavirus diagnosis using human respiratory sounds such as cough, voice, and breath by assessing respiratory sound characteristics. Recent studies have shown that respiratory sounds (e.g., breathing, voice, and coughing) from COVID-19 positive individuals in hospitals vary from healthy people's noises [11]. Respiratory sonography is a non-invasive diagnostic procedure for the respiratory system and its associated organs. The fundamental architecture of coronavirus detection from breathing and coughing sounds is demonstrated in Figure 1.

Brown et al. [12] suggested utilizing breathing and cough noises to identify Covid-19 utilizing crowdsourced dataset. Their model was trained with pre-trained models and MFCC (Mel Frequency Cepstral Coefficients) statistical features. Grant et al. [13] trained a machine learning model using 150 recorded crowd-sourced sound data. They examined a random forest algorithm utilizing MFCCs features and obtained an AUC of 0.7983 for identifying coronavirus utilizing speech sound and a 0.7575 AUC for identifying coronavirus utilizing breathing sounds. Cohen-McFarlane et al. [14] emphasized the need for developing a coronavirus cough database to aid in the creation of an algorithm for identifying coronavirus from coughs. They emphasized the need for dataset uniformity/consistency in order to design dependable algorithms. Mouawad et al. [15] retrieved MFCC features from a Corona Voice Detect project dataset by using XGBoost and obtained 89% for the vowel "eh" and F1-score of 91% for cough. Imran et al. [16] suggested AI4COVID-19, a smartphone app that collects 3 seconds of cough noises and analyses them automatically for COVID-19 identification within two minutes using deep transfer learning. Erdoğam and Narin [17] used the ReliefF algorithm and discrete wavelet transforms (DWT) to analyze cough spectrogram data attaining a 98.06% F1-score. Pal and Sankarasubbu [18] studied deep CNN on 328 cough sounds received from 150 individuals of four distinct types and got an accuracy of 96.83%. Bagad et al. [19] utilized the ResNet18 model on 3621 cough datasets got an AUC of 0.72. Laguarta et al. [11] achieved sensitivity of 98.5% and AUC of 0.97 using ResNet50 pre-trained method on 4256 patients' data. Pahar et al. [20] utilized LSTM deep CNN and got an AUC of 0.98. Table 1 presents a summary of several unique deep CNN and ensemble approaches used by various authors to identify COVID-19 utilizing cough and breathing noises.

III. IDENTIFICATION OF COVID-19 UTILIZING CXR IMAGES

Deep neural network learning is a new field that may play an important role in COVID-19 identification. Previously, researchers used DL or ML models to recognize COVID-19 in clinical images such as X-rays or CT scans, with outstanding results. To increase the accuracy of their results, several researchers utilized Gradient-weighted Class Activation Mapping and TL approaches [31]. Figure 2 depicts the basic architecture of COVID-19 identification from CT-Scan and CXR images.

To identify COVID-19, Ilyas et al. [32] and Shi et al. [33] developed AI-powered techniques. Chowdhury et al. [34] recommended a novel deep CNN architecture by utilizing 2905 CXR and got 96.6% accuracy. Ulhaq et al. [35] also examined several studies on COVID-19 detection, prevention, control, therapy, and clinical management. Furthermore, Ismael et al. [36] investigated several kinds of ML/ DL approaches for coronavirus identification utilizing X-ray pictures. Chandra et al. [37] also use a majority voting-based ensemble classifier approach. However, as time passes, researchers discover new and superior strategies for

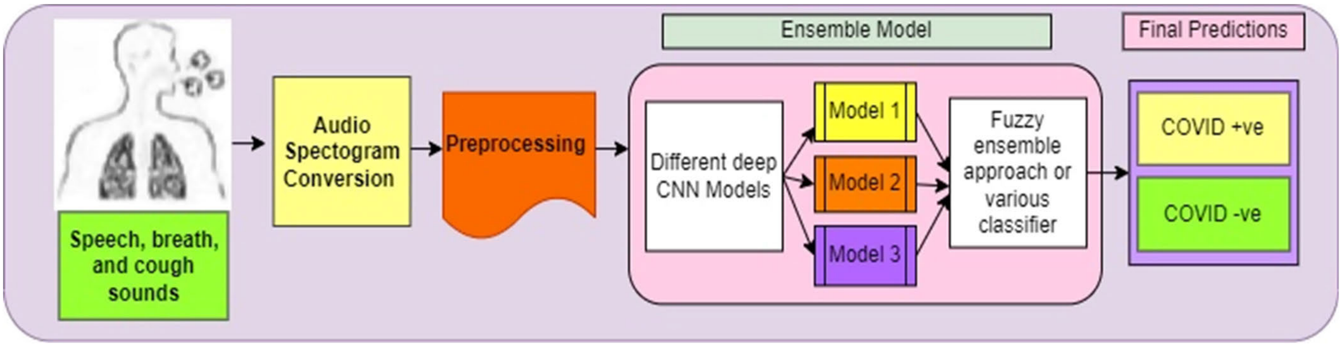

FIGURE 1. Fundamental Architecture of COVID-19 detection from breathing and coughing sounds.

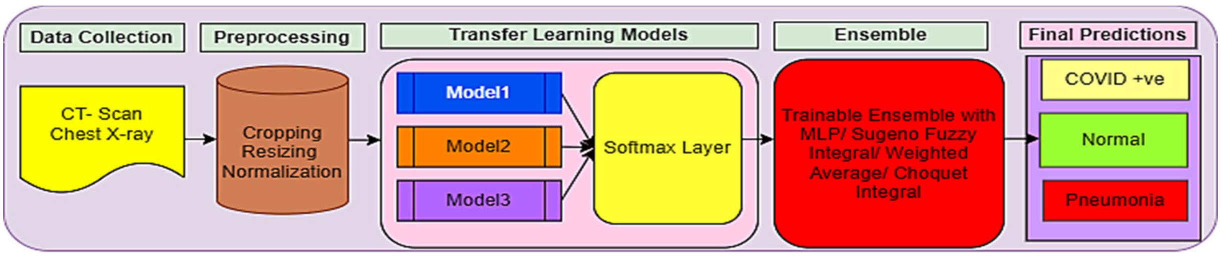

FIGURE 2. Basic architecture of COVID-19 identification from CT- Scan and CXR images.

diagnosing COVID-19. Because CT scans are reported to be more precise than CXR images, utilizing CT-scan pictures to detect COVID-19 and construct a model becomes easier. The CXR picture data set is more commonly accessible than the CT picture because taking an X-ray picture is much less expensive than producing a CT image. VGG16 paired with SVM was utilized by Alawad et al. [38] utilized 7329 CXR images and obtained an accuracy of 99.82%. Wang et al. [39] recommended a deep TL technique based on 565 COVID-19, 537 healthy patientCXR images and got 96.7% accuracy. Das et al. [40] created an AI-enabled Covid-19 diagnosis approach TLCoV based on a pre-trained VGG-16 technique by using 2905 CXR images and got 97.67% accuracy. Heidari et al. [41] concentrated on data preprocessing strategies for the VGG16 model by using 8474 CXR images and obtained an accuracy of 94.5%. Monshi et al. [42] concentrated on data augmentation technique and CNN hyperparameter adjustment, enhancing the accuracy of ResNet50 and VGG19. They also suggested CovidXrayNet, an EfficientNet-B0-based model that obtained an accuracy of 95.82% on 15496 CXR pictures. On 7,406 CXR pictures, Narin et al. [43] employed the ResNet50 technique and obtained 99.7% accuracy. Pavlova et al. [44] proposed COVID-Net CXR-2 model using COVIDx8B open access large dataset and obtained 95.5% accuracy. Zhao et al. [45] utilized ResNet50V2 model by using the same dataset and obtained 96.5% accuracy. Goel et al. [46] proposed a novel model constructed using ResNet50, InceptionV3, and Multi-COVID-Net models. They have utilized 2700 CXR images and obtained 98.27% accuracy. Gayathri et al. [47] presented deep CNN model using 2092 CXR image datasets. The accuracy and AUC of the InceptionResnetV2 and Xception models were 0.9578, and 0.9821 respectively. Marques et al. [48] used the B4 version of the EfficientNet model for diagnosing Covid-19 on binary and ternary CXR pictures. They have obtained 96.70%, 99.62% accuracy for ternary and binary classification respectively.

Ozturk et al. [49] enhanced the Darknet-19 model, achieving accuracy of 0.8702 and 0.9808. They utilized Darknet-19,a feature extraction approach based on YOLOV3. A model with fusion effects was created using ResNet-151 and ResNet-101 [50]. The weight ratio of the resultant model was interactively enhanced by examining 18567 CXR pictures and got an accuracy of 96%. COVID-Net, a customized DL network built via generative synthesis was utilized in Reference [51] to detect COVID-19 instances using CXR pictures. Before using ResNet-8 to create two lightweight DL models for ternary and binary classification, Karakanis et al. [52] utilized GAN to increase datasets. They got an accuracy of 98.3%, 98.7% for ternary and binary classification respectively. The authors of [53] created the DeTraC model for identifying coronavirus in 196 CXR images. They received 93% after proposing a decomposition approach to examine the dataset for anomalies by locating class boundaries. Jia et al. [54] introduced an enhanced MobileNet for CXR image classification by eliminating layers and adding filters for tertiary and binary classification. They tested their approach on 7,592 CXR pictures and found it to be 99.3% accurate. Chhikara et al. [55] presented and tested an

TABLE 1. Summary of several unique deep CNN and ensemble approaches used by various authors to identify COVID-19 utilizing cough and breathing noises.

Authors	Dataset	Methods/ Models	Respiratory Sound	Accuracy (%)
Mohammed et al. [21]	2 open datasets of crowdsource	Ensemble CNN	Cough Sounds	77.00
Sait et al. [22]	Digital stethoscope (own dataset)	Inception-v3	Breathing Sounds	80.00
Al Ismail et al. [23]	Merlin Inc.	Random forest Logistic regression and AdaBoost	Breathing recordings	81.20
Evangeline et al. [24]	DiCOVA	Ensemble of 4 dense neural network and 3 CNN models	Cough and Breathing Sounds	88.75
Imran et al. [16]	ESC-50	Deep CNN Multi Class classifier	Cough Sounds	92.85
Chang et al. [25]	FluSense and COUGHVID	ResNet-6, MobileNet-6, VGG-7 and CNN-4	Cough Sounds	93.91
Melek et al. [26]	Cough sound data	Support vector machine	Cough Sounds	94.21
Alkhodari et al. [27]	Coswara	Deep CNN combined with bi-directional LSTM	Breathing recordings	94.58
Lella et al. [28]	Cambridge	CNN	Cough and Breathing Sounds	95.45
Laguarta et al. [11]	MIT Open Voice	ResNet-50	Cough Sounds	97.10
Hassan et al. [29]	Breathing Sounds	Long Short Term Memory (LSTM)	Breathing Sounds	98.20
Rahman et al. [30]	Cambridge	Stacking CNN model and 8 Deep CNN Models	Cough and Breath Sounds	98.85

TABLE 1. *(Continued.)* Summary of several unique deep CNN and ensemble approaches used by various authors to identify COVID-19 utilizing cough and breathing noises.

InceptionV3-based model on three independent CXR image datasets. On 11,244 CXR pictures, the accuracy was 97.7%. Hasani et al. [56] built COV-ADSX utilizing the Django web module, allowing the user to submit a CXR picture to detect COVID-19. They employed the XGBoost algorithm and got an accuracy of 98.23%. A fuzzy edge detection approach is developed to deal with the ambiguities, uncertainties, and vagueness that are especially prevalent in CXR pictures. Indeed, applying fuzzy logic to preprocess CXR pictures enhances the edge recognition step when the borders are not clearly characterized by locally fluctuating hues [57].Table 2 provides a summary of several unique deep CNN and ensemble approaches used by various authors to identify COVID-19 utilizing CXR images.

IV. COVID-19 IDENTIFICATION USING CT SCAN IMAGES

Images from chest CT have lately been employed as an effective diagnostic technique for COVID-19. Radiography pictures are distinguished by their simplicity, accessibility, and speed of diagnosis. CXR is less costly; nonetheless, its effectiveness in COVID-19 scanning is inferior to CCT because a CXR scan picture contains less information. CCT imaging has a higher sensitivity than RT-PCR for identifying COVID-19, with up to 98% sensitivity compared to 71% for RT-PCR [87]. A multitasking learning system for automatic COVID-19 identification was recommended by Bao et al. [88]. They used 1329 CCTT images with an accuracy rate of 90.23%. The DRE-Net model was created by Brown et al. [12] utilizing 88 CT pictures. They combined ResNet-50 model with feature pyramid network and obtained 86% accuracy. Murugan et al. [90] suggested WOANet model utilizing pre-trained ResNet-50 model by

TABLE 2. Summary of several unique deep CNN and ensemble approaches.

Authors	Models	Class Label and Sample Size			Accuracy (%)
3 Class dataset:		Normal	Pneumonia	COVID-19	
Toğaçar et al. [58]	MobileNetV2 and SqueezeNet	65	98	295	99.27
Loey et al. [59]	Bayesian-based optimized deep CNN	3616	3616	3616	96.00
Khasawneh et al. [60]	CNN and machine learning classifiers	225	4292	1583	98.50
Perumal et al. [61]	InceptionNet and deep CNN	8066	5538	183	94.00
Li et al. [62]	Cov-Net	1341	1345	219	99.66
Wang et al. [51]	COVID-Net	8066	5538	358	93.30
Farooq et al. [63]	COVID-ResNet	1203	1591	68	96.23
Ucar et al. [64]	COVIDiagnosis-Net	1583	4290	76	98.26
Banerjee et al. [65]	COFE-Net	8851	6052	568	96.39
Aslan et al. [66]	VGG16 network	10192	1345	3616	99.14
Rajpal et al. [67]	ResNet50	520	520	520	97.40
Ozturk et al. [49]	DarkCovidNet	500	500	125	87.02
Ouchicha et al. [68]	CVDNet	1341	1345	219	96.69
Kedia et al. [69]	CoVNet-19	5538	8086	266	98.28
Nigam et al. [70]	EfficientNet	795	711	795	93.48
El-Dahshan et al. [71]	RESCOVIDTCNnet a residual neural network model	1672	1670	1670	99.00
Dey et al. [72]	CovidConvLSTM a fuzzy ensemble model	11533	5077	4540	98.62

TABLE 2. *(Continued.)* Summary of several unique deep CNN and ensemble approaches.

Goel et al. [46]	Multi-COVID-Net	900	900	900	98.21
Gupta et al. [73]	InstaCovNet-19	1341	1345	361	99.08
Banerjee et al. [74]	Random Forest with ensemble	1341	1345	219	98.13
Kong et al. [75]	VGG16 and DenseNet with feature fusion	1583	4273	576	97.30
Liu et al. [76]	Deep feature fusion classification	3270	4657	1281	99.89
Kumar et al. [77]	Hybrid deep CNN	2000	2000	2000	98.20
Tuncer et al. [78]	Novel ensemble Classification	150	150	135	97.01
Lee et al. [79]	VGG-16, VGG-19	607	607	607	95.90
Liang et al. [80]	cGAN and ResNet	219	1345	219	97.80

4- Class dataset:

Authors	Models	Class Label and Sample Size				Accuracy (%)
		COVID-19 +ve	Normal	Bacterial pneumonia	Viral pneumonia	
Mousavi et al. [81]	CNN-LSTM model	2923	2840	2778	371	91.70
Hussain et al. [82]	CoroDet	500	800	400	400	91.20
Mostafiz et al. [83]	Random forest deep CNN Wavelet with ResNet50 + RF classifier	790	1500	1304	1215	99.45
Mondal et al. [84]	Deep CNN	2358	1583	2780	1493	95.87

TABLE 2. ***(Continued.)*** **Summary of several unique deep CNN and ensemble approaches.**

Gopatoti et al. [85]	CXGNet deep CNN with enhanced grey-wolf optimizer	69	25	73	81	94.00
V. Perumal et al. [86]	Haralick + VGG16, Resnet50 and Inception V3	1345	1349	2538	1345	93.00

employing back propagation for better accuracy. They have utilized 2700 CCT pictures and obtained 98.78% accuracy. The genetic algorithm and deep CNN model were combined by Carvalho et al. [91] to get the best feature subset selection and classification results. Alom et al. [92] proposed a recurrent CNN model utilizing inception module and attained an accuracy of 98.78%. Amyar et al. [93] recommended deep CNN models on 1369 CT images and acquired 94.67% accuracy. Shaik et al. [94] proposed an ensemble deep CNN technique using multiple TL-based pretrained models utilizing 3228 CCT pictures and obtained 93.33%, minimizing misclassifications. Vinod et al. [95] developed DeepCovix-Net model and obtained 96.8%, 97% for ternary and binary classification respectively. Ouyang et al. [96] recommended 3D CNN model to perform segmentation in the diagnosis of coronavirus. They have acquired 4982 CT pictures in all. They attained 87.5% accuracy. Yousefzadeh et al. [97] suggested EfficientNet approach and obtained 98.6% accuracy. Gao et al. [98] created a Dual-branch network technique using 1918 CT images with lesion attention module. They acquired 96.74% accuracy. Canayaz [99] categorized deep features using SVM called MH-CovidNet for COVID-19 identification. They have utilized Meta-heuristic approach and got an accuracy of 99.38%. Jaiswal et al. [100] recommended Dense201 model and obtained 96.25% accuracy. By combining a deep CNN approach with a Bayesian technique, Nour et al. [101] were able to obtain 98.97% accuracy. With 460 CT images and Deep 3D Multiple Instance mechanism, Han et al. [102] were able to successfully diagnose Covid-19 with a success rate of 97.9%. A Light CNN SOTA model based on SqueezeNet coronavirus detection was presented by Polsinelli et al. [103].

In summary, the COVID-19 categorization has generated a substantial amount of literature. However, the majority of these studies suffer from a lack of data, poor accuracy, and significant computational complexity. Table 3 provides a summary of several unique deep CNN and ensemble approaches used by various authors to identify coronavirus utilizing CT images.

V. COVID-19 IDENTIFICATION BASED ON SYMPTOMS

Due to its superior accuracy, the RT-PCR test is regarded as the benchmark for coronavirus diagnostics. However, this examination is costly, intrusive, and tedious. The researchers developed noninvasive, low-cost, and quick TL/ ML based coronavirus detection techniques based on labelled patient symptoms. The initial stages toward a health issue diagnosis are symptom recognition and early identification. Many present detection strategies concentrate on symptoms of comparable relevance. However, it has been shown that certain symptoms are more common than others.

For detecting early coronavirus, Ali et al. [137] recommended a hybrid ML strategy on symptoms dataset. The physiological parameters of 40 subjects, such as breathing patterns, coughing, and temperature, were analyzed for anomalies in a dataset of 25000 samples. They proposed a lightweight fast-converging method with an accuracy of 89% for anomaly identification. Omer et al. [138] studied abnormalities in patient physiological data to identify early coronavirus symptoms. They used ML model to investigate cough and fever symptoms. They developed some parameters to track breathing and cough patterns and used the DBSCAN approach for clustering and outlier identification. Their suggested model has a detection accuracy of 90.34% overall. The gradient boosting machine learning strategy described by Zoabi and Shomron [139] was trained on 51,831 patients. They got 86.2%accuracy using five clinical and three non-clinical characteristics. Antoañzas et al. [140] proposed a ML algorithm to estimate the necessity for a COVID-19 test in children and acquired ROC of 0.65. The most significant indicator of coronavirus in younger children was the absence of a high fever, but in older children, loss of taste was the most significant symptom. Effati et al. [141] suggested a multimodal method for predicting COVID-19 that combines deep learning classifiers with probability-based weighting functions. This method takes into account a person's temperature, breathing, and different cough symptoms. Chetupalli et al. [142] employed SVM and logistic regression to separate coughing and breathing signals. Canas et al. [143] suggested a logistic regression model and the NHS algorithm to predict early indicators of COVID-19 infection in a dataset of 198040 symptoms from patients in the United Kingdom. Their model has an AUC of 0.80%. Marateb et al. [144] suggested an autonomous AI system to identify coronavirus based on demographics, symptoms, and blood test results. On three datasets, they employed SVM, Gradient Boosting, and XGBOOST classifiers. Ahamad et al. [145] suggested a gradient-boosting machine learning approach with 87.30% sensitivity and 71.98% specificity on a dataset of 99,232 patients. Koushik et al. [146] suggested a hybrid modelling approach that included the MaxVoting ensemble, random forest algorithms, and the gradient boosting technique. They

TABLE 3. Summary of several unique deep CNN and ensemble approaches used by various authors to identify COVID-19 utilizing CT images.

Authors	Models	Total Image	Accuracy (%)
Baghdadi et al. [104]	MobileNetV3Large	22,779 (3-class)	98.00
Kundu et al. [105]	Deep CNN ensemble With Sugeno fuzzy integral	2481 (2-class)	98.93
Zhao et al. [106]	DenseNet	746 (2-class)	89.00
He Xuehai et al. [107]	Self-Trans DenseNet-169	746 (2-class)	94.00
Wu et al. [108]	ResNet-50 and Segmentation	495 (2-class)	76.00
Wang et al. [109]	Inception	453 (2-class)	82.90
Liu et al. [110]	Pre-trained VGG16	1224 (2-class)	94.00
Pathak et al [111]	ResNet-32	852 (2-class)	93.00
Castiglione et al. [112]	Automatic Detection Coronavirus Optimized CNN	2482 (2-class)	99.99
Singh et al. [113]	DenseNet201, VGG16, and ResNet152V2	11494 (4-class)	98.29
Ouyang et al. [96]	3D ResNet34 and VB-Net	4982 (3-class)	94.40
Wang et al. [114]	3D-ResNet and 3D-UNet	4657 (3-class)	93.30
Polsinelli et al. [103]	SqueezeNet	757 (3-class)	85.30
Matsuyama et al. [31]	ResNet-50	720 (2-class)	92.20
Hu et al. [115]	ShuffleNet V2	918 (2-class)	96.90
Ibrahim et al. [116]	VGG-19	618 (4-class)	98.05
Rahimzadeh et al. [117]	ResNet-50 V2	377 (2-class)	98.50
Shuyi Yang et al. [118]	DenseNet	295 (2-class)	98.00
Alshazly et al. [119]	COVID-Nets based DensNet and ResNet	4173 (3-class)	83.89
Sertan et al. [120]	ResNet-50	99 (2-class)	96.00
Shaik et al. [94]	Multiple deep CNN ensemble	2482 (2-class)	98.99
Sadik et al. [121]	P-DenseCOVNet	23460 (3-class)	87.50
Heidari et al. [122]	lightweight deep CNN	7421 (4-class)	99.34
Zhang et al. [123]	ResNet50 + Attention + SSL	1735 (2-class)	90.10
Santa Cruz et al. [124]	Novel ensemble approach	746 (2-class)	86.70
Aswathy et al. [125]	ResNet-50 with data augmentation	1496 (2-class)	98.50
Ahuja et al. [126]	ResNet18	746 (2-class)	99.50
Hasan et al. [127]	2-D Empirical Mode Decomposition with deep CNN	2482 (2-class)	99.49
Hasija et al. [128]	Multiclass Classification	2482 (2-class)	98.38
Li et al. [129]	Adversarial Learning	2000 (2-class)	96.85
Canayaz et al. [130]	Convolutinal Block Attention Module with EfficientNet	1601 (2-class)	99.00
JavadiMoghaddam et al. [131]	Novel deep CNN Squeeze Excitation layer	19685 (3-class)	99.03
Li, Z., Zhao et al. [132]	Deep-CNN using 3D CT scans	1750 (4-class)	86.70
Mishra et al. [133]	VGG16 based on ResNet50	400 (2-class)	86.74
Turkoglu et al. [134]	Multiple Kernels-Extreme Learning based deep CNN	746 (2-class)	98.36
Ameer et al. [135]	Gray level co-occurrence matrix	654 (2-class)	94.00
Kai Hu et al. [136]	deep CNN with self-adaptive auxiliary loss	6982 (3-class)	99.43

used a dataset of 112345 patent symptoms and got an accuracy of 90%. Zoabi et al. [147] recommended a strategy for categorizing symptoms based on age. On the Chunxiaozheng dataset, they trained several models such as GBM, XGBoost, SVM, and decision tree to identify the most prevalent symptoms. Attaullah et al. [148] achieved an accuracy of 78.88% by using logistic regression and CNN methods to identify COVID-19 on 800 patients' symptoms and 800 chest X-Ray picturedataset. Imtiaz et al. [149] used a logistic regression model on a dataset of 675 coronavirus positive individuals and got an accuracy of 77%. Shatnawi et al. [150] suggested a fuzzy inference method to identify coronavirus based on the patient's symptoms. Their model does not incorporate factors such as smoking, chronic illness, or age. Their technology is incapable of providing a very precise COVID-19 identification.

VI. DISCUSSIONS

According to the study results, cough sound spectrogram pictures are more trustworthy than breath sound spectrogram pictures in recognizing COVID-19 individuals. As a result, automated COVID-19 identification utilizes cough sound spectrogram pictures and greatly reducing clinical expenditures. In the biological and engineering fields, future results on classification and regression algorithms for identifying COVID-19 disorders using respiratory sound data have been established. Researchers have used AI-based strategies to solve a broad range of clinical and bioengineering concerns. Many AI strategies for identifying COVID-19 disease with data on respiratory sounds have been seen, and authors may use the model on COVID-19 cough and breathing sound data using pre-processed data in the future to improve their performance to identify COVID-19. In the future, the authors may use de-noising auto encoder technique on pre-processed sound dataset to diagnose COVID-19. We anticipate that our assessment will act as a spark for clinical scientists and researchers to initiate accessible COVID-19 research.

We evaluated several published articles on COVID-19 identification. The majority of these publications used DL models to get good results. Most authors used heavyweight deep CNN models which require major computing capabilities and were thus unsuitable for implementation on resource limited equipment such as smartphones. Handheld medical imaging solutions for coronavirus identification are being promoted as a critical tool to meet the exorbitant need for quick diagnosis, which is critical to limiting the pandemic's spread, particularly in rural and financially deprived regions. The assessment of lightweight deepCNN models fit with the operational criteria for use in handheld phones for effective COVID-19 identification utilizing CXR pictures was inspired by demand. The existing gap is the absence of parameter adjustment in CNN utilizing various optimization techniques that may significantly enhance accuracy. Building bigger and more validated coronavirus radiological imaging databases will be a key undertaking in the future. It is suggested that future studies develop techniques for decreasing the computing cost for the various proposed approaches. Furthermore, using novel approaches for feature extraction and hyperparameter tuning will improve algorithmic performance accuracy. The majority of studies have only been able to classify COVID-19 patients based on 2-4 chest imaging categories and get reliable results in the lab, which is far away from actual clinical applications. Researchers must create models that are adaptable to a wide range of application circumstances. Every researcher's ultimate objective is to identify COVID-19 sufferers using CXR images and allowing patients to get immediate care. Future research might look at the effects of picture quality on COVID-19 identification owing to differences in various image sources. Future researchers are encouraged to be more realistic and to concentrate on one of the present issues or limits.

Deep learning and AI have been employed in a number of studies and research projects to diagnose medical imaging. The majority of COVID-19 diagnostic work has made use of segmentation and classification algorithms. In general, TL and CNNs procedures have been used in the majority of classification-based systems. Pre-trained models are more effective when there is a limited amount of data because they avoid overfitting, allow faster training convergence, and are more efficient. Because of the limited amount of COVID-19 CT pictures available, the bulk of the DL system was built using unbalanced CT data, according to the results of the relevant research. Several DL/ML systems are now in use, however the majority of them are sophisticated and utilized GAN techniques, which are unsuited for real-world applications.

One of the disadvantages of the above research is that the three symptoms of weariness, dry cough, and fever were used as the evaluation criteria; however, authors could examine additional symptoms such as vomiting, diarrhea, and so on. Additional criteria like vomiting, diarrhea, and other symptoms should be added to input variables in future studies in order to improve the number of membership functions and produce more accurate decision support systems. It is recommended that an adaptive neuro-fuzzy inference system be developed employing combined data science and subject-matter expertise for managing epidemic outbreaks.

VII. CONCLUSION

The chronic pandemic COVID-19 has endangered the lives of millions of individuals. In this paper, we endeavor to provide a comprehensive evaluation of AI-driven solutions that utilize medical images to combat this epidemic. The principal objective of this review is to provide an up-to-date account of methodologies so that aspiring researchers may understand and be cognizant of present knowledge, with the intention of developing a cost-effective and expeditious model for the accurate diagnosis of COVID-19 illness. The primary focus of the preponderance of researchers was the binary classification of CXR images. CNN is the most widely utilized technique for feature extraction, while nature-inspired methodologies are the most widely used algorithm for feature selection. ML methods are frequently utilized as an alternative for categorization duties. We conclude by discussing some possible avenues of research concerning the classification of images regarding medical conditions. Expanding COVID-19 image datasets, reducing the computational cost of deep learning approaches, and improving parameter optimization are all potential future research topics. The accessibility of the CXR image surpasses that of the CT image. The CT scan method requires more time and money to perform than an X-ray. As a consequence, CXR images were utilized in the majority of studies to detect COVID-19. A review of the pertinent literature revealed that annotated medical images of COVID-19 patients are scarce. Increasing the quality of annotated medical images of COVID-19 patients could have a substantial impact on performance. While not entirely effective, data augmentation strategies might be able to circumvent this issue. The training phase of these models could potentially benefit from the inclusion of supplementary data. By incorporating further annotated data, it is possible that the enhanced data's quality could be improved, thereby facilitating the development of a more precise deep learning model. This article presents a range of recommendations aimed at aiding researchers in the development of more suitable forecasting models.

A. FUTURE PROSPECTS

1) DIFFICULTY FACED BY THE DATASET

A significant proportion of datasets are divided into two distinct categories: lung scans of individuals who are in good health and those who are affected by COVID-19. Although the evaluation of COVID-19-infected lungs is relatively uncomplicated, distinguishing between healthy lung images and those indicative of pneumonia is a more intricate yet valuable undertaking. One potential avenue for future research involves the creation of challenging datasets that can be utilized to develop effective classifiers within the medical domain.

2) MULTI-CLASS IMPUTATION

Balancing is a straightforward categorization system. For this reason, more than sixty percent of research has been devoted to the issue of binary categorization. The consequence is a dearth of research concerning multi-class categorization. A selection of various categories of viral pulmonary diseases in conjunction with COVID-19 images could constitute an exceptionally intriguing and beneficial research topic.

3) NOISY PROCESSING OF DATA

The CXR screening method involves radiation exposure to the human body. Radioactivity can introduce disturbances into CXR images. The uneven distribution of X-rays on the surface generates Poisson noise, whereas salt and pepper noise manifest as chaotic particles that are white and black, respectively. It is caused by the abrupt and intense radiation from the surface.

4) IMAGES SHOWING ENHANCED ATTRIBUTES

Medical imaging primarily utilizes two types of datasets, with a specific focus on COVID-19 thorax images. CT scans are feature-rich, high-quality data sources. Prior research indicates that CT-scan images were examined in only 20% of studies, with the remaining research focusing on CXR data or attempting to combine the two. One prospective strategy entails the reduction of image parameters during various stages of the image analysis process. Metaheuristics may compromise the quality of an image across multiple dimensions.

5) STRATEGY FOR ADAPTIVE LEARNING PERTAINING TO VARIOUS MEDICAL IMAGES

We evaluated the work performed on COVID-19 chest images for this study, but comparable findings could be applied to other types of medical imaging, including cancer imaging.

6) SCALABILITY

On the basis of a provided dataset, DL/ML algorithms identify patterns. An extensive volume of training data enhances the model's realism and discernment. Notwithstanding this advantage, increased processing and memory utilization isconsequences. The absence of publications pertaining to large-scale data-driven research in this study is the reason for this. As a result, this research requirement could be fulfilled through the utilization of Spark and Hadoop to analyze enormous COVID-19 datasets.

7) PARAMETER OPTIMIZATION

A limited number of studies have optimized DL model parameters using metaheuristics. Numerous studies have been conducted in recent times with the objective of developing DL models that can acquire superior feature knowledge while reducing the quantity of network parameters. These may also be evaluated for the purpose of classifying COVID-19 images.

B. LIMITATIONS

Despite the fact that several studies on COVID-19 identification using TL have been published, research in this sector remains restricted. Many restrictions must be addressed in order for COVID-19 detection studies to be more productive. The key restrictions are as follows:

1) UNCERTAIN DATA

Because the CXR datasets utilized in coronavirus studies are noisy, it is difficult to identify any abnormalities with the naked eye. While differentiating COVID-19 damaged lungs from healthy lungs is very straightforward, separating two ill lung images caused by different illnesses is more difficult. Lung images of pneumonia patients must be included in the negative cases. This is done to ensure that the DL approaches can learn COVID-19-specific features.

2) CLASS IMBALANCE

The majority of the datasets utilized for coronavirus identification suffer from a severe class imbalance. DL methods will be unable to learn the optimum attributes for exact categorization of new pictures due to a shortage of positive examples.

3) DATASET SIZE

Experiments utilizing deep learning models on restricted datasets might yield biased findings. Because they were trained on a restricted number of photos, these DL models may fail in new types of instances. There is currently no significant annotated picture collection available for COVID-19 detection. Manual annotation of photographs, which takes time and requires human labour, is a significant difficulty in building a huge dataset.

4) INADEQUATE MULTIDISCIPLINARY KNOWLEDGE

COVID-19 detection by TL requires expertise in various fields. Interaction between virologists, computer science researchers, and biologists' experts is lacking. To overcome this challenge, AI professionals must have extensive medical imaging and biology expertise for COVID-19 challenges. To achieve advances in COVID-19 detection, it is vital to coordinate efforts across all of these areas.

ABBREVIATION

AI	Artificial Intelligence.
AUC	Area Under the Roc Curve.
CNN	Convolutional Neural Network.
CT	Computerized Tomography.
CXR	Chest X-Ray.
DL	Deep Learning.
DWT	Discrete Wavelet Transforms.
GAN	Generative Adversarial Networks.
LSTM	Long Short-Term Memory.
MFCC	Mel Frequency Cepstral Coefficients.
ML	Machine Learning.
RT-PCR	Real-Time Reverse Transcriptase-Polymerase Chain Reaction.
SVM	Support Vector Machine.
TL	Transfer Learning.
WHO	World Health Organization.

CONFLICTS OF INTEREST

None

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