

Artificial Intelligence (AI) in the diagnosis of COVID-19 Detection: A Review

Neethu Mohan
Dept. of Electrical Engineering
UAE University
Al Ain, UAE
neethumohan12@gmail.com

Saifudeen Kabeer
Dept. of Electrical Engineering
UAE University
Al Ain, UAE
201790519@uaeu.ac.ae

Nida Nasir
RISE
University of Sharjah
Sharjah, UAE
nnasir@sharjah.ac.ae

Abstract—Coronaviruses are a large viral family that attacks key organs, particularly the lungs. The infection spread is growing by the day, affecting almost every industry. Various Artificial Intelligence studies have been proposed, to learn the measurable information of people who have been affected with COVID-19 and those who have recovered, as well as the death rate. Various data samples like chest images, lung images, swab results, blood samples, and CT scans are used to predict the COVID-19. The paper gives an in-depth look at how AI and machine learning techniques can be used to accurately predict COVID-19. The proposed review is centered around investigating the different AI methods, models, and logical registering procedures used in foreseeing the COVID-19 sickness. The study also summarizes the difficulties associated with current methods and future exploration works.

Keywords—COVID-19, coronavirus detection, machine learning, artificial intelligence.

I. INTRODUCTION

COVID-19 (Corona Virus 2019) began spreading in late 2019 from Wuhan, China. Soon it became pandemic and affected people worldwide in different forms, ranging from very mild throat infection to fatality, including internal organs failure and death [1]. Coronavirus infection is contagious, spread through direct physical contact with the influenced patients and the air. Thousands of people worldwide showed tremendously concerning consequences like severe respiratory failure and cardiovascular troubles [2]. The infection directly influences the lung cells through the respiratory system and tends to reoccur, which makes it a fatal ailment. The most well-known symptoms of COVID-19 are a dry hack, fever, windedness, unsteadiness, migraine, and extreme muscle torment. Individuals with susceptible health backgrounds are highly influenced by COVID 19. For curbing the pandemic, various protocols and procedures have been experimented with all over the world, to cure and restrict the transmission of the infection. All non-medical researches are focused on the analysis of numerous aspects of this virus, which goes through processing big data. Hence, Artificial Intelligence (AI) is helping to analyze and support health care structure universally [3].

The proposed study deals with the review of current COVID-19 studies mainly focused on machine learning techniques, moreover, their comparisons, pros, and cons of AI in corona, future scope, and usage complexities of AI methods are examined. This review includes research journals and articles which are mainly pre-prints and peer-reviewed articles. This study can give an insight to the researchers working in the field of AI and healthcare.

II. AI PROCESS ON COVID19 DATA

A. COVID-19 Data

The essential source for the analysis is the variety of datasets accessible in the clinical centers, hospitals, and test labs. These datasets are open-source and are freely accessible for research purposes. Many specialists or research groups have published data and articles on Covid-19 which are useful for the treatment of COVID-19. Swab tests, X-rays, blood [4] and urine tests [5], and other physiological data including CT scans are considered for the dataset. Different datasets for COVID-19 are illustrated in Fig.1. The datasets are partitioned into two sections. i.e., medical images and textual data. The medical images are gathered from X-rays and CT-Scans containing Chest and Lung scans. However, the text data is from social media and case studies. Different works of literature investigated the COVID-19 based on these datasets. The global reporting studies are helpful for the research field to comprehend the seriousness that continues in the Coronavirus.

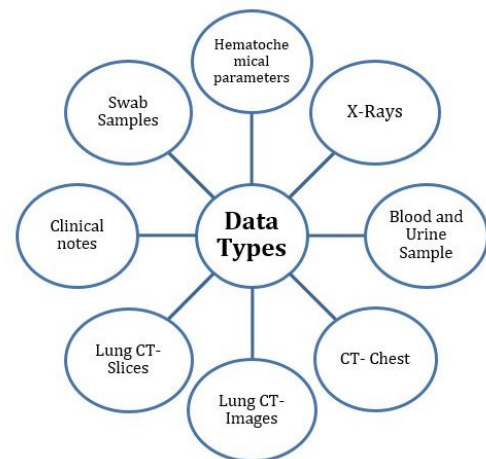


Fig. 1. Categories of COVID-19 dataset.

B. Data Processing

The generalized flow of COVID-19 diagnosis has been depicted in Fig. 2. All the datasets are preprocessed to remove noise, sampling, normalization, etc. Processed data or images are applied to the segmentation processor feature extraction, which leads to testing and training using machine learning and deep learning algorithms, such as, neural networks, classifiers, etc. Later, the classification and performance metrics of all models/ algorithms can be calculated to depict the quality of results. The performance

measures include accuracy, sensitivity, errors, Pearson coefficient, etc.

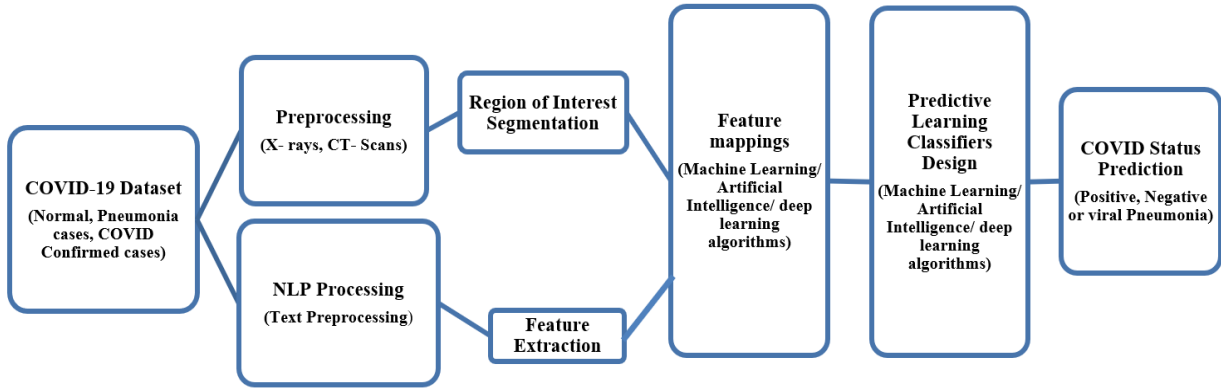


Fig. 2. The generalized workflow of COVID-19 Detection and Diagnosis

III. LITERATURE REVIEW

Sohan et al. cover numerous forms of datasets available for COVID-19 prediction [6]. The study focused on the collection of top datasets that were considered for scientific analysis of COVID-19. The test dataset covers blood samples, X-rays, Scan reports, the textual dataset of tweets, text reports of the patients, etc. The collected samples are broadly classified as positive test samples, negative test samples, and both combined datasets. The community links are helpful for researchers for reference inappropriate analysis of the dataset. Vaid et al. conducted research work on COVID-19 detection through the artificial intelligence method [7]. During their ongoing work, 2.7 million people were confirmed with the vulnerable disease. Over 0.9 million people have died, and 0.75 million patients recovered completely from the widespread Coronavirus. They have utilized chest X-ray traces of patients and developed a deep convolutional neural network to detect the abnormalities present in the structures. They approached the transfer learning method to detect deeply hidden traces using radiographs of the patients. The proposed CNN model scores 96.3% accuracy and loss of 0.151 through binary cross-entropy.

Punn et al. stated in their research work on epidemic analysis using a dataset collected from Johns Hopkins. The datasets used for the analysis are collected as time-series summary tables containing the detailed structure of the updated status of COVID-19 confirmed cases, death rate, and recovery rate of the country [8]. They developed a novel model using polynomial regression to detect the status of the fast-spreading disease. The proposed methodology was also compared with Support vector regression, deep neural networks, and Long-short term memory in artificial neural networks. Progressive results are showing minimum RMSE in the Polynomial regression model. Horry et al. evaluated a VGG19 classifier model for the prediction of COVID-19 using CT Lung images of infected patients [9]. The only limitation beyond the detection process is the limitations persisting in the availability of ground truth data. The publicly available images are poor in quality to produce novel structures. The model produced is always focused on reducing the false-positive diagnosis.

A. Deep Learning Techniques For Covid Detection

Wang et al., evaluated a Random Deep learning model using a CT-EGFR dataset containing 5372 patients; original

records were collected from 7 cities [10]. The training set consists of 4106 patients with lung cancer with EGFR (epidermal growth factor receptor) mutation status. The evaluated model uses DenseNet121 for the automatic segmentation of the lungs. The trained image dataset is a pattern recognized and the proposed accuracy scores around 80% for the Deep learning method in comparison with Random Deep learning methods. Zhang et al., conducted a study and implementation of automated detection on COVID-19 pneumonia using deep learning tools [11]. Ultra-artificial intelligence tools are implemented to accurately evaluate viral pneumonia that includes multi-focus, bilateral GGOs where the common infection is affecting the dorsal segment of the right lower lobe of the lungs. The study reveals the need for localization of infectious regions that are not only required for COVID-19 detection but also provide further assistance to the physicians in developing the treatment plan. Zebin et al., evaluated profound learning principles using classifier models such as VGG16, ResNet50, and EfficientNetB with pre-trained CT-Chest images of COVID-19 infected patients [12]. The generative adversarial network-based system is evaluated. EfficientNetB0 achieves 96% accuracy in the prediction of the three categorized diseases such as pneumonia, COVID-19, and Normal.

Ko et al. developed an FCONet deep learning model to diagnose COVID-19 pneumonia in a short period [13]. The detection process with ResNet 50 combined provides an excellent diagnostic performance. They adopted an AI-based image training sequence using the Convolution neural network framework. The system architecture is done using the publicly available COVID-19 dataset established by SIRM. Although the publicly available datasets are helpful for the prediction process in the initial stages, the rapidly updated test cases, and the death rate of patients with different physiological obligations created contradictory results on the prediction process. The datasets considered are CT scans of people infected by lung cancer, pneumonia, and lung images of normal patients. Yoo et al., explored deep learning algorithms with a three-level decision tree classifier to detect the COVID-19 symptoms more comprehensively [14]. Both Tuberculosis and COVID-19 are having the same symptom of shortness of breath. They defined a novel classifier that analyzes the symptoms with other physiological parameters to identify the disease as coming under the class of TB-related or NON-TB-related. A two-

dimensional CNN algorithm is developed in which the ResNet18 model is utilized with the PyTorch framework for data optimization.

B. Machine Learning Techniques For Covid Detection

Khanday et al. stated in their research work that prediction of COVID-19 in this vulnerable situation is mandatory and utilization of machine learning algorithm helps the most [15]. Their study is based on analyzing various machine learning algorithms and their performance in predicting COVID-19. Algorithms such as gradient boost model, logistic regression, multinomial Naïve Bayes classifier, decision tree, and random forest, etc are discussed. The preprocessing is done using input datasets having the advanced treatment procedures and case statements using NLP. Comparing the various machine learning classifiers, the Naïve Bayes model produced an accuracy of 96.2% stated in their paper. Brinati et al., [16] developed a machine learning model to evaluate the COVID prediction using hematochemical values of routine blood samples such as white blood cells count [17], [18], the platelets, CRP, AST, ALT, GGT, ALP, LDH plasma levels, etc. They collected the dataset from IRCCS Ospedale that includes 279 cases randomly distributed in the analysis. Machine learning algorithm such as random forest and decision tree is evaluated and compared in the research work.

Ghafoor et al. researched with the CT scan image dataset to determine pneumonia present in the lungs [19]. The method proposed in their study is mainly focused on improving the accuracy of diagnostic lung prediction. They utilized a multi-feature model for medical image recognition with several filter stages to work out well with noise removal. The multi-feature model is achieved by combining the EOH method and HOG transform. K-Nearest neighbor (KNN) and Convolution Neural network (CNN) are used to detect lung pneumonia. The highest prediction accuracy of KNN and CNN was achieved with 91.3% and 95.6% respectively. Ahuja et al. stated a novel methodology that contains two levels of classification using four different transfer learning architectures [20]. ResNet18, ResNet50, ResNet101, and SqueezeNet are the methods used in the proposed approach. The highest training accuracy achieved is 99% and the validation accuracy of 97.3%. The architecture compares the three learning models and selects the best-performing one based on accuracy.

Yao et al., developed an efficient COVID-19 severeness detection model using SVM (support vector machine) [21]. They collected test samples of blood and urine and extracted 32 different parameters to be considered for COVID-19 prediction [22]. The prediction process handles datasets of severely affected patients to mild symptoms. They implemented a binary classification model with the help of Mathew's correlation constant (MCC) to determine the similarity metrics between the normal samples and COVID-infected samples. Alazab, et al., stated in their research work that COVID-19 diagnosis models are implemented in various phases in which the present study evaluated AI-based prediction techniques such as (PA) prophet algorithm, (ARIMA) autoregressive integrated moving average, and (LSTM) long short-term memory neural network [23]. The analysis is formulated with the help of Chest X-Rays of 133 infected people and Normal people. From the aforesaid prediction model, LSTM produced 94% accuracy in the prediction of COVID-19 infection from the given dataset.

Elaziz et al. evaluated an optimized method for extracting the unique features from the Chest X-Rays of COVID-19 test cases. Both the normal and COVID infected patient's X-Ray images are analyzed by extracting fractional multi-channel Exponent moment (FrMCEM) [24]. The X-ray dataset is collected from GitHub. The evaluated prediction model uses the K-Nearest Neighbor algorithm for classifying the positive and Negative cases of COVID-19. They achieved 98.91% accuracy in predicting the positive and negative cases from the given dataset. Tulin et al. worked on COVID-19 techniques and implemented a Deep learning-based model to detect and classify the disease using X-ray images [25]. Their system is a fully automated end-to-end design structure with a flexible and automated feature extraction technique. They designed a hybrid model using DarkCOVIDNet with the help of the CNN model at its initial phase to extract the features. They defined that the proposed model suppresses the manual examination time of the radiologist in this pandemic situation. Their simulated results achieved about 98.2% accuracy using Chest X-ray traces.

Panwara et al., conducted a deep stimulated analysis on handling the X-rays and CT scans of the patients in this pandemic situation to improve the diagnosis procedures [26]. They have proposed a prediction model using Deep learning neural networks. Initially with 19 COVID-19 infected patients' records such as X-rays and CT scans are considered for analysis. By carefully analyzing the X-ray patterns they found a robust model that incorporates the fast prediction of COVID-19. The novel algorithm was created as nCOVnet that includes 24 layers stacked in the CNN model. Their promising model achieves 98-99% accuracy for the static dataset they utilized. Raajan, et al. discussed on COVID-19 prediction system using Reverse Transcription Polymerase Chain (RT-PCR). They utilized the CT images alone without considering other parametrical information [27]. Regardless of location and severity status, they evaluated deeper on the examination of CT scans to obtain sensitive information. Alex-net, ZFNet, GoogLe Net, and VGG Net are evolved in the CNN architecture to produce the prediction accuracy better. The comparative analysis was overwhelmed with maximum footage on COVID prediction that scores higher inaccuracy at ResNet. They achieved 95% accuracy and the examination of test cases took 2-4 hours.

Li et al. evaluated a detailed study on COVID-19 prediction using volumetric chest CT, Pulmonary CT, etc. A dedicated stacked layer of Covid-Net is utilized here for the accomplishment of COVID prediction and other abnormalities present with the patients [28]. The large dataset of 4352 Chest CT images is considered for processing. 51-1094 slices of CT images with varying thickness derived from the GitHub community. 90% of the training dataset is compared with the ground truth images. The research defines the future scope to improve the accuracy of the prediction system by enhancing the size of the dataset. The dataset need to be collected from different hospitals and various geolocations are recommended. Mei et al. stated in their research study that COVID-19 prediction with CNN and radiological information is quite accurate [12]. The system incorporates artificial intelligence models such as Convolution Neural Network (CNN), Multi-layer perceptron (MLP), and Joint model, which is the combination of CNN outputs integrated with the MLP model to produce the acceptable level of image matching. The comparison of three systems with the manual verification of

radiologists is evaluated. The dataset considered for the evaluation is the publicly available GitHub dataset containing the sliced CT images. The presented model performs at the highest accuracy of 99.4% for the static dataset available on the public website. Ardakani et al. evaluated a major prediction framework and application that associated with ten different Convolution neural network models such as AlexNet, VGG-16, VGG-19, SqueezeNet, GoogleNet, MobileNet, ResNet18, ResNet50, ResNet101, Xception layers, etc. [30]. A sequence of lung CT images are sequenced with the slices, fetched back to the integrated CNN model. The results of each model showing COVID positive or Negative with the highest accuracy of 99%. Kumar et al. evaluated a novel COVID-19 diagnosis method that inhibits nano-BioSensors [31]. It is a self-integrated analytical device receptor. The test also implies the rapid test and antigen-antibody-based test methods, antibody detection test, POCT, etc. These tests further were applied for determining the sensitivity, specificity, and reproducibility of test methods. Samson et al., reveals the comparative study on traditional techniques vs. the modern biosensors-based prediction methods for COVID-19 [31]. Sensor detection is performed through direct contact with the surface and internal genetic materials. The study provides the future scope of portable RNA extraction preparation in the current pandemic scenario.

IV. COMPARISON ANALYSIS

Table 1 describes the detailed comparison of COVID datasets available. The detail includes the clinical notes from the hospitals that are used for various COVID infected patients, Lung CT images and X-rays of the normal persons and COVID infected patients, Blood test and urine test reports from multiple clinical centers [4].

TABLE I. COMPARISON OF COVID-19 MEDICAL DATASETS.

Ref.	Application	Data Type	Dataset Details
[7]	COVID-19 Diagnosis	X-rays	NIH Clinical Centre
[12]	Pneumonia/ COVID-19 Prediction / Monitoring	CT-Chest	Clinical Data
[19]	Test & Diagnosis	Lung CT-Images	Open source
[20]	COVID-19 Diagnosis	Lung CT-Slices	Clinical Data
[14]	COVID-19 Diagnosis	CT images	NIH Clinical Centre
[23]	COVID-19 Diagnosis	X-rays	Clinically Collected
[24]	COVID-19 Diagnosis	X-rays	GITHUB
[25]	COVID-19 Diagnosis	X-rays	Cohen JP-Clinical
[26]	COVID-19 Diagnosis	X-rays	Radiopedia
[27]	COVID-19 Diagnosis	Ct images	Kaggle / GitHub
[13]	COVID-19 Diagnosis	Ct images	SIRm
[28]	COVID-19 Diagnosis	Ct images	GITHUB
[18]	COVID-19 Diagnosis	Ct images	GITHUB
[8]	COVID-19 Diagnosis	Clinical Notes	Open source
[31]	COVID-19 Diagnosis	oropharynx swab samples	Open-source
[16]	COVID-19 Diagnosis	Hematochemical Parameters	IRCSS

Ref.	Application	Data Type	Dataset Details
[21]	COVID-19 Severeness Detection	Blood & Urine Samples	clinical Data
[15]	COVID-19 Diagnosis	Clinical Notes	Clinical Notes

TABLE II. COMPARISON OF SUPPORTIVE MEDICAL DATASETS AND THEIR BENEFITS IN COVID PREDICTION.

Ref	Methodology Adopted	Datatype	Attributes
[8]	polynomial Regression	Clinical Notes	More precede data on Location, Age, Frequency of infection, Confirmed Death Cases, Recovered rate, etc.
[16]	Random Forest / Decision Tree	Hematochemical Parameters	Most Early dataset, all blood parameters such as Leukocytes (WBC), Platelets Numerical, C-reactive Protein (CRP) Numerical (continuous), Transaminases (AST) Numerical, Transaminases (ALT), Gamma Glutamyl Transferase (GGT), Lactate dehydrogenase (LDH), Neutrophils, Lymphocytes, Monocytes, Eosinophils, Basophils, Swab
[21]	Binary Classifier	Blood & Urine Samples	body temperature, heart rate, respiratory rate, blood pressure, and the blood/urine tests data. Features studied is 100, 8 clinical study, 76 blood test, 16 urine tests
[15]	Random Forest, Scaled Gradient, Decision tree, Naïve Bayes classifier	Clinical Notes	finding, survival, intubated, went ICU, needed supplemental, O2, extubated, temperature, pO2 saturation, leukocyte count, neutrophil count, lymphocyte count, view, modality, date, location, folder, filename, DOI, URL. License.

TABLE III. COMPARISON OF MACHINE LEARNING AND DEEP LEARNING TECHNIQUES IN TERMS OF ACCURACY.

Ref.	Methodology	Accuracy (%)	Data Type
[7]	Deep CNN	96.3	X-rays
[10]	Deep-CovidNet	85	Ct images
[11]	Ultra AI models	90	CT-Chest
[12]	VGG16, ResNet50, and EfficientNetB	96.8	CT-Chest
[19]	Multi-feature/ HOG+EOH/ CNN, KNN	95.65, 91.304	Lung CT-Images
[20]	ResNet18, ResNet50, ResNet101, and SqueezeNet	99.4	Lung CT-Slices
[16]	RF/ DT	86	Hematochemical Parameters
[21]	Binary Classifier	81	Blood & Urine Samples
[14]	CNN, 3-Level DT	95	CT images
[23]	PA, ARIMA, LSTM	94.8, 88.43	X-rays
[24]	KNN, FRMEM	96.09	X-rays
[15]	RF, SGB, DT, NB	96.2	Clinical Notes
[25]	DarkCovid-Net,	98.08	X-rays

Ref.	Methodology	Accuracy (%)	Data Type
	CNN		
[27]	CNN	95.09	Ct images
[13]	FconNet	99.87	Ct images
[18]	MLP/CNN/Joint	83.5	Ct images
[30]	Ten integrated CNN Layers	99.51	Ct images

Table 2 depicts the second category of data that plays a major part in COVID detection. The major part of coronavirus detection is the clinical notes that depict the patient records and treatment timelines. 76 types of blood tests and 16 types of urine tests were collected from various patients and other physiological parameters such as temperature, blood pressure, etc. [33]. Table 3 depicts the detailed study and their results on finding the best performing machine-learning techniques. Most of the results help to treat the COVID-19 diagnosis in a better way by keeping these parameters as references. Applications of AI in medical imaging are illustrated in fig 4, patient medical images are stored in local databases and with the help of AI, medical imaging techniques are used to analyze the images.

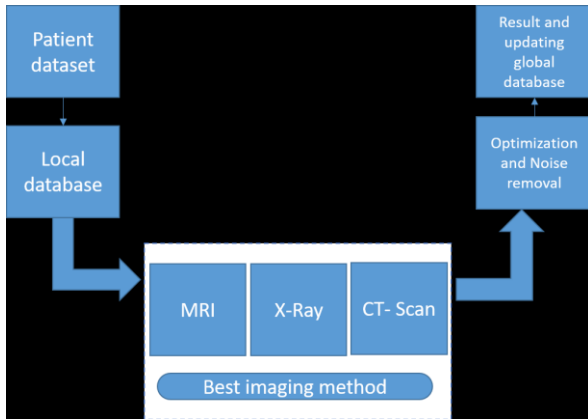


Fig 4. Applications of AI in medical imaging

V. DISCUSSIONS AND FUTURE CHALLENGES

It is easy to train these algorithms due to the availability of a considerable amount of pre-existing data in today's digital age. Moreover, increased computing capability due to the availability of unconventional processors like GPU (Graphic Process Unit), and TPU (Tensor Process Unit). This enhances the ability of AI methods to scale better while using a huge amount of data [34]. Along with, high accuracy in arduous appositeness which is not easy for humans to understand [35]. The organization BlueDot uses natural language processing and machine learning to source data and track infectious disease outbreaks [36]. Furthermore, AI supports the mining of research databases and published research findings to find clues about the protein structure of the virus, mechanisms of infection, and possible treatments for respiratory illness hence being viable and reliable [36]. However, the use of CNN with X-Ray trained models hasn't worked well equivalently in all hospitals from where data sets were collected [37]. Another disadvantage is the existence of biases in image sets [38]. Due to the existence of biases, which if not considered carefully considered, can result in miscalculation. This is possibly due to the

imbalance in the amounts of positive and negative images used for training, most of the time with different provenance, different properties of images in each set, because of various mAs, kVp, detection geometry, image size, pixel intensity, art facts, labels, etc. [34].

From the unequivocal examination of various review papers and journals, the assessment perceives the focal issues that help the experts proceeding further with the point-by-point assessment. Research articles with numerous AI computations, artificial cognizance models are surveyed and are found to give the best results. Ko [27] investigated and gave the end on Fast COVID Net for better figure execution of around 99.87%. Results mentioned in [30] are spectacular in which they have utilized ten unique CNN layers to improve the prediction performance and have achieved 99.5%. Ahuja [20] using a python tool, executed ResNet 18, 50, and 101 and differentiated and Squeezenet. The cultivated precision is 99.4%.

Diverse tools and solutions are defined by the investigating social orders which are depicted above in Table 3. Probably the greatest challenge influencing COVID-19 test advancement lies not in innovation, yet rather, as expected – the most essential factor when lives can be secure and death rate should be controlled. Another challenge is the limitations of reference material for development and research. Inalienably, there are no all-around published reference materials accessible for novel patients like SARS-CoV-2. Testing should be possible in every individual association, nonetheless, contrasting surveys on paper are incomprehensible without commutable reference material and must be refined. Testing stays a pillar of any pandemic situation. Many test procedures are amped up for new developments and approaches created by the research community and industry that may extend the testing limit and increment the dataset sets available.

VI. CONCLUSION

COVID-19 prediction accuracy has improved by the integration of artificial intelligence and machine learning techniques. The primary goal of all the research is to develop a competent and strong system that provides views and procedures to control the rapid spread of infection and to demonstrate an effective and accurate model utilizing AI and machine learning techniques. The research uncovers the unique organization on high-performing classifiers that accomplish precision of around 99% in a limited period. Most of the studies described in the paper are based on a static dataset of CT scans, X-rays, and medical data accessible in Open Source. As a result, future works should be focused on accurate datasets available in the current scenario for further accuracy and efficiency.

REFERENCES

- [1] C. Huang *et al.*, "Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China," *The Lancet*, vol. 395, no. 10223, pp. 497–506, Feb. 2020, doi: 10.1016/S0140-6736(20)30183-5.
- [2] T. Guo *et al.*, "Cardiovascular Implications of Fatal Outcomes of Patients With Coronavirus Disease 2019 (COVID-19)," *JAMA Cardiol.*, vol. 5, no. 7, pp. 811–818, Jul. 2020, doi: 10.1001/jamacardio.2020.1017.
- [3] P. Hamet and J. Tremblay, "Artificial intelligence in medicine," *Metabolism*, vol. 69S, pp. S36–S40, Apr. 2017, doi: 10.1016/j.metabol.2017.01.011.

- [4] N. Nasir *et al.*, "Electrical detection of blood cells in urine," *Heliyon*, vol. 6, no. 1, p. e03102, Jan. 2020, doi: 10.1016/j.heliyon.2019.e03102.
- [5] N. Nasir, "Electrical Characterization and Detection of Blood Cells and Stones in Urine," *Dissertations*, Feb. 2020, [Online]. Available: https://scholarworks.uaeu.ac.ae/all_dissertations/97
- [6] M. F. Sohan, "So You Need Datasets for Your COVID-19 Detection Research Using Machine Learning?," *ArXiv200805906 Cs Eess Stat*, Aug. 2020, Accessed: Aug. 14, 2021. [Online]. Available: <http://arxiv.org/abs/2008.05906>
- [7] S. Vaid, R. Kalantar, and M. Bhandari, "Deep learning COVID-19 detection bias: accuracy through artificial intelligence," *Int. Orthop.*, vol. 44, no. 8, pp. 1539–1542, Aug. 2020, doi: 10.1007/s00264-020-04609-7.
- [8] N. S. Punna, S. K. Sonbhadra, and S. Agarwal, "COVID-19 Epidemic Analysis using Machine Learning and Deep Learning Algorithms," Jun. 2020, doi: 10.1101/2020.04.08.20057679.
- [9] M. J. Horry *et al.*, "COVID-19 Detection Through Transfer Learning Using Multimodal Imaging Data," *IEEE Access*, vol. 8, pp. 149808–149824, 2020, doi: 10.1109/ACCESS.2020.3016780.
- [10] S. Wang *et al.*, "A Fully Automatic Deep Learning System for COVID-19 Diagnostic and Prognostic Analysis," *Eur. Respir. J.*, Jan. 2020, doi: 10.1183/13993003.00775-2020.
- [11] H. Zhang *et al.*, "Automated detection and quantification of COVID-19 pneumonia: CT imaging analysis by a deep learning-based software," *Eur. J. Nucl. Med. Mol. Imaging*, pp. 1–8, Jul. 2020, doi: 10.1007/s00259-020-04953-1.
- [12] T. Zebin and S. Rezvy, "COVID-19 detection and disease progression visualization: Deep learning on chest X-rays for classification and coarse localization," *Appl. Intell.*, pp. 1–12, Sep. 2020, doi: 10.1007/s10489-020-01867-1.
- [13] H. Ko *et al.*, "COVID-19 Pneumonia Diagnosis Using a Simple 2D Deep Learning Framework With a Single Chest CT Image: Model Development and Validation," *J. Med. Internet Res.*, vol. 22, no. 6, p. e19569, Jun. 2020, doi: 10.2196/19569.
- [14] S. H. Yoo *et al.*, "Deep Learning-Based Decision-Tree Classifier for COVID-19 Diagnosis From Chest X-ray Imaging," *Front. Med.*, vol. 7, p. 427, 2020, doi: 10.3389/fmed.2020.00427.
- [15] A. M. U. D. Khanday, S. T. Rabani, Q. R. Khan, N. Rouf, and M. Mohi Ud Din, "Machine learning based approaches for detecting COVID-19 using clinical text data," *Int. J. Inf. Technol.*, vol. 12, no. 3, pp. 731–739, Sep. 2020, doi: 10.1007/s41870-020-00495-9.
- [16] D. Brinati, A. Campagner, D. Ferrari, M. Locatelli, G. Banfi, and F. Cabitza, "Detection of COVID-19 Infection from Routine Blood Exams with Machine Learning: A Feasibility Study," *J. Med. Syst.*, vol. 44, no. 8, p. 135, Jul. 2020, doi: 10.1007/s10916-020-01597-4.
- [17] N. Nasir and M. Al Ahmad, "Cells Electrical Characterization: Dielectric Properties, Mixture, and Modeling Theories," *J. Eng.*, vol. 2020, p. e9475490, Jan. 2020, doi: 10.1155/2020/9475490.
- [18] M. Al Ahmad *et al.*, "Label-Free Cancer Cells Detection Using Optical Sensors," *IEEE Access*, vol. 6, pp. 55807–55814, 2018, doi: 10.1109/ACCESS.2018.2872768.
- [19] K. Ghafoor, "COVID-19 Pneumonia Level Detection using Deep Learning Algorithm," Jul. 2020, doi: 10.36227/techrxiv.12619193.v1.
- [20] S. Ahuja, B. K. Panigrahi, N. Dey, V. Rajinikanth, and T. K. Gandhi, "Deep transfer learning-based automated detection of COVID-19 from lung CT scan slices," *Appl. Intell.*, pp. 1–15, Aug. 2020, doi: 10.1007/s10489-020-01826-w.
- [21] H. Yao *et al.*, "Severity Detection for the Coronavirus Disease 2019 (COVID-19) Patients Using a Machine Learning Model Based on the Blood and Urine Tests," *Front. Cell Dev. Biol.*, vol. 8, p. 683, 2020, doi: 10.3389/fcell.2020.00683.
- [22] N. Nasir, S. Raji, and M. Ahmad, "Electrical Characterization of Calcium Oxalate Hydrate in Urine," *Instrum. Mes. Métrologie*, vol. 19, no. 1, pp. 25–33, Mar. 2020, doi: 10.18280/i2m.190104.
- [23] M. Alazab, A. Awajan, A. Mesleh, A. Abraham, V. Jatana, and S. Alhyari, "COVID-19 Prediction and Detection Using Deep Learning," *Int. J. Comput. Inf. Syst. Ind. Manag. Appl.*, vol. 12, pp. 168–181, May 2020.
- [24] M. A. Elaziz, K. M. Hosny, A. Salah, M. M. Darwish, S. Lu, and A. T. Sahlol, "New machine learning method for image-based diagnosis of COVID-19," *PLOS ONE*, vol. 15, no. 6, p. e0235187, Jun. 2020, doi: 10.1371/journal.pone.0235187.
- [25] T. Ozturk, M. Talo, E. A. Yildirim, U. B. Baloglu, O. Yildirim, and U. Rajendra Acharya, "Automated detection of COVID-19 cases using deep neural networks with X-ray images," *Comput. Biol. Med.*, vol. 121, p. 103792, Jun. 2020, doi: 10.1016/j.combiomed.2020.103792.
- [26] H. Panwar, P. K. Gupta, M. K. Siddiqui, R. Morales-Menendez, and V. Singh, "Application of deep learning for fast detection of COVID-19 in X-Rays using nCOVnet," *Chaos Solitons Fractals*, vol. 138, p. 109944, Sep. 2020, doi: 10.1016/j.chaos.2020.109944.
- [27] N. R. Raajan, V. S. R. Lakshmi, and N. Prabakaran, "Non-Invasive Technique-Based Novel Corona(COVID-19) Virus Detection Using CNN," *Natl. Acad. Sci. Lett. Natl. Acad. Sci. India*, pp. 1–4, Jul. 2020, doi: 10.1007/s40009-020-01009-8.
- [28] L. Li *et al.*, "Using Artificial Intelligence to Detect COVID-19 and Community-acquired Pneumonia Based on Pulmonary CT: Evaluation of the Diagnostic Accuracy," *Radiology*, vol. 296, no. 2, pp. E65–E71, Aug. 2020, doi: 10.1148/radiol.20200905.
- [29] X. Mei *et al.*, "Artificial intelligence-enabled rapid diagnosis of patients with COVID-19," *Nat. Med.*, vol. 26, no. 8, pp. 1224–1228, Aug. 2020, doi: 10.1038/s41591-020-0931-3.
- [30] A. A. Ardakani, A. R. Kanafi, U. R. Acharya, N. Khadem, and A. Mohammadi, "Application of deep learning technique to manage COVID-19 in routine clinical practice using CT images: Results of 10 convolutional neural networks," *Comput. Biol. Med.*, vol. 121, p. 103795, Jun. 2020, doi: 10.1016/j.combiomed.2020.103795.
- [31] R. Kumar, S. Nagpal, S. Kaushik, and S. Mendiratta, "COVID-19 diagnostic approaches: different roads to the same destination," *VirusDisease*, vol. 31, no. 2, pp. 97–105, Jun. 2020, doi: 10.1007/s13337-020-00599-7.
- [32] R. Samson, G. R. Navale, and M. S. Dharne, "Biosensors: frontiers in rapid detection of COVID-19," *3 Biotech*, vol. 10, no. 9, p. 385, Sep. 2020, doi: 10.1007/s13205-020-02369-0.
- [33] N. Nasir, A. Najar, and M. Al Ahmad, "Optical Characterization of Calcium Oxalate Hydrate in Urine," in *2018 IEEE 5th International Conference on Engineering Technologies and Applied Sciences (ICETAS)*, Nov. 2018, pp. 1–5, doi: 10.1109/ICETAS.2018.8629252.
- [34] J. D. López-Cabrera, R. Orozco-Morales, J. A. Portal-Díaz, O. Lovelle-Enríquez, and M. Pérez-Díaz, "Current limitations to identify COVID-19 using artificial intelligence with chest X-ray imaging," *Health Technol.*, vol. 11, no. 2, pp. 411–424, Mar. 2021, doi: 10.1007/s12553-021-00520-2.
- [35] M. A. Nielsen, "Neural Networks and Deep Learning," 2015, Accessed: Aug. 14, 2021. [Online]. Available: <http://neuralnetworksanddeeplearning.com>
- [36] F. Al-Turjman, Ed., *Artificial Intelligence and Machine Learning for COVID-19*. Springer International Publishing, 2021, doi: 10.1007/978-3-030-60188-1.
- [37] J. R. Zech, M. A. Badgeley, M. Liu, A. B. Costa, J. J. Titano, and E. K. Oermann, "Variable generalization performance of a deep learning model to detect pneumonia in chest radiographs: A cross-sectional study," *PLOS Med.*, vol. 15, no. 11, p. e1002683, Nov. 2018, doi: 10.1371/journal.pmed.1002683.
- [38] L. M. Prevedello *et al.*, "Challenges Related to Artificial Intelligence Research in Medical Imaging and the Importance of Image Analysis Competitions," *Radiol. Artif. Intell.*, vol. 1, no. 1, p. e180031, Jan. 2019, doi: 10.1148/ryai.2019180031.