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The Role of Machine Learning Techniques and Internet of Things Devices in COVID-19 Detection: A Mapping Study

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Abstract- The COVID-19 outbreak has affected numerous facets of human life. It is still an ongoing epidemic with multiple variants emerged since its first outbreak. To detect COVID-19 machine learning and the Internet of Things are the most widely proposed methods in the literature showing favorable performance. This paper presents a complete mapping and assessment of recent research efforts on COVID-19 detection using both machine learning techniques and the Internet of Things devices. The objective of this research work is to identify machine learning techniques and IoT devices that are used in combination to effectively detect COVID-19 and its variants. The synthesis of the mapping study is provided as the analysis of the IoT devices, and the effectiveness of machine learning techniques in disease detection. This study will help the researchers and health practitioners in deploying an effective method for detecting COVID-19, and its variants using machine learning techniques and IoT devices.

Keywords- COVID-19, Internet of things, Internet of Medical Things, Machine Learning Techniques, Detection, Mapping Study

I. INTRODUCTION

The World Health Organization (WHO) claims that COVID-19 is comprised of those viruses that cause flu-like diseases in both humans and animals. The virus is dangerous as it is easily transmitted by contact with an infected individual, whether directly or indirectly. By detecting and isolating early-stage COVID-19 patients, its spread can be delayed, potentially sparing many lives. The existing methods of COVID-19 detection, i.e., RT-PCR have a false positive rate of 0.05% for the uninfected cases and a false negative rate of 2% for the infected cases [1]. The requirement for speedy and accurate identification and surveillance are the main factors that led to the introduction of Machine Learning (ML) and Internet of Things (IoT) technology for COVID-19 detection. The Internet of Medical Things (IoMT) is part of IoT and is specified for the domains and areas of medicine and healthcare [2]. Medical records of patients are maintained and transferred to nearby clinics and also to the Centres for Disease Control and Prevention through the Internet by IoT devices. The IoT environment helps patients observe their disease level and get medication without physical contact which helps governments efficiently manage national health plans [3].

ML has a significant role in medical care. ML is playing a significant role in predicting COVID-19 disease [4]. Deep learning and other approaches are used for the detection, identification, and treatment of different respiratory diseases and in multiple other critical situations regarding health. Similarly, IoT and IoMT also contribute a lot to the facilitation of health care and medicine. Currently, a comprehensive study providing a complete mapping and assessment of contemporary research efforts in detecting COVID-19 using both ML and IoT technologies is missing. Therefore, the objective of this research is to provide an in-depth understanding of different machine learning and IoT technologies that are used in combination for COVID-19 detection. A systematic mapping review is performed to provide a complete mapping and assessment of contemporary research efforts in detecting COVID-19 using both ML and IoT devices. For this purpose, five databases, i.e. IEEE, Springer, Science Direct, ACM, and Taylor & Francis are searched for the relevant literature (table 1). The mapping is performed by classifying and summarizing the most recent patterns, and methods employed by the researchers to detect COVID-19 using ML and IoT technologies. The future research directions in this research domain are shared with both the computing and health sector communities to help improve the severity prediction of COVID-19, its existing variants, and its unseen variants that are yet to come.

This paper is structured as follows: In section 2 the methodology is discussed. The mapping and research findings are discussed in section 3; Section 4 is about limitation and future direction, finally, in section 5 the overall research work is concluded with future research direction.

II. RESEARCH METHODOLOGY

This section outlines the research techniques used to find and evaluate relevant papers for this systematic mapping study. The planning, implementation, and reporting are the three basic building blocks of the methodology. A review process that specifies a list of inquiries, inclusion and exclusion standards, article sources, search terms, and mapping procedures should be developed at the planning stage. Selecting and acquiring the research articles for data extraction is recommended during the implementation stage. In the reporting phase, it is advised to analyse the findings in order to respond to the pre-established questions.

Research Questions

The main purpose of this systematic literature review is to provide the current status of recent research trends in COVID-19 detection using ML and IoT-based technologies. To ensure a fair selection process, the following research questions were considered:

Research Question (RQ) 1: Which ML techniques and IoT devices are used for COVID-19 detection?

This investigation looks on studies that use Internet of Things (IoT) devices and machine learning methods to identify COVID-19.

Research Query 2: How efficacious are machine learning techniques and Internet of Things (IoT) devices in the detection of COVID-19?

This inquiry explores the efficiency of machine learning techniques and Internet of Things (IoT) devices in detecting COVID-19, aiming to identify the ML techniques and IoT devices that exhibit greater effectiveness in COVID-19 detection.

Literature Search and Selection

This section describes the selection process that was performed as a part of this study. It consists of four steps. 1) Term and search string 2) Search source 3) criterion for inclusion and exclusion 4) saving data

Terms, Search Strategy, and Search String

The foundational search query comprises three pivotal phrases originating from diverse realms of knowledge: "machine learning," representing the field of artificial intelligence; "Internet of Things," embodying the interconnected network of devices; and "COVID-19," encapsulating the global health crisis caused by the novel coronavirus. This combination of key terms forms the basis for a comprehensive exploration across the interdisciplinary landscape, facilitating a nuanced understanding of the intersections between artificial intelligence, connected devices, and the ongoing impact of the COVID-19 pandemic. A search string is created by combining terms with the "AND" link. Before applying the search string syntax to the three research paper metadata, namely the title, summary, and keywords, it was modified to account for the specifics of each source (placeholders, connectors, apostrophes, quotations, etc.). The search technique is an approach to:

a) Creating search words by determining the population, the intervention, and the result
b) A search for synonyms and alternate spellings
c) Making use of Boolean operations

Results for a:

Population: People with COVID diagnoses, machine learning techniques, and Internet of Things (IoT) gadgets.

Intervention: COVID-19 detection by effective machine learning implementation.

Relevant Results: Figuring out the effective machine learning techniques that IoT devices employ to recognize COVID-19.

Design of Experiments: Experimental design integrates case studies, comprehensive literature reviews, expert insights, theoretical exploration, and empirical inquiries, fostering a multifaceted approach to research methodology. It encompasses diverse methodologies, including case studies, rigorous literature reviews, expert consultations, theoretical inquiries, and empirical investigations, ensuring a robust framework for experimentation.

Findings for b and c:

Research Query 1 and 2: (("Internet of Things" OR "IoT" OR "Internet of Medical Things" OR "IOMT") AND (("COVID-19" OR "coronavirus variants” OR "Delta" OR "SARS-COV-2) AND ("Detection" OR "diagnosis" OR "discovery" OR "identification") AND ("treatment" OR "cure" OR "therapy") AND ("Machine Learning" OR "ML" OR "Supervised Learning" OR "Reinforcement Learning" OR "Deep Learning"))

Search Sources

A preliminary selection of papers from the search results that might meet the selection criteria based on reading their titles and abstracts was made, and then a final selection of papers from the preliminary list that meet the selection criteria based on reading the entire research paper was made. This was how the selection process was divided into two stages. Although a huge number of papers were retrieved as a search result, only a few met the final inclusion criterion. Those studies were excluded which have not considered ML and IoT technologies for COVID-19 detection. A high number of irrelevant publications were also discovered due to synonyms in our search string. After the first round of filtering and duplication removal, we were left with a handful of researches to use in the final selection process. Table 1 shows each selected search source. Table 2 shows the result of the search string.

In the first round, there were 1629 papers chosen in all from the mentioned databases. In the second round of the initial selection from this batch, a total of 212 papers were chosen. In the final round, 48 studies relevant to our research problem were selected.

Table 1: Search sources employed in SLR of COVID-19 detection using ML techniques and IoT devices

S. No.	Search Source	Electronic address	Kind
1	IEEE	http://ieeexplore.ieee.org	Digital library
2	Science Direct	https://www.sciencedirect.com	Digital library
3	Springer Link	https://link.springer.com	Digital library
4	ACM	https://www.acm.org	Digital library
5	Taylor & Frances	https://taylorandfrancis.com	Digital library
6	Google Scholar	https://scholar.google.com	Search engine

Table 2. Results of a search string for RQ 1, and RQ 2

Search Source	Total Results	Initial Selection	Final Selection
IEEE	298	46	17
Science Direct	289	85	15
Springer Link	828	46	13
ACM	160	9	2
Taylor & Frances	54	26	1
Google Scholar	298	46	17
Total	**1629**	**212**	**48**

Publication selection

In this section, the inclusion, and exclusion criteria for selecting research papers are mentioned. The details related to data storage, public quality assessment, data extraction, and data syntheses are also provided.

Conditions for Inclusion

The literature, which included papers, technical reports, and other related written materials found by the search term, was sorted according to the inclusion criteria listed below to see if it was suitable for further data extraction:

a) The inclusion criterion emphasizes the consideration of research papers published exclusively in the English language.
b) The temporal scope for the literature review spans from the year 2000 to 2022, ensuring a comprehensive examination of relevant materials over a substantial timeframe.
c) c) Inclusion is extended to papers featuring the specified keywords outlined in the search string, ensuring a focused and relevant selection aligned with the research objectives.
d) The inclusion criteria are broadened to include research articles that engage in meaningful discourse on the use of ML methods and IoT devices that are especially employed for COVID-19 detection.

Conditions for Exclusion

The following list contains the exclusion criteria for choosing research papers:

a) Research papers that fit into books, editorials, thesis, or news stories are excluded from consideration. The goal is to keep the focus on academic works that are suitable for in-depth examination.
b) Excluded are introductory papers from special issues, workshops, and posters that lack substantive discussion on techniques, ensuring a focus on literature with meaningful technical content.
c) Studies that don't cover COVID-19 detection using machine learning and Internet of Things devices are not included.

Data storage

In a spreadsheet that contained all the key information from the chosen work, the data that was extracted during the search phase was saved. Throughout the systematic literature review, this table aided the classification and analysis processes.

Publication quality assessment

After the final selection, the publications' quality was evaluated. The subsequent inquiry was verified as a criterion for selection: Does the article investigate the use of IoT devices and machine learning approaches for COVID-19 detection? Each paper received one of three scores for this question: "YES," "NO," or "Partially." The research papers satisfying the criteria were selected. It was noticed that the chosen articles are trustworthy because they have undergone external reviews to ensure that they are of sufficient quality to be used in this research.

Data extraction

Data extraction was the responsibility of a pair of researchers and subsequent review procedures. If a problem with the data extraction is encountered, the reviewer rechecked their work. After the data extraction procedure was completed, the inter-rater reliability was examined by the primary reviewers. A list of quotes was extracted from each article, with each phrase describing a set of essential components for the detection of COVID-19 and its variants using ML techniques and IoT devices.

Data synthesis

It was the reviewers who synthesized the data. Following the data extraction process, the sample of papers was used to compile a list of trust criteria. The reviewers looked at these elements to create a list of categories, and they ultimately created a list of categories. The three-stage selection procedure used in the current mapping study is shown in Figure 1. According to the inclusion and exclusion criteria, the sample size was decreased at each stage.

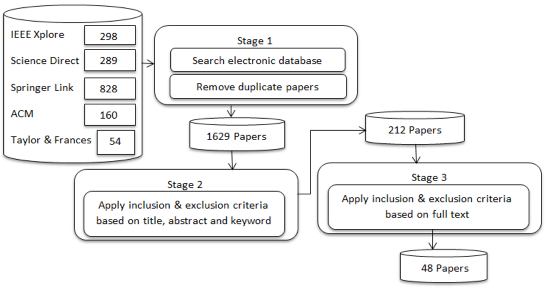

Figure 1 Data Extraction Stages

III. RESEARCH FINDINGS AND DISCUSSION

The findings of the mapping study are discussed in this section. The answer to each research question is presented below in tables.

Research Query 1: What machine learning techniques and Internet of Things (IoT) devices are employed in the detection of COVID-19?

A thorough examination of COVID-19 detection with IoT devices and machine learning approaches is given. In Table 3, the results for RQ 1 are reported. It describes ML techniques and IoT devices used in each research work for COVID-19 detection.

The ML techniques used for COVID-19 detection are Deep Learning (DL) [5], [9], [12], [14], [23], [25], [27], [36], [40], [43], [44], [48-50], Support Vector Machine (SVM) [6], [10], [11], [15-17], [19], [29], [33], [34], [37], [43], [51], Artificial Neural Network (ANN), Convolution Neural Network (CNN), K Nearest Neighbour (KNN), Decision Tree (DT), Random Forest (RF), Naive Bayes (NB), Logistic Regression (LR), Multiple Linear Regression (MLR), Light Gradient Boosting Machine (LightGBM), K means, Hidden Markov Model (HMM), and Expectation Maximization (EM), Voting Classifier (VC), and Extra Tree Classifier (ETC), Multi-Layer Perceptron (MLP), Generative Adversarial Networks(GAN), Ensemble Learning (EL), Classical Machine Learning-based Multi-Class classifier (CML-MC) and Deep Transfer Learning-based Binary-Class classifier (DTL-BC), AdaBoost, Gradient Boosting(AGB), Artificial Bee Colony(ABC) and Multi-Task Gaussian Process (MTGP). MTGP is the most popular regression model for predictive analysis that is based on the basic Gaussian Process Regression (GPR) model.

IoT-based sensor devices can be categorized as wearable and non-wearable. Those devices that are in physical contact with the human body are known as IoT-based wearable sensors, such as Contact Temperature Sensors (CTS), Airflow Breathing Sensors (ABS), Galvanic Skin Response Sensors (GSR), Electrocardiography Sensor (ECS), Electromyogram Sensor (EMS), Accelerometer (sense blood pressure, heartbeat rate, and muscular activities), Body Humidity Sensor (BHS), Pulse Oximeter Sensor (POS), X-Ray, CT-Scan, Smart Ventilator (SV), Electrocardiography Sensor (ES). Pressure Sensor (PS), Smart Watches (SW), Digital Stethoscopes (DS), Glucose Monitors (GM), Smart Beds (SB), Smart Clothes (SC).

POS measures the blood oxygen saturation levels using red and infrared light. By monitoring the airflow in the lungs, the DS is used to listen to the sounds made by the lungs as they expand and contract during breathing. SW are watches that have sensors that continuously record information about your blood oxygen levels, temperature, and heart rate could function as COVID-19 personal warning systems. Built-in sensors in SC are smart garments that allow for the tracking and monitoring of body temperature, ECG levels, stress levels, and sleep quality. They come in the form of shirts, masks, and comfy, machine-washable smart clothing.

Those devices that are not in physical contact with the human body are known as IoT-based non-wearable sensors, such as Non-contact Thermometer Sensor (NTS), Audio Sensor (AS), Monitoring Camera (MC), Environmental Sensors (ES), Smart X-ray device (SXD).

ES is used to determine the air's temperature and humidity. AS measures the intensity of the disease through the sound of the coughing patterns of the patient. SXD captures X-ray images without touching or moving the human body.

The other kinds of IoT devices that are non-medical and are used to transfer sensors' data for COVID-19 detection are Mobile Applications (MA), drones, cloud, and fog nodes.

Mobile applications collect data about the person, recode cough sounds, and query about the symptoms of COVID-19 for detection. IoT-based frontend COVID screening system (ICSS) is an IoT-cloud-based healthcare model for COVID-19 detection.

ML techniques, such as SVM, RF, KNN, and DL have more frequency of usage in research articles for COVID-19 detection. Table 3 shows the usage frequency of ML techniques. It can be seen that the DL and SVM have been used in 14 and 13 research articles respectively. The reporting frequency of RF, CNN, LR, KNN, NB, ANN, and DT is 12, 11, 8, 7, 7, 6, and 4 respectively. The less frequently used techniques are MTGP, MLR, K-MEAN, MLP, K-STAR, HMM, and EM. Their detection accuracy is also less than the frequent techniques.

Medical sensors such as wearable and non-wearable sensors are used as IoT devices. Out of these, the most frequently reported wearable sensor is CTS. It is reported in 15 research articles. The research article reports that the usage frequency for COVID detection of accelerometer, POS, X-Ray, ABS, and SW is 9, 9, 6, 5, and 4 respectively. The less frequently observed IoT devices in research articles are SV, PS, ES, GSR, ECS, EMS, BHS, and DS.

The most frequently observed non-wearable sensor in research articles is MC. It is reported in 8 research articles. The research article reports that the frequency of other non-wearable sensors, such as AS 7, NTS 3, SXD 3, and ES is 7, 3, 3, and 2 respectively.

Table 3: A summary of COVID-19 detection using IoT devices and machine learning algorithms

S #	Research Paper Reference	ML Techniques	IoT Sensor devices
1	[5]	DL	CTS, ABS, GSR, ECS, EMS, and MC.
2	[6]	LR, KNN, SVM, ANN, and LightGBM	CTS, ABS, AS, and Accelerometer
3	[7]	KNN	Accelerometer
4	[8]	LR	CTS, Accelerometer, BHS, ES, and MC
5	[9]	DL	NTS, AS, and POS
6	[10]	SVM, DT	CTS, and POS
7	[11]	NB, RF, and SVM	X-Ray, and CT-Scan
8	[12]	DL	POS, CTS, SW, Accelerometer
9	[13]	AGB, RF, VC, ETC	NTS
10	[14]	DL, and CNN (Faster-RCNN)	SXD
11	[15]	SVM, and radial basis function	sensor-connected device/gateway device and edge devices
12	[16]	SVM, LR, KNN, and RF	SV
13	[17]	SVM, RF, NB, K-Star, MLP	Accelerometer
14	[18]	CNN, image processing, LSTM	MC
15	[19]	RF, LR, NB, SVM, and MLP	CTS, POS, PS
16	[20]	CNN	SXD
17	[21]	LR	CTS, POS, Accelerometer, AS, and ABS
18	[22]	EL	smart CT scanners
19	[23]	DL	ES
20	[24]	KNN	ICSS
21	[25]	DL	X-Ray, and CT-Scan
22	[26]	ANN	SW
23	[27]	DL based on long short term memory (LSTM).	Wearable IoT sensors
24	[28]	MLR	NTS, MC, and SW
25	[29]	SVM, ANN, NB, KNN, DT, OneR, and ZeroR	CTS, AS, Accelerometer, and ABS
26	[30]	RF	AS, and SXD
27	[31]	LR, DT, and RF	CTS
28	[32]	CNN based on long short term memory (LSTM)	DS, AS, POS, and CTS
29	[33]	RF, SVM, DT, and LR	CTS, Accelerometer, and POS
30	[34]	CNN, SVM	IoT devices
31	[35]	TinyML, patient-ventilator asynchrony (PVA) classifier	ABS
32	[36]	DL, KNN	MC, CT scan
33	[37]	RF, MLP, NB, LR, SVM	PS, CTS, POS
34	[38]	K means, HMM, and EM	MA
35	[39]	CML-MC and DTL-BC	MA (user-friendly mobile app called AI4COVID-19)
36	[40]	DL, and CNN	MC, and AS
37	[41]	CNN	CTS, Accelerometer, and POS
38	[42]	CNN	X-ray, and CT scan
39	[43]	NB, ANN, KNN, RF, SVM, DL, and CNN	MA, and X-ray
40	[44]	DL, and CNN	chest X-Ray
41	[45]	RF, NB, GAN	CTS, MC, X-ray sensor, ECG sensor
42	[46]	MTGP	GM, and SB
43	[47]	ANN	SW, and SC
44	[48]	DL	MC, CTS, MA
45	[49]	DL	X-ray (chest radiograph)
46	[50]	DL, CNN	mobile CT scanners
47	[51]	SVM, and ABC	CTS
48	[52]	RF	SV

Research Query 2: How efficacious are machine learning techniques and Internet of Things (IoT) devices in the detection of COVID-19?

ML and IoT play a vital role in detecting COVID-19 effectively. The effectiveness of ML techniques used for COVID-19 detection is shown in Table 4.

The evaluation parameters, such as Accuracy, Sensitivity, Specificity, Precision, Recall, Area under the Curve (AUC), and F-Score are used to assess the effectiveness. It is found that the DL, SVM, and RF, CNN, KNN are most frequently used in COVID detection and they perform better than other techniques, like DT, K-star, NB, and

ANN. The results of the research article [6] show that KNN is better than LR, SVM, ANN, and LightGBM. The accuracy of KNN is 97.51%, precision is 99.65%, recall is 97.31, AUC is 0.9788, and F-Score is 0.9847. SVM has high accuracy reported in articles [11], [29]. SVM is also showing high accuracy for COVID-19-confirmed case prediction in China [4]. Their highest accuracy is 95% and it is the most frequent technique for COVID-19 detection. Based on these results, it is recommended to use SVM in the cases of COVID-19 variants. Along with SVM, the recommended IoT devices for COVID-19 are CTS, Accelerometer, and POS.

Table 4: A Summary of Effectiveness of ML techniques in COVID-19 detection

Paper Reference	Technique(s)	Effectiveness						
		Accuracy	Sensitivity	Specificity	Precision	Recall	AUC	F-Score
[5]	Proposed method	97.95%	95.39%	97.60%	95.47%	---	---	---
[6]	LR	96.04%	---	---	98.08%	97.09%	0.94	0.98
	KNN	97.51%	---	---	99.65%	97.31%	0.98	0.99
	SVM	96.22%	---	---	95.71%	99.88%	0.89	0.98
	ANN	96.68 %	---	---	96.33%	99.77%	0.94	0.98
	LightGBM	96.87%	---	---	97.46%	98.77%	0.93	0.98
[8]	Proposed method	85.71%	---	---	---	---	---	---
[10]	Proposed method	74.7%	---	---	---	---	---	---
	DT	72.9%	---	---	---	---	---	---
	SVM	72.6%	---	---	---	---	---	---
[11]	RF	94.16%	---	---	95%	94%	0.93	0.93
	SVM	95%	---	---	95%	95%	0.95	0.94
	NB	92.5%	---	---	86%	93%	0.89	0.89
[12]	Proposed method	98.1%	---	---	---	---	---	---
[13]	AdaBoost	60.4%	---	---	71.2%	78.1%	---	0.746
	Voting Classifier (VC)	59.2%	---	---	70.2%	76.9%	---	0.735
	Gradient Boosting	67.1%	---	---	78.2%	77.1%	---	0.776
	Extra Tree classifier (ET)	69.7%	---	---	74.8%	78.4%	---	0.766
	RF	75.4%	---	---	79.4%	81.0%	---	0.802
[14]	Proposed method	98%	98%	95%	---	---	---	---
[16]	Proposed method	72.1%	---	---	---	---	---	---
[17]	K-star	95%	---	---	94.5%	93.5%	---	0.9399
	RF	90%	---	---	87.5%	82.3%	---	0.8482
	ANN	84%	---	---	75%	70.5%	---	0.7268
	SVM	78%	---	---	70%	67.6%	---	0.6877
	J48	63%	---	---	62%	62.4%	---	0.6219
[19]	RF	88.6%	99.8%	99.5%	---	---	---	---
	LR	78.6%	79.1%	20.9%	---	---	---	---
	NB	80.4%	81.15	18.9%	---	---	---	---
	SVM	79.1%	83.3%	57.8%	---	---	---	---
	MLP	87.8%	98.1%	96.1%	---	---	---	---
[20]	Proposed method	98.98%	---	---	---	---	---	---
[21]	Proposed method	91.71%	---	---	---	---	---	---
[22]	Proposed method	86.2%	---	---	---	---	0.898	---
[23]	Proposed method	96.2%	---	---	---	---	---	---
[24]	Proposed method	95.75%	---	---	---	---	---	---
[25]	Proposed method	98.6%	97.3%	98.2%	---		---	0.9787
[26]	Proposed method	89.3%	---	---	87.7%	86.4%	---	90.9%
[27]	Proposed method	97.59%	---	---	---	---	---	---
[28]	Proposed method	93.4%	---	---	---	---	---	---
[29]	SVM	92.95 %	---	---	---	---	---	---
	ANN	92.89 %	---	---	---	---	---	---
	NB	90.58 %	---	---	---	---	---	---
	KNN	92.89 %	---	---	---	---	---	---
	Decision Table	92.95 %	---	---	---	---	---	---
	Decision Stump	70.73 %	---	---	---	---	---	---
	OneR	68.36 %	---	---	---	---	---	---
	ZeroR	57.86 %	---	---	---	---	---	---
[30]	Proposed method	100%			100%	100%		
[31]	LR	88.9%	---	---	---	---	---	---
	DT	92.6%	---	---	---	---	---	---
	RF	94.4%	---	---	---	---	---	---
	Gaussian Naive Bayes (GNB)	90.7%	---	---	---	---	---	---
	SVM	92.6%	---	---	---	---	---	---
	XG Boost (XGB)	88.9%	---	---	---	---	---	---
	ANN	92.6%	---	---	---	---	---	---
	KNN	92.6%.	---	---	---	---	---	---
[32]	Proposed method	80%	---	---	---	---	---	---
[33]	Proposed method	99.26	---	---	---	---	---	---
[34]	CNN (Binary)	98.54%	---	---	---	---	---	---
	CNN(multiclass)	99.06%	---	---	---	---	---	---
[35]	Proposed method	97.18%	---	---	---	---	---	---
[36]	Proposed method	92%	---	---	---	98%	---	0.95
[37]	RF	88.7%	99.9%	99.6%	91.7%	88.7%	---	---
	LR	78.7%	79.2%	21.0%	78.5%	79.2%	---	---
	NB	80.5%	81.2%	19.0%	80.5%	81.1%	---	---
	SVM	79.2%	83.4%	57.9%	78.6%	79.2%		---
	MLP	87.9%	98.2%	96.2%	90.5%	87.9%	---	---
[39]	Proposed method	88.76%	91.71%	95.27%	86.60%	---	---	0.89.08
[40]	Proposed method	96%	---	---	---	---	---	---
[41]	Proposed method	97.5%	---	---	---	---	---	---
[42]	Proposed method	94.96%	---	---	89.74%	94.59%		0.921%
[43]	Proposed method	---	92.31%.	---	---	---	---	---
[45]	Proposed method	---	---	---	---	93%	---	0.871
[48]	Proposed method	95.6	---	---	---	---	---	---
[49]	Proposed method	97.47%	---	---	---	---	---	---
[50]	Proposed method	96.58%	---	99.16%	99.16%	---	0.966	---
[52]	Proposed method	---	---	92%	91%	88%	0.88	---

IV. Limitations and Future Directions

The proposed mapping review spans critical enhancements needed in COVID-19 detection systems, focusing on multiple fronts. It explores the potential shift of neural communities to cloud-based systems, emphasizing their impact on record management and safety. It highlights the pressing need for improved biological sensors and machine learning algorithms due to current sensors' lack of precision. Additionally, it addresses technical requirements for the Covidrone, focusing on advanced scanning technologies and safety measures for efficient and secure operations. It emphasizes the imperative of globally expanding X-ray image datasets, foreseeing the enormous data output from IoT models, and proposing frameworks to harness this volume effectively. Furthermore, it highlights the need to support cough-based detection against noise interference and advocates for rapid-learning adaptations in ML techniques for more robust infectious disease diagnosis. The importance of enriching federated models with additional real data and labelled datasets to refine GAN learning processes is highlighted, aiming for high accuracy and reliability. Lastly, the mapping review centres on optimizing disease detection system responsiveness by considering various Quality of Service factors, foreseeing substantial improvements through the integration of blockchain, software-defined networking, 5G, containers, and artificial intelligence to elevate overall system efficiency and performance.

In the future, the neural community may step forward with the aid of switching from the database to the cloud era which may validate quality for records management and control issues. Much development may be achieved on safety factors with the aid of offering a 5G community which may be used for extra compatibility [5]. It is important to prioritize the development of a system equipped with highly accurate biological sensors and to improve the efficiency of machine learning algorithms. The current biological sensors being used lack the necessary precision, highlighting the urgency for enhancement [8]. Onboard the Covidrone, more sophisticated cameras, and processing technologies are required to scan the patient's prior health and diagnostic records. To avoid dangerous chemical leaks, the drone's battery needs to be securely fastened and well-sealed. To prevent unexpected occurrences that could endanger nearby persons, the drone's rotors should be appropriately secured. The drone can become unable to return to its base of operations if its rotors are damaged. Therefore, it is important to concentrate on these problems and how to fix them [9]. Considering the number of instances reported globally, the data set of X-ray images must be significantly expanded. The amount of data that a pure IoT-based model may produce is enormous, and in the future, the framework should be created utilizing enormous X-ray images [14]. To enhance cough-based detection methods, it's crucial to augment their resilience against noise interference. Additionally, a rapid-learning adaptation of the ML techniques must be developed for a large-scale infectious disease diagnosis system, as the existing approaches using SVM classifier lacks resistance to noise [15]. The federated models must be trained and tested with more real data to make it more reliable and accurate [21]. More labeled data might be incorporated to enhance GAN's learning process, which would increase the quality of the synthetic samples generated [44]. The disease detection system's responsiveness relies on completing checks for all patients. To improve this in the future, it's crucial to consider diverse Quality of Service factors, such as scalability, security, and network traffic related to fog and cloud technologies. Advancements in this domain, incorporating blockchain, software-defined networking, 5G, containers, and artificial intelligence, can significantly enhance system efficiency and performance [45].

V. Conclusion

The significance of ML and IoT technologies for the early detection of diseases has been growing. The ML techniques and IoT paradigms can be used to create clinical decision support systems for dealing with COVID-19 pandemic-related problems. A mapping study review gives a research report-type structure that enables categorization and visual summaries of findings from papers in a particular field of study. This identifies machine learning techniques and covid features and IoT technology that help out in the identification and detection of similar pandemics in the future and, are being used as a foundation for new research initiatives. The most recent mapping review effectively represented the current status of research on COVID-19 detection and identified the main approaches for COVID-19. This research is the first mapping study for COVID-19 detection using ML techniques and IoT devices. The study discovered and examined 48 relevant research articles. Although these publications have contributed significantly to COVID-19, the overview provided in this mapping study review implies that there may be opportunities for additional research in this area. Out of many ML Techniques DL, SVM and RF are the most frequent machine learning techniques that are used for COVID-19 detection. Sensor mostly used as IoT devices and the most frequently used sensors are Wearable CTS, accelerometer, and

POS. In the future, the aim is to examine the COVID-19 datasets to identify the data features of the disease that are used to train the machine learning models.

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