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A systematic mapping review of COVID-19 data feature for infection detection

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A B S T R A C T

The coronavirus disease (COVID-19) has become widespread. It has caused outbreaks in more than 213 nations leading to many fatalities. It is still going around in all its forms. The diagnosis, prognosis, and treatment of disease include a variety of novel approaches, including machine learning, artificial intelligence, and the Internet of Things (IoT). Numerous studies on the detection of COVID-19 using various techniques have been conducted. Numerous strategies are used and suggested in the literature. This study aims to pinpoint the data features of COVID-19 that have been employed for disease detection by IoT devices using machine learning techniques. This research project offers a comprehensive mapping and evaluation of current studies on COVID-19. The focus is on IoT gadgets employing machine learning for detection. The study is conducted using a systematic mapping review. For the mapping study review, five electronic databases were searched. Studies published until April 2022 were considered. There are 50 studies selected that address COVID-19, IoT devices, and machine-learning approaches. This research concludes the investigation of data features that are usually used for effective, and efficient detection. This research will be useful for a future COVID-19 variant pandemic, as it provides a comprehensive review of the best data features for disease detection. Also, the data features identified in this research can aid in the early and precise exposure of COVID-19 in existing circumstances.

1. Introduction

The Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) is the main source of the COVID-19 disease. It is becoming a significant infectious disease epidemic over the globe. The coronavirus was first detected in December 2019 in Wuhan, China. The source of the disease is unknown. However, early verified cases are strongly associated with contact with wild animals at the Huanan seafood wholesale market. In this case, prolonged human-to-human transmission has also been observed, especially among close relatives. The coronaviruses are a significant viral family that affects both people and animals. The information flood spreads more swiftly than the infection itself, putting the health of millions of individuals throughout the world in danger. Health apps are designed to provide accurate information. These apps use Machine Learning (ML) techniques for disease prediction. At that time, the virus was dangerous for two reasons: first, the absence of immunizations; and second, it could spread through indirect or direct contact with an infected person. The clinical signs of COVID-19 include fatigue, a dry cough, and fever. The acute respiratory distress syndrome affected about one-third of infected individuals and nearly half of them had severe pneumonia. Furthermore, COVID-19 currently does not have a specific treatment available. The RT-PCR test based on patient nasopharyngeal and throat samples is the standard method for the medical evaluation of COVID-19. Only seven coronaviruses have been found to infect humans, even though many coronaviruses have been found to cause respiratory, gastrointestinal (GI), hepatic, and neurologic illnesses in animals. Three of these seven coronaviruses have large-scale epidemics of lethal pneumonia in the twenty-first century, making them much more potent than other coronaviruses at inflicting serious and occasionally fatal pulmonary infections in humans. These coronaviruses, which are all enclosed in RNA viruses, include SARS, COVID-19, and Middle East Respiratory Syndrome (MERS) [1].

There are multiple and different data features used for COVID-19 detection in research studies. Some studies consider non-image-based features, such as fever, cough, and sore throat. Whereas, in some studies, image-based features are considered. These features are collected by various medical sensors that are embedded in the human body or worn. These features are used in training machine learning techniques for accurate COVID-19 and its variants detection. Multiple variants of COVID-19 have appeared, such as Omicron, delta, alpha, and n delta. There are many variants which are still appearing.

The objective of this research work is to report the data features of COVID-19 employed by ML techniques and IoT devices for detection in the literature. Machine learning is playing an important role in medical treatment. Numerous data features and machine learning techniques are used for the diagnosis and treatment of various respiratory conditions, as well as in a range of life-threatening medical situations. Similarly, the Internet of Things and the Internet of Medical Things both contribute significantly to the improvement of health care and medical services. The objective of the systematic mapping review is to examine various data features used by ML techniques and IoT technology for detecting COVID and its variants. For this purpose, the literature related to COVID, machine learning, and IoT devices was searched in five renowned databases, including Google Scholar, IEEE, Springer, Science Direct, ACM, and Taylor & Francis (Table 1). The related literature published till April 2022 was considered. In the initial round of research paper selection for review, 1427 documents were retrieved by the mentioned databases. In the second round, after title and abstract scrutiny, 289 papers were selected. In the third round, a quick review of the whole content of the research papers was performed for a final selection. There were 50 research papers selected. The research papers in the final selection address COVID detection and characterization using machine learning and IoT technologies. The contributions of this research study are:

- A comprehensive review of the data features of COVID-19 reported in the recent literature is provided
- The data features are classified based on the IoT technology employed for collecting data, i.e., image-based, and non-image-based approaches for data collection
- An overview of the COVID variants considered in the literature is provided
- The research findings are summarized, and research gaps are identified

The section-wise division of the research paper is as follows: The background of the research study is discussed in section 2. The methodology is given in 3. Section 4 provides the findings, conclusions, and gaps in the research. In section 5, the comparison of non-image-based features in IoT-ML mapping review with the previous study is provided. In section 6, the conclusion to the research work is presented.

2. Background

The spread of coronavirus is a major public health hazard across the globe. A dry cough, fatigue, and fever are some of the indications of COVID-19. On the other hand, patients with severe COVID-19 can suffer from lung failure, breathing distress syndrome, and extreme blood pressure drop. Due to the severity of the disease people die within a short period. The severity of the disease increases when the age is above 65, the patient has elevated lactate dehydrogenase, has higher D-dimer, and abnormalities are highlighted in chest X-ray. The chest X-ray (CXR) is frequently used to diagnose COVID-19. Chest X-rays and CT (computed tomography) scans can be used to identify the abnormalities in the lungs associated with COVID-19 infection. The trials, however, were unable to demonstrate how the markers altered the severity of COVID-19 upon admission. Identifying the importance of sickness characteristics is essential for prioritizing medical resources and delivering earlier, more focused care [2].

It is possible to evaluate machine learning algorithms and deep learning for COVID-19 identification by utilizing Computed Tomography (CT) scans, x-rays, and other machine learning model approaches thanks to the availability of open-source data sets containing COVID-19 data. Data features utilizing ML and the IoT can also be used to make an accurate diagnosis, find drugs that are currently available on the market that can be helpful, predict the spread of disease, identify severe cases, diagnose patients, early cure development, understand viral infections, map virus origins, forecast the next pandemic, predict COVID-19 variants and provide alternative treatments. To diagnose COVID-19 instances utilizing CT scans and X-rays, some of the best hospitals in the world are applying machine learning and artificial intelligence algorithms as well as numerous data aspects of COVID-19. The World Health Organization (WHO) declared 6,390,401 deaths from COVID-19 as of July 29, 2022 [3]. Given this, it is important to control the severity of the pandemic with early and effective detection of the unseen variants of COVID-19. For this purpose, this study reports and classifies the existing data features of COVID-19 used to train machine-learning models for disease detection. The aim is to identify the features that are more effective in COVID-19 detection.

3. Mapping Review Methodology

This section describes the search strategies that were employed to locate and assess relevant papers for this systematic mapping evaluation. It is essentially built around the three processes of planning, implementing, and reporting review process including a list of survey questions, inclusion and exclusion criteria, article sources, search terms, and mapping strategies that should be developed during the planning phase. During the implementation phase, selecting and buying the research articles for data extraction is advised. Analyzing the data used to answer the survey's initial set of questions is encouraged during the reporting phase.

3.1 Research Questions

The key objective of this study is to provide the research community with the most recent progress in COVID-19 identification using the pandemic data trends. The following research inquiries were taken into account to provide a fair selection procedure:

Research Question (RQ) 1: To detect COVID-19, which data features are considered by ML methods and IoT gadgets?

This question investigates data features of COVID-19 datasets used for detection. It helps identify those features which are more effective in COVID-19 detection.

RQ 2: Which COVID-19 variants are considered by ML techniques and IoT devices?

This research question gives the researchers knowledge about which variants of COVID-19 have been considered so far for detection purposes using ML techniques and IoT devices.

3.2 Literature Search and Selection

This section outlines the method used to make the selections for this systematic mapping review. There are four steps to it. 1) The term and the search term 2) look for sources 3) Requirements for inclusion and exclusion 4) data saving methods.

3.2.1 Phrases, search method, and search string

The core search terms were "machine learning," "Internet of Things," and "COVID-19," and they were related to three distinct knowledge domains. Using the "AND" link, you can combine phrases to form a search string. The search string syntax was adjusted to include placeholders, connectors, apostrophes, quotation marks, and other elements specific to each source before it was applied to the three metadata fields of research papers, namely the title, summary, and keywords. The plan for the mapping review search strategy is to:

a) Identify the population, the intervention, and the result to generate search terms.

b) Researching synonyms and other spelling variations

c) Employing Boolean operators.

Results for a:

Population: Machine learning techniques, COVID-19 pandemic, data features.

Intervention: Effective data features for COVID-19 detection

Outcomes of relevance: Efficient data characteristics for COVID-19 and its version detection.

Experimental Design: Case studies, systematic mapping reviews, theoretical research, empirical studies, and expert comments.

Results for b and c:

RQ 1, RQ 2: (("Machine learning" OR "ML" OR “Deep learning”) AND ("COVID-19" OR "SARS-COV-2" OR "SARS-COV" OR "MERS-COV" OR" HCOV-NL63" OR "HCOV-229E" OR "HCOV-OC43" OR "HKUI" OR "coronavirus" OR "omicron" OR "delta" OR "covid variants") AND ("internet of things" OR "IOT" OR "IOMT" OR "internet of medical things") AND ("identifying" OR "finding" OR "detection") AND ("treatment" OR "cure" OR "therapy")).

3*.2.2 Search sources*

An initial selection of research literature from the search results was performed based on the titles and abstracts. The final selection of research literature was performed by reading the entire research article. Only a small proportion of the papers returned in the search results matched the final inclusion criteria. The detail of search sources is provided in Table 1.

Table 1

Search sources employed in systematic mapping review

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

In Table 2, the statistics of search results are shown.

Table 2

Findings for RQ 1 and RQ 2 using a search string

Search Source	Total Results	Initial Selection	Final Paper
IEEE Xplore	259	101	16
Science Direct	399	57	17
Springer	561	82	14
ACM	111	26	1
Taylor and Frances	97	23	2
Total	1427	289	50

3.3 Selection of Research Papers

To select research articles precise criteria are required. These criteria specify the kind of literature that will be included and the kind of literature that will be excluded. Along with the literature selection criteria, here we also describe where the additionally supplied information is stored, public quality evaluation, data extraction, and data syntheses.

3.3.1 Criteria for inclusion

The inclusion criteria help decide the relevant research literature, such as articles, technical reports, or any other material. In the following the inclusion criteria used to perform this systematic mapping review are given:

- Only English-language research publications are taken into consideration
- The period covered by the collected literature study is from 2000 to 2022
- The mapping review search process spans from January 1, 2022, to August 1, 2022.
- Papers with the targeted keywords in the search string are considered

3.3.2 Criteria for exclusion

The exclusion criteria for research paper selection are given below:

- If the research paper is a book, editorial, thesis, or news piece, it is not included
- Posters without any technique, workshops, and introductory articles for special issues are not included
- Studies on COVID-19 identification utilizing machine learning algorithms and data attributes are not included

3.3.3 Data storage

The data related to the research papers search and selection was stored in a spreadsheet. It contained all the important information, research notes along dates.

3.3.4 Quality assessment of the publication

The quality of the publications was assessed after the final selection. As selection criteria, the following checkbox was selected: COVID-19 detection using IoT gadgets and ML techniques addressed in the paper. For this question, each paper was scored as "YES," "NO," or "Partially." The studies meeting the requirements were chosen. The chosen articles were found to be reliable since they had been subjected to outside reviews to make sure they were good enough to be included in this study.

3.3.5 Data extraction

A team of two researchers, who were also in charge of the data extraction, carried out the evaluation process. The reviewer double-checked their work in case there was an issue with the data extraction. The data extraction process was finished, and the primary reviewers tested the reliability. Each article yielded a series of statements, each describing a set of factors essential for the detection of COVID-19 and its variations utilizing machine learning techniques and Internet of Things sensors.

3.3.6 Data synthesis

The reviewers combine the data in their analysis. A list of trust factors is formed from the paper’s sample. As a result of the reviewers' consideration of these factors, a final list of classes is created.

4. Results And Research Findings

This section summarizes the results of the SLR. Tables and graphs with the answers to each research topic are shown below.

4.1 Image-Based Features of COVID Datasets

The image-based features utilize the characteristics and the specifications of patients to identify COVID.

These features are shown in Table 3. Image-based COVID datasets typically include image qualities, specifications, and dimensional details. The non-image-based datasets, however, contain a variety of data elements, such as coughing data, which also includes audio signal, noise, distortion, wave curve, and frequency. The image-based data features for COVID-19 detection are shown in Table 3.

The most frequently addressed feature of image-based datasets is the pixels of the image [5, 12, 15, 16, 17, 26, 29, 34, 35, 42, 47, 49, 50, 51]. The second most frequently used image feature is the image pattern reported in [5, 12, 15, 16, 17, 26, 29, 34, 35, 42, 47]. The rest of the features are resolution [5, 26, 29, 49, 50], grayscale [5, 12, 26, 34], width, height, dimension [42, 50, 51], RGB [26, 34], segmentation [16, 26], flip [16, 26, 42], transform spectrum [37], format [37], center point [37], optimizer [42], total epochs [42], cross-entropy [42], loss function [42], orientation [49], fill mode[49], principal component value [50], spatial [29], zoom [42], HSV [34], size [37, 49], learning rate [42], range of rotation [42], shear range [42], rescale [16, 26, 42], and resizing [15, 42, 49]. Among all these features image pixels, image pattern, resolution, grayscale, width, height, dimension, RGB, segmentation, resizing, rescale, and flip are the most frequent features of COVID because these features make disease detection easy and clear. These are also prominent specifications of the images. Infrequent features include format, center point, optimizer, total epochs, cross-entropy, orientation, fill mode, principal component value, spatial, zoom, Herpes Simplex Virus (HSV), loss function, size, learning rate, range of rotation, and shear range.

The most often occurring feature of image-based data sets is pixels, which are covered in every study. In digital graphics and images, a pixel is the tiniest element rendered on a digital screen. Pixels make up a whole image or video. Since pixels define an image's visibility, all articles extensively examine this aspect of the image. The quality of the image is based on the number of pixels. To identify COVID and image alterations, image quality is crucial. The majority of publications concentrate on this feature of the dataset as a result. Another common data attribute is image pattern, which is reported in many studies. An image pattern is a collection of images that have a similar feature, such as a pattern of soothing or disturbing images, or a pattern of sharp or smooth images. Researchers may readily spot the issue by evaluating these traits, as an infected patient's lung or CT scan has different image patterns than a healthy person. This aspect is addressed more in articles because it aids in the detection of COVID by evaluating various patterns of image and making early detection possible.

The resolution of the image is another common feature of the image-based datasets used in many papers. Higher-resolution images have more Pixels Per Inch (PPI), which leads to a higher-quality, and sharp image. For COVID-19 research, higher-resolution medical imaging is required since it enhances diagnostic accuracy, makes it possible to identify minor abnormalities in the lungs, and gives a clearer picture of the breadth and severity of the disease. This increased information facilitates the creation of AI models for more accurate diagnosis and treatment planning, helps track the course of the disease, and assists in studying the impacts of the virus. This feature is used frequently to analyze the details of COVID-19-affected persons. Another most frequent feature is grayscale. Each pixel’s value in the grey scale depicts the information about the intensity of the light. Such snaps reflect either the dark black or the bright white. In other words, the image only has black, white, and grey hues, each of which has many levels of grey. This feature is frequent because X-rays have a high gray scale. The zoom feature of an image is the most uncommon element of a dataset that is addressed since images are not fixed and might be of varying sizes depending on the capturing devices or recognition devices.

Fig. 1 shows the percentage and research study count of Image-Based Features for COVID-19 detection using ML. The x-axis represents the image-based features of COVID-19 detection using IoT-ML techniques, while the y-axis on the left side indicates the study count. It shows that the most frequently used data feature is the pixels of the images. After that image pattern has the highest frequency. A few features have the lowest frequency such as format, optimizer, transform spectrum, center point, and total epochs. A line graph superimposed on Fig. 1 shows the cumulative percentage of total frequency as the features are added from left to right.

Table 3

Search sources employed in systematic mapping review

S. no	Paper	Image-based Data Features of COVID
1	Ahmed et al. [5]	Anchor points, Resolution, Grayscale, Color Scheme, pixels, and patterns
2	Salehi et al. [12]	Patterns, pixels, edges, Grayscale, Directional Patterns, Matrix of Grey-Level Run-Length, and Discrete Wavelet transform
3	Khan et al. [15]	Pixels and patterns, and anchor boxes for resizing
4	Alhudhaif et al. [16]	Pixels, patterns, segmentation, grayscale, flip, and rescale
5	Jayachitra et al. [17]	Audio signals, waveforms, pitch, frequency, pixels, patterns, and anchor points

6	Nunes et al. [26]	Pixels, patterns, segmentation, grayscale, flip, rescale, Resolution, and RGB
7	Waheed et al. [29]	Pixel, low spatial resolution, rescaling, and patterns
8	Madhavan et al. [34]	Pixel, patterns, RGB, grayscale, binary, and HSV
9	Das et al. [35]	Pixels, patterns, color conversion, and intensities
10	Le et al. [37]	Center point, pixel, Fourier transform spectrum, frequency signals, noise, pattern, size, format, and color conversion
11	Nasser et al. [40]	Pixels, patterns, resolution, pixels frequency, resizing, and rescaling.
12	Shorfuzzaman et al. [42]	Data points, Total Epochs, Optimizer, Loss function, cross-entropy, learning rate, rotation's range, range of sheer, range of zoom, breadth, shifting of height, Flip of image, mode of fill, Re-scaling, and pixel values
13	Rohila et al. [49]	Dimensions, size, resizing, tuning, randomized crop, scale, orientation, or framed, pixels, resolution, and density
14	Rasheed et al. [50]	Height and width dimensions, scale, pixels, Principal component values, and resolution
15	Muhammad et al. [51]	Chest CT scans height, width dimensions, scale, and pixels

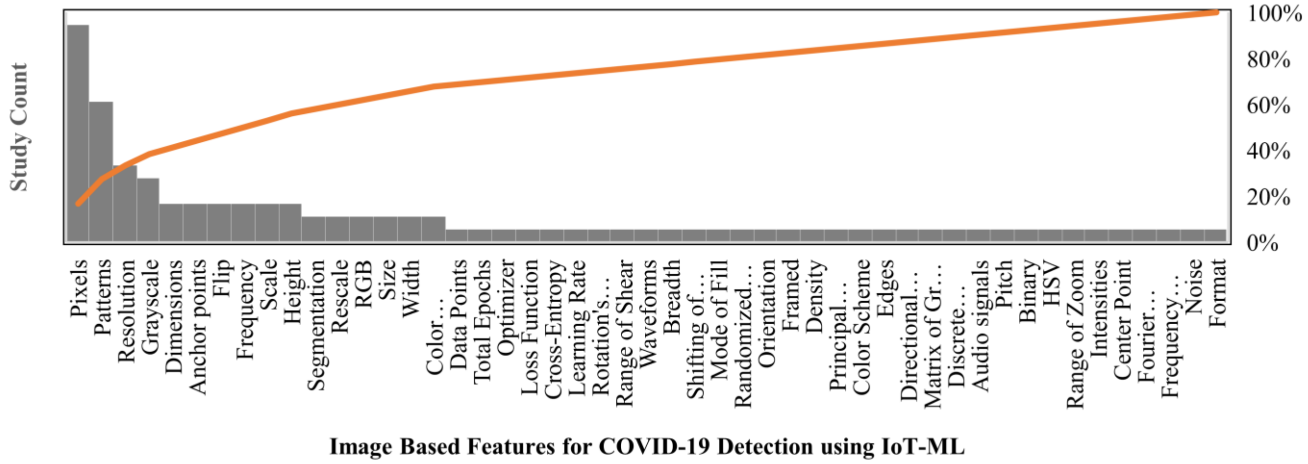

Fig. 1. Percentage and Research Study Count of Image-Based Features for COVID-19 Detection Using IoT-ML

4.2 Non-Image Based Features of COVID Datasets

The non-image-based data features differ from paper to paper depending on the machine learning techniques utilized and the IoT devices used to detect COVID and its variants. Non-image-based datasets contain a variety of data features that are collected by various embedded sensors or collected from hospitals or repositories. These features are discussed in Table 4.

Non-image-based features considered in the literature are huge in number. The most frequently addressed feature is cough reported in [4, 7, 10, 11, 12, 13, 14, 19, 21, 22, 25, 27, 28, 31, 33, 38, 41, 43, 44, 48]. The second most frequent feature is body temperature reported in [7, 11, 12, 13, 14, 15, 19, 20, 21, 22, 23, 25, 27, 28, 30, 32, 38, 39, 41, 46, 47, 48]. The other features are shortness of breath [4, 21, 22, 25, 28, 43], presence of Fever [4, 7, 10, 13, 21, 22, 28, 31, 33, 43, 44, 45], oxygen saturation in blood [7, 11, 14, 19, 21, 22, 25, 27, 28, 39, 41, 46, 48], pulse rate [19, 41, 48], sore throat [4, 6, 10, 13, 24, 28, 31, 43, 45], blood pressure [11, 15, 28, 39, 41, 48], fatigue [4, 13, 22, 24, 45], diarrhoea [6, 11, 13, 22, 28, 31, 43], headache [10, 11, 13, 28, 31, 33, 43], age [9, 18, 19, 24, 25, 31], gender [18, 19, 24, 25, 31], muscle ache [28, 43, 45], sneezing [48], chronic disease [8, 25], nausea [11, 43, 48], rhinorrhoea [13, 43], body pain [6], glucose neuropil [8], travel history [24, 47], facial expression [32, 38], vomiting [43, 45], stomach issue [33, 44], pneumonia, hypertension [31], chest pain [24, 28], face mask [7], haemoglobin, platelets [8, 9], red blood cells count, lymphocytes, leukocytes, basophil, monocytes, [8], diabetic [31], running nose [47], drowsiness [7], nasal congestion[6], dry mouth [11], Joint pain, eye pain [45]. These infrequent features appear in special cases of COVID-19 in which the research studies want to detect COVID-19 without frequent features and mostly depend on the environment in which detection is performed.

Cough is the most commonly cited data feature of COVID-19 (shown in Fig. 2), and it is mentioned in all research studies. It is a key symptom from which COVID can be easily identified using patterns and frequency of widely available cough datasets. As a result, several authors include this aspect in their research. The body temperature of a person is another frequently employed feature in COVID-19 detection. Most authors use this feature since body temperature is a critical predictor of acute COVID-19 and respiratory system disorders caused by high temperatures. Shortness of breath is another common aspect of the COVID-19 dataset since COVID-19 destroys lungs and as a result of lung injury, there is shortness of breath. The most unusual aspect of this research is joint pain, which is not a major symptom and is not commonly seen in COVID-19 patients; therefore, it is included in only one study. Another uncommon aspect of COVID-19 is drowsiness, which is not examined in much research due to its influence and is also not a key feature that causes severe problems. It may occur in unusual circumstances but not in all.

Table 4

Non-image-based data features used for COVID-19 detection

S. no	Paper	Non-Image Data Features of COVID-19
1	Otoom et al. [4]	Fever, Fatigue, dyspnea, Cough, and Sore Throat
2	Nalavade et al. [6]	Aches, rhinitis, sore throat, dysentery, and nasal congestion
3	Rahman et al. [7]	Cough, emotions, fever, drowsiness, heartbeat, face mask, electrocardiogram, oxygen saturation, and body temperature
4	Abdulkareem et al. [8]	Volume of packed red cells, Hemoglobin, Red blood cell count, lymphocytes, white blood cell count, Basophils, macrophages, Serum Glucose, Neutrophils, Urea, Creatinine, Potassium, Sodium Aspartate, transaminase, Platelets, Alanine Transaminase, Eosinophils, and Protein C reactive mg/dL
5	Tongguang et al. [9]	Age, Hematocrit, Hemoglobin, and Platelets
6	Kielienyu et al. [10]	Fever, cough, sore throat, and headache
7	Shabbir et al. [11]	Maximum Body Temperature, Systolic Blood Pressure, Breath Rate, Pulse, Oxygen Saturation, prothrombin time, Diarrhea, Headache, Nausea, Dry mouth, Breathlessness Condition, and cough.
8	Yadav et al. [13]	Fatigue, cough, fever, headache, dyspnea, lymphopenia, diarrhea, sore throat, sneezing, rhinorrhea, large white blood cell numbers, hemoptysis, inflammatory cytokines, and sputum generation
9	Al Bassaum et al. [14]	Pulse rate, temperature, oxygen saturation (SpO2), and cough
10	Choyon et al. [15]	Body temperature, blood pressure, and heart pulse
11	Siddhartha et al. [18]	Gender, Age, location, Previous sickness, and Health history.
12	Sreehari et al. [19]	Age, Sex, Fever, oxygen saturation, Heart Rate, and Cough
13	Karmore et al. [20]	Body temperature, respiratory/breathing rate, SaO2 value, CVP value, systolic value, heart rate, diastolic value, and mean pressure
14	Naren et al. [21]	Fever, shortness of breath, dry cough, body temperature, oxygen saturation level, and audio input
15	Tai et al. [22]	Lymphocyte quantity, mitochondria quantity, neutrophil, fever, shortness of breath, dry cough, body temperature, oxygen saturation level, fatigue, snivel, and diarrhea
16	Waheed et al. [23]	Body temperature, stress levels, sleep quality, heart rate, temperature, blood oxygen, and breathing pattern of patients
17	Castiglione et al. [24]	Breath, chest pain, sore throat, age, gender, fatigue, illness history, and travel history
18	Vedaei et al. [25]	Gender, age, body temperature, shortness of breath, cough severity, Body Mass Index (BMI), oxygen saturation, presence of chronic respiratory disease, and blood oxygen saturation level
19	Saha et al. [27]	Pulse rate, Fever, SpO2, and cough count
20	Hassantabar et al. [28]	Pulse rate, fever, SpO2, blood pressure, bronchopulmonary dysplasia, cough, dyspnea, body pain, headache, aching throat, loss of smell and taste, and upset stomach
21	Thukral et al. [30]	Temperature, facemask, and oxygen saturation
22	Mukherjee et al. [31]	Age, sex, country, date, diabetes, tobacco, pneumonia, high blood pressure, Chronic Obstructive Pulmonary Disease, diabetes, cough, diarrhea, pregnancy, sore throat, dyspnea, renal comorbidity, headache, fever, smoking
23	Mondal et al. [32]	Temperature, heart rate, respiratory rate, facial expressions, voice, and cough
24	Bilandi et al. [33]	Breathing Issues, Headache Stomach Issues, Cough, High Fever, and Muscular Issues
25	Arowolo et al. [36]	neutrophils proportions, increase in intestinal goblet cells, dendritic cells, B lymphocyte cells, genes, and macrophages
26	Ketu et al. [38]	Temperature, heart and respiratory rate, facial expressions, voice, and cough
27	Akhbarifar et al. [39]	Respiratory rate, Heart rate, Isolated diastolic blood pressure, Oral temperature, oxygen saturation, Cholesterol, HDL, cholesterol, LDL cholesterol,

		Triglycerides, and Isolated systolic blood pressure
28	Kallel et al. [41]	Temperature, Oxygen saturation, cough level, respiratory rate, pulse rate, and blood pressure.
29	Emokpae et al. [43]	Shortness of breath, cough, fever, sore throat, muscle ache, confusion, rhinorrhea, chest pain, diarrhea, headache, nausea, and vomiting.
30	Baskar et al. [44]	Respiration problems, severe fever, stomach problems, cough, and muscular problems
31	G. Rathee et al. [45]	Rash in skin, Temperature, bleeding, sore throat, pain in eyes, pain in joints, sickness, fatigue, itch, vomiting, muscle pain, breathing issues, and cold
32	Hussain et al. [46]	Pulse rate, Fever, SpO2, and current health condition
33	Singh et al. [47]	Hypertension, Fever, Dyspnea, environmental temperature, Chest tightness, pains, last fortnight travel history, diabetes history, Asthma, and rhinitis
34	Sharma et al. [48]	Cough, sneezing, air aerosols, droplets, temperature, Oxygen saturation, cough level, respiratory rate, pulse rate, and blood pressure

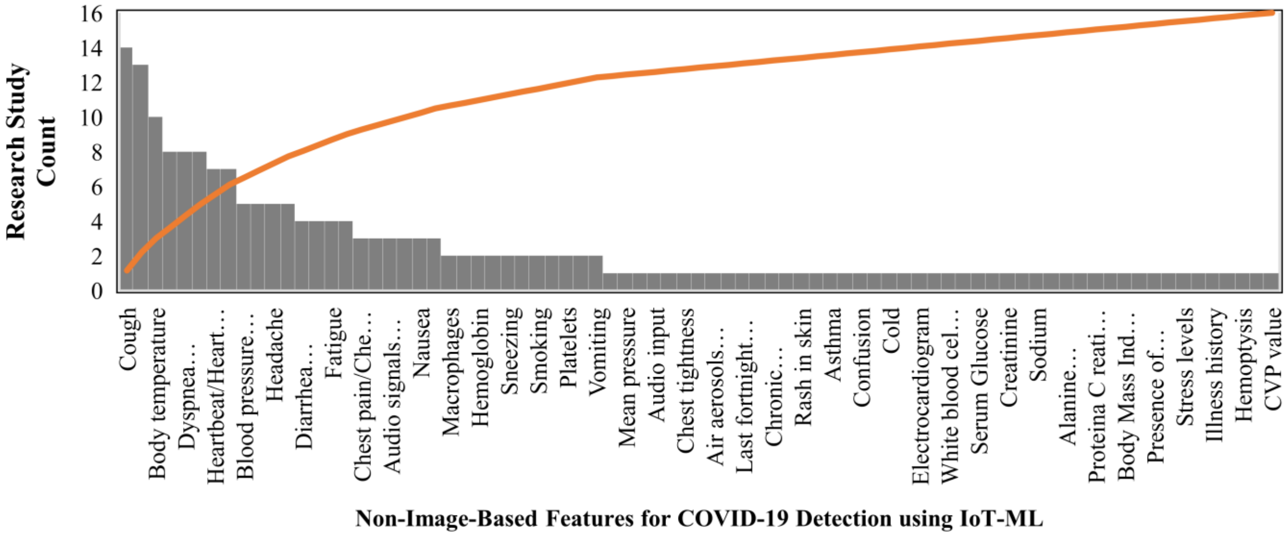

Fig. 2. Percentage and Research Study Count of Non-Image-Based Features For COVID-19 Detection Using IoT-ML

4.3 COVID Variants Considered by IoT Devices Using Machine Learning

In this section, the answer to the second research question is provided. There are a few articles that discuss COVID variants. Nearly all authors describe and take into account COVID-19 or Sars Cov 2, but many other COVID varieties result in serious illness, including omicron, the most prevalent type of COVID at the moment. Although there are still a few omicron occurrences, most academics are concentrating on COVID because it has wreaked havoc on countless lives and caused considerable damage. A pandemic is being managed and treated with caution. The severity of this epidemic has decreased since its inception. Pharmaceutical treatments and vaccines are now readily available.

The CoV Coronavirus, CoV-2 Coronavirus 2, SARS-CoV-2, SARS-CoV, MERS-CoV, CoVs (HCoVs), SARS-CoV-2 RNA, and ARDS are only a few of the many mutations that the CoV Coronavirus 19 carries. A viral respiratory infection MERS is related to the Middle East. There is a wide range of symptoms of all these variants. The common symptoms include breathing problems, coughing, upset stomach, and high body temperature.

The first kind of the SARS coronavirus is also known as SARS-CoV or SARSCoV1. Animals are afflicted by this respiratory condition. A pandemic of swine flu was brought on by the H1N1 influenza virus. Acute respiratory syndromes come in different varieties, including SARS. SARS is a respiratory infection that initially occurred in the United States in 2002 and persisted until 2004. SARSCoV1 (also known as SARS-CoV) is a coronavirus that causes SARS. This positive-sense virus infects lung epithelial cells and has a single-stranded RNA envelope. Coronavirus Disease 2019 (COVID-19) is a coronavirus 2 infection that results in severe acute respiratory disease (SARSCoV2). All studies only consider and discuss COVID-19 because it has spread widely and has harmed human health, and only a few papers just mention the name of its variants and don't go into detail about its variants or the family of COVID variants. In Table 5 the variants of COVID-19 discussed in research articles are shown.

Table 4

COVID-19 Variants discussed in research articles

S.no	Paper	Covid Variants
1	Yadav et al [13]	SARS-CoV-2, SARS-CoV, MERS-CoV, CoVs (HCoVs)
2	Ketu et al [38]	SARS, SWINE FLU, EBOLA, MARS
3	Asif et al [52]	SARS-CoV-2 RNA, SARS-CoV-2, MERS, MERS-CoV

All these papers mentioned in the table primarily consider COVID and discuss the details of its detection. COVID variant names are mentioned in the literature review of these papers. Currently, research papers have not focused on recent COVID variants such as delta and omicron. The main research gap that was found in existing studies was that COVID variants are not considered for detection.

Sensor-equipped Internet of Things (IoT) devices allow for remote health monitoring by continually recording several physiological indicators, providing real-time information about a patient's health. Simultaneously, these data, coupled with patient-reported symptoms, are utilized by machine learning algorithms to predict the likelihood of COVID-19. IoT devices evaluate dependability directly, but machine learning improves accuracy by identifying complex patterns. By combining these technologies, remote COVID-19 monitoring and detection are greatly improved, utilizing their combined strengths and capacities.

Traditional statistical methods might give priority to demographic information and the prevalence of symptoms, while advanced methods like deep learning are excellent at deciphering intricate temporal patterns from wearable sensor data. Furthermore, a variety of IoT devices produce a range of data kinds, from heart rate variability to metrics related to air quality, which affect the choice of features and the effectiveness of the model.

5. Comparison with Previous Review Studies

We compared our systematic mapping review with two recent and relevant review articles [53, 54] to provide a comprehensive comparison of features with existing works. The first study examines studies utilizing machine learning to predict COVID-19 and its severity based on both image-based and non-image-based features [53]. The second study focuses on the application of machine learning and artificial intelligence models for COVID-19 detection using image-based features only [54]. In contrast, our mapping review specifically examines studies that explore the use of IoT gadgets employing machine learning for COVID-19 detection.

The systematic literature review in the study [53] covers the period from January 1 to June 31, 2020, and includes 66 studies, making it older than our review. Our mapping review, spanning from January 1, 2022, to August 1, 2022, encompasses 50 studies. This provides a more comprehensive picture of the rise of COVID-19, the emergence of different variants, the increased use of IoT-based technology, the availability of more refined datasets for machine learning, and the drastic decline in the disease. It includes the latest IoT and ML-based COVID-19 research studies. The second study [54] examines 50 research articles from 2020 and 2021, focusing exclusively on image-based radiological modalities for COVID-19 detection, and is also older than our review.

The first study [53] reports on predictors of interest such as dataset features for COVID-19, machine learning models, and their accuracy. There are 79% of studies that employ chest images for prediction. While the remaining 21% of studies are based on non-image-based laboratory test features. The lab tests include blood-based, bio-molecular, and immunity-related observations. The features from image-based studies are extracted from X-ray and CT-Scan images. The detailed features and the extraction processes are not discussed. The second study [54] is confined to image-based modalities (CT-Scan and X-ray) where most studies used deep learning models for feature extraction, but details of these features were not provided. In contrast, our mapping review includes 49 features for image-based COVID-19 detection. The features are Anchor points, Resolution, Grayscale, Color Scheme, Pixels, Patterns, Edges, Directional Patterns, Matrix of Grey-Level Run-Length, Discrete Wavelet Transform, Segmentation, Flip, Rescale, Audio signals, Waveforms, Pitch, Frequency, RGB, Binary, HSV, Color conversion, Intensities, Center point, Fourier transform spectrum, Frequency signals, Noise, Size, Format, Data points, Total Epochs, Optimizer, Loss function, Cross-entropy, Learning rate, Rotation's range, Range of shear, Range of zoom, Breadth, Shifting of height, Mode of fill, Dimensions, Randomized crop, Scale, Orientation, Framed, Density, Height, Width, and Principal component values. The comprehensive utilization of these features helps in effectively detecting COVID-19. Consequently, it is impossible to compare the image-based features reported in this mapping review with those in the existing studies [53, 54].

In the first study [53], 36 non-image-based features were identified, whereas our mapping review encompasses 85 non-image-based features. Table 6 provides a comparative analysis of these features, revealing 25 that are common to both studies. Our review incorporates a broader spectrum of non-image-based features crucial for machine learning-based COVID-19 detection, contrasting with RT-PCR testing known for its false-negative rates ranging from 2% to 29% [55]. Machine learning models have achieved nearly 99% accuracy, highlighting their potential superiority. The diverse range of features in our review includes patient medical histories, particularly related to pulmonary and respiratory conditions, travel histories, geographic locations, and current health status, such as pregnancy or smoking habits. Additionally, IoT devices play a pivotal role by capturing data such as cough acoustics and pulse rates. Factors like facial expressions, emotions, and mental states are also considered, enriching the dataset and enhancing the accuracy of COVID-19 detection models.

Table 4

Comparison of non-image-based features in IoT-ML mapping review with previous study [53]

Non-Image Based Features	Dabbagh et al. [53]	IoT-ML mapping review	Non-Image Based Features	Dabbagh et al. [53]	IoT-ML mapping review	Non-Image Based Features	Dabbagh et al. [53]	IoT-ML mapping review
Fever	✓	✓	Serum Glucose	×	✓	Breathing Difficulty	✓	✓
Cough	✓	✓	Urea	×	✓	Dyspnea	✓	✓
Runny Nose	✓	✓	Creatinine	×	✓	Fatigue	×	✓
Hematocrit	✓	✓	Potassium	×	✓	Rhinitis	×	✓
Hemoglobin	✓	✓	Sodium Aspartate	×	✓	Dysentery	×	✓
Platelets	✓	✓	Headache	×	✓	Emotions	×	✓
Eosinophils	✓	✓	Systolic Blood Pressure	×	✓	Drowsiness	×	✓
Neutrophils	✓	✓	Breath Rate	×	✓	Heart Beat	×	✓
Basophils	✓	✓	Pulse	×	✓	Facemask	×	✓
Lymphocytes	✓	✓	Prothrombin Time	×	✓	Oxygen Saturation	×	✓
Leukocytes	✓	×	Nausea	×	✓	Macrophages	×	✓
Monocytes	✓	×	Dry Mouthed	×	✓	Country	×	✓
RBC Count	✓	×	Lymphopenia	×	✓	Diabetic History	×	✓
Mean Corpuscular Volume (MCV)	✓	×	Sneezing	×	✓	Pneumonia	×	✓
Mean Corpuscular Hemoglobin (MCH)	✓	×	Hemoptysis	×	✓	Pregnancy	×	✓
Mean Corpuscular Hemoglobin Concentration (MCHC)	✓	×	Rhinorrhea	×	✓	Renal Comorbidity	×	✓
Mean Platelet Volume (MPV)	✓	×	Inflammatory Cytokines	×	✓	Facial Expressions	×	✓
Red Cell Distribution Width (RDW)	✓	×	Sputum Generation	×	✓	Muscular Issues	×	✓
Age	✓	✓	Location of Patient	×	✓	Increase in Intestinal Goblet Cells	×	✓
Gender	✓	✓	Previous Sickness	×	✓	Dendritic Cells	×	✓
Body Temperature	✓	✓	Health History	×	✓	Genes	×	✓
WBC Count	✓	✓	CVP Value	×	✓	HDL/ LDL cholesterol	×	✓

C-reactive protein								
Aspartate Transaminase (AST)	✓	✓	Mean Blood Pressure	×	✓	Triglycerides	×	✓
Alanine aminotransferase (ALT)	✓	×	Cough Audio	×	✓	Confusion	×	✓
Gamma Glutamyl Transferase (GGL)	✓	×	Mitochondria Quantity	×	✓	Rash in skin	×	✓
Lactate Dehydrogenase (LDH)	✓	×	Snivel	×	✓	Pain in Eyes	×	✓
ECG	✓	✓	Stress Level	×	✓	Bleeding	×	✓
Smoking History	✓	✓	Sleep Quality	×	✓	Asthma History	×	✓
Sore Throat	✓	✓	Chest Pain	×	×	Air Aerosols	×	✓
Aches	✓	✓	Travel History	×	✓	Presence of chronic respiratory disease	×	✓
Nasal Congestion	✓	✓	Cough Severity	×	✓	Bronchopulmonary dysplasia	×	✓
Absence of smell and taste	✓	✓	Body Mass Index	×	✓	Vomiting	✓	✓
Diarrhea	✓	✓						

6. Conclusion

Approaches of machine learning and IoT can provide medical decision support system for dealing with problems related to the COVID-19 pandemic. The objective was achieved by performing a comprehensive literature review. There were 50 studies relevant to the research problem. The articles included in the literature review are valuable contributions in the domain of COVID-19 detection, however, there are potential research opportunities regarding COVID variant detection using machine learning and IoT technology. From a detailed study, we analyzed that two types of COVID features are considered, i.e. image-based and non-image-based using machine learning and IoT. The most frequent image-based features are pixels, patterns, grayscale, resolution, and the most frequent non-image-based features are fever, cough, sore throat oxygen saturation, temperature, shortness of breath, headache, age, gender pulse rate, and diarrhea, etc. In this study, we also analyze that frequent COVID features help out inaccurate detection. In literature, only names of COVID variants are mentioned. In future, we aim to collect data related to COVID variants and immunization and detect COVID and its severity using machine learning classifiers.

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