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Advancements in AI-Guided Analysis of Cough Sounds for COVID-19 Screening: A Comprehensive Review

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Abstract: The COVID-19 pandemic, a severe lung condition that produces excessive coughing, has placed an undue strain on healthcare systems throughout the globe. Screening that is dependable, inexpensive, and simple to get becomes critical for COVID-19. Even if the symptoms of severe and moderate diseases vary, coughing is still regarded as one of the most crucial indicators. Tools led by artificial intelligence (AI) have made it feasible to discover and test COVID-19 infections by using cough sounds for mass screening in areas with limited resources. In this paper, we examine the state of the art from 2020 to 2022 by examining AI-guided tools that employ machine learning and deep learning algorithms to analyze cough sounds for COVID-19 screening. We utilized the terms "(Cough OR Cough Sounds OR Speech) AND (Machine Learning Deep Learning OR Artificial Intelligence) AND (COVID-19 OR coronavirus)" in our research. To execute a better meta-analysis, we sought for a suitable dataset (size and source), algorithmic components, and performance ratings. We avoided pre-prints since they are not peer-reviewed; however, we did include publications from IEEE Explore, PubMed, Science Direct, ARXIV, and Springer Link to ensure we didn't overlook any current studies based on experimental research. This might be utilized for both early and long-distance diagnosis, assisting the globe in its battle against the epidemic. However, the best state-of-the-art approach for screening for COVID-19 was examined in this research.

Keywords: COVID-19, Deep Learning, Machine Learning, Cough Sound.

1. Introduction

There are many different viruses, with the common cold being the most widespread. However, some viruses have been linked to more severe illnesses like Middle East respiratory syndrome and severe acute respiratory syndrome. Coronavirus is one of them in the large virus family[1]. Everywhere is influenced by the SARS-CoV-2 virus. To begin with, it was evident in Wuhan, China, in Dec 2019. This new coronavirus has never been identified in people before and might lead to the very severe respiratory infection known as coronavirus 2019 (COVID-19). The situation quickly deteriorated as a result of a high number of affected individuals found in the "Huanan Seafood Market. The Chinese government documented the cases of an illness with six symptoms that were similar to pneumonia; however, the nature of the virus remained a mystery[2]. In thirty days, the number of instances increased to approximately forty. This virus had a history in China and was known there as the SARS disease. During the years 2002 and 2003, it was responsible for the deaths of approximately 770 individuals in China[3]. This virus has been shown to cause respiratory problems, and the incubation period for it is between 2 and 14 days (Lauer et al., 2020). Patients seeking medical treatment for a variety of conditions frequently report having a cough as one of their symptoms. The most frequently mentioned symptoms during medical visits are related to the respiratory system, and the cough is the most frequently mentioned reason having to do with sickness or injury. Moreover, the most frequently mentioned symptom is related to the respiratory system[4]. Indeed, cough is a symptom of more than a hundred different diseases, such as chronic bronchitis, acute tracheitis, pneumonia, lung abscess, tuberculosis, lung cancer, and pulmonary disease. Additionally, coughing is correlated with more than fifty different medical complications[5].

This is particularly true in resource-limited areas of the world where screening tests are one of the most crucial components of fully containing this virus because vaccines are either unavailable or unreliable there. China and the United States each have independently developed their distinct kinds of vaccines. Now, let's say that one day we find out that this epidemic is about to end, and that we also have a vaccine that is effective against it[6]. However, as of right now, the only thing that can be done to ensure our safety is to adhere to the recommendations provided by the government and various health organizations. However, our study is confined to the analysis of cough sounds since it is one of the most common symptoms and can be rapidly and readily analyzed for a large number of individuals using low-cost equipment.[7]

The Coronavirus is spreading all over the world. Pakistan has been suffering from it since December 2019, so diagnosing this infection at an underlying stage is essential. When dealing with a large number of cases, the length of the current diagnosis procedures, which take more than 48 hours to finish, slows down the rate of diagnosis. The principal issue looked at by the specialists was that the side effects are practically like other chest illnesses and coughs. Thusly, the recognizable proof of COVID-19 at an underlying stage is a major issue. Given that prevailing problem, an automatic screening system is required to diagnose this virus at the mild stage of an infected person using a cough sound. As cough is the major issue, we analyzed the cough sound for a further better classification model. From the start of COVID-19 to now, many kinds of research have been conducted regarding cough sound analysis using Machine learning, deep learning, and AI-guided tools, but here is the problem of finding state-of-the-art work. For this purpose, there is a dire need to conduct a systematic review of available research and declare the state-of-the-art work done.
The main goals of doing this research are:

- To diagnose the Covid-19 disease by analyzing Covid-19 symptoms already declared by World Health Organization and finding out more effective symptoms at an early stage.
- To screen and select the previous research for complete meta-analysis.
- Different data sets are used in the different papers we have to analyze laboratory-confirmed and non-laboratory-confirmed data.
- To identify the Methods/Models that might predict Covid-19 very effectively.
- To identify additional advancements in characteristics, databases, and pre-processing methods utilized for predicting or identifying Covid-19.

The introduction of the different signal analysis techniques used in this study and a demonstration of their immediate effects on data will follow the overview of initiatives that collected the data required for this study and the characteristics of the data collected. After that, in chapter four, we will examine machine learning strategies tailored to our requirements. Finally, we'll analyse and debate the results of the signal processing methods that are mentioned in our chosen papers. This SLR also aims to understand the role of the researcher in the field of Cough data analysis for covid-19 disease prediction and detection.

This work is organized as follows: Section 2 contains the literature review. Section 3 presents the methodology of the study. Section 4 discusses the results. In last, the conclusion and future work is described in section 5.

2. Literature Review

Trends in instrumental audio modelling and interpretation may turn this trend reverse and offer audio as an inexpensive and easy-to-distribute alternative. Microphones have subsequently been used to process audio on simple devices like smartphones and mobile devices. This study was utilized to distinguish different breathing patterns, and this technology can be used for effective application in the world. The paper starts by presenting a novel and powerful RS (Respiratory Simulation) Model. The purpose of the aforementioned model is to bridge the gap between a huge quantity of training data and inadequate real-world data for examining the features of real-world respiratory sounds[8]. The study's findings demonstrated that six different respiratory orientations, with accuracy percentages of 94.5%, 94.4%, 95.1%, and 94.8%, may be used to predict retrieval using the suggested model. The obtained BI at GRU respiratory pattern classification model beat the most recent state-of-the-art methods in comparison experiments. The suggested deep-learning model and principles have great potential to be used in a variety of applications, including ergonomics, public settings, and sleeping conditions[9]. The basic components of this system are an Android device and a thermal camera with FLIR (potential infrared). This can aid in identifying prospective COVID-19 patients in practical settings like pre-screening in institutions and clinical settings. In this study, they used thermal and RGB videos from cameras with DL architecture to perform a health check. First, used lung data analysis techniques to identify people wearing a mask; To obtain the medical examination result, the BI_at_GRU is applied to get the result of the lung disease, and finally, an accuracy of 83.7% is achieved for the classification of the patient's respiratory health conditions[10].

Establish a method for positively diagnosing COVID-19 using the RNN model. They explained the main effect of Recurrent Neural Networks using SSP (Speech Signal Processing) for disease detection more precisely, In the process of early identification and diagnosis of the COVID-19 virus, LSTM (Long Term Memory) is utilized to assess the acoustic features of the patient's voice, respiration, and cough. The model's findings show that the speech test is not very accurate when compared to audio recordings of breathing and coughing. The COUGHVID collection comprises over 20,000 cough records that represent a wide variety of participants in terms of gender, age, geographic region, and COVID-19 status. To train the classifier, they gathered a sequence of 121 Sneezing noises and 94 non-coughing sounds, including speech, laughing, quiet, and other background sounds[8]. To select recordings for labelling, they utilized self-reported case variants 25% audio recordings with healthy values, 25% audio recordings with COVID values, 35% audio recordings with symptom values, and 15% audio recordings with unreported conditions; to ensure that the three examiners identified 15% of the audio recordings as cough. The percentage of positive, symptomatic, and healthy subjects were 7.5%, 15.5, and 77% of the participants 65.5% male and 34.5% female, respectively. They caused shortness of breath (93.0%), wheezing (90%), stridor (98.7%), Nasal congestion (99.2%), and choking (99.1%) of 632 records of the labelled COVID-19 cough[8].

Research shows that cough sound samples are collected from smartphones around the world. Various groups have collected multiple cough recording datasets for COVID-19 and used them in the development of machine-learning models for COVID-19 detection. Although each of these models was trained using data from a range of recording formats and environments, the authors also gathered additional counts, sonograms, and cough recordings[11]. In addition, these datasets come from different sources, for example, data collection from clinical, crowdsourcing, and mining from public media interviews. In combination with COVID-19 case nomenclature, it is used to generate an AI algorithm that correctly predicts COVID-19 infection with a ROC-AUC of 77.1% (75.2–78.3%). Moreover, without further training with relevant samples, this AI Model could generalize to Latin American population samples and South Asian clinical samples[12].

The COVID-19 speech data analysis research proposed considers four aspects, including; I. Sleep quality II. Gravity III. Anxiety and IV. Tiredness. Jing Han and other Scientists and researchers from the University of Cambridge issued the "COVID-19 Sounds App," which collected data, while scientists and researchers from Mellon University also released the "Corona Voice Detection App." [13]These participants processed the data to produce a total of 378 segments; they took 260 recordings from this first trial for later investigation. 50 COVID-19 patients provided 256 audiograms, which were then shifted at a sampling frequency of 0.016 MHz for future research. In this investigation, they used two sets of acoustic features: ComParE and eGeMAPS[14].

3. Materials and Methods

The intended SLR is carried out following the Cochrane Handbook for the Systematic Research of Interventions, the Suggested Items for presenting in systematic Research, and the Meta-Analyses declaration with varied standards. This section goes into great detail on the systematic study process that was employed to carry out this review. We performed a series of operations to achieve our work objectives as shown in Figure 1.

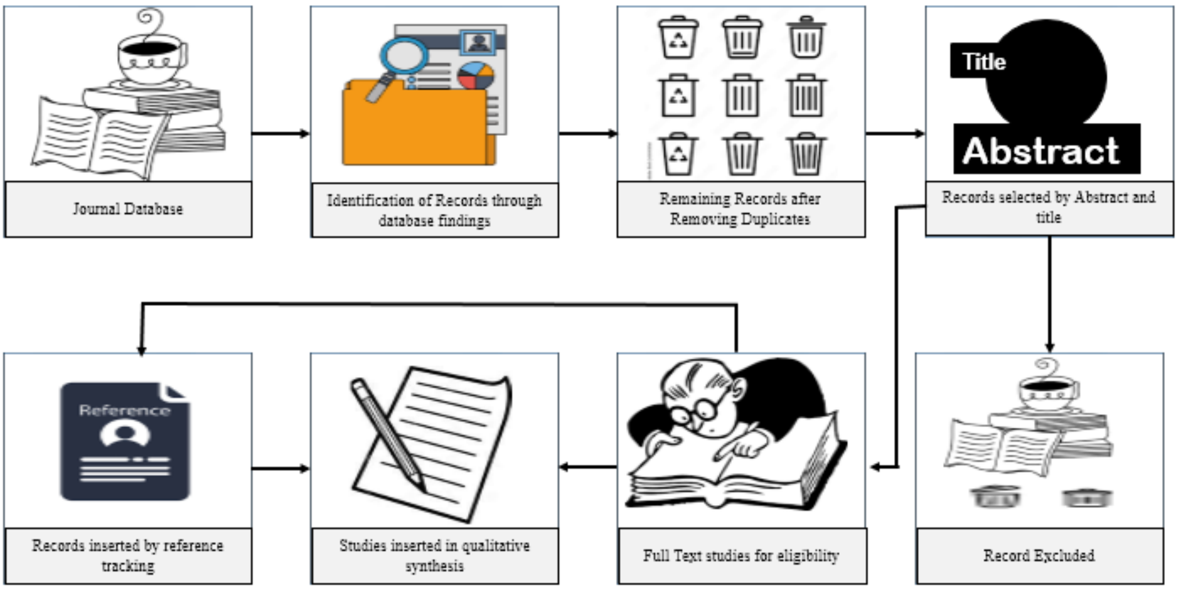

Figure 1. Series of Operations For SLR

3.1. Research Strategy

From 2020 to 2022, related articles were searched using the databases IEEE Explore, Science Direct, Springer Link, Pub Med, and ACM. The aforementioned databases are utilized to locate relevant articles for SLR. The IEEE Explore was chosen for its greater concentration of studies in the computer science discipline, and Pub Med was considered for its information on biomedical research. Science Direct is used because of its larger number of papers. Using the various keywords listed below, we looked up similar abstracts and titles for this SLR. In addition, the citations of articles in this SLR were hand-checked to include more relevant studies.

The following search string was used to find the research articles.

"(Cough OR Cough Sounds OR Speech) AND (Machine Learning OR Deep Learning OR Artificial Intelligence) AND (COVID-19 OR coronavirus)".

3.2 Study Design

The related studies are identified using the Mendeley tool based on their titles and abstracts. The selection criteria for the study are carefully followed to raise the quality of the research study. The main goal is to identify papers that predicted COVID-19 in people who had never received medical conditioning using AI tools and the Cough Audio Dataset. The methods for figuring out if someone has COVID-19 are looked at, but the main focus is on how AI algorithms can be used to predict COVID-19. The study inclusion and exclusion criteria are strictly followed to extract the most relevant studies and the criteria. Figure 2 illustrates the PRISMA diagram for the study design.

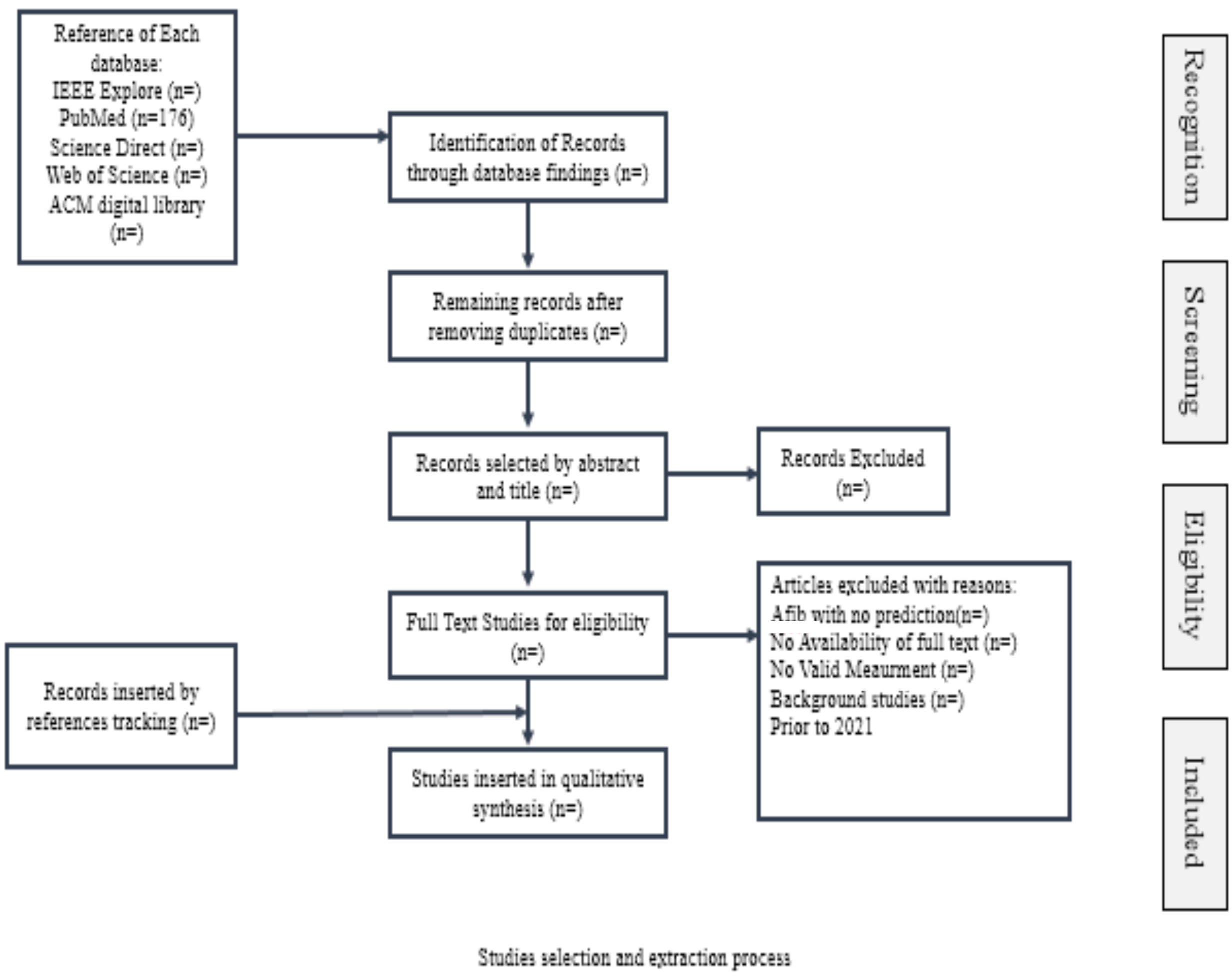

Figure 2. PRISMA Diagram

3.3 Study Selection

The selection process of the study was followed strictly, defined in (Table 1).

Table 1. PRISMA Diagram

Type	Inclusion Criteria	Exclusion Criteria
Publishing	Conference and general	All except Conference and general
Reported Results	however, one, efficiency, sensitivity, Specificity, Confusion matrix	All others that did not result in any metric
Nobel Review	Journal and conference	All others except Journal and conference
The geographic location of studies	All	None
Exposure of interest	All	None
Data	All	None
Study type	Qualitative & quantitative Experimental Research. Letters, protocol articles, systematic reviews, and editorials.	letters, systematic reviews, and protocol papers
Date	Dec 2019 to Oct 2022	All Other
Language	English	All Others

Research papers from 2020 to 2022 have been selected for the Meta-analysis figure 3 shows year-wise paper selection for review.

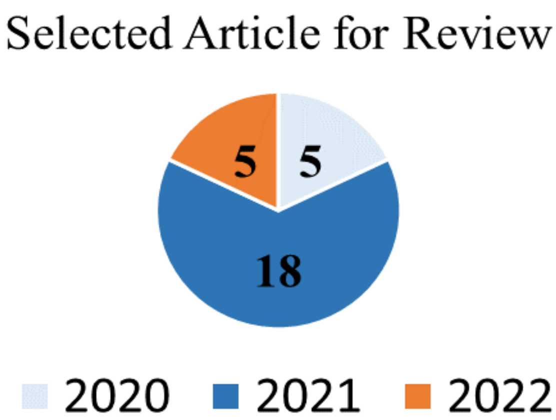

Figure 3. Sleeted Articles for Review

3.4 Study Extraction

Data is obtained from selected studies using the pre-defined kinds to acquire relevant data, examine and assess the properties of the model, and set up the experiment as detailed below,

1. Study Knowledge: Describes the citation of studies and publication year. As papers taken from 2020 to 2022.
2. Data Insertions: Analyze the things that went into making the procedures, such as the datasets that were used, patient outcomes, and the ages of the patients that were figured out from the datasets.
3. Signal Treatment: This paper explains the utilization of cough audio data obtained as input, as well as the signal duration, applied for training and the tools applied for processing.
4. Methodologies: Details about the algorithms used for Cough Audio Data, signal preprocessing, predicting COVID-19, evaluating the model, and the total number of iterations during data separation training and testing phases.
5. Performance: Identifies the evaluation metrics applied for prediction assessment.

4. Results and Discussions

The outcomes of the purposed SLR are described in this work. In the first step, 1813 of 1597 papers are obtained after removing duplicate articles, and in the second stage, all duplicated studies are removed based on title and abstract using the inclusion and exclusion criteria. The final step included the examination of full-text papers, which yielded 60 relevant research. By using the qualifying criteria with no Covid-19 Prediction, the 112 research studies are excluded. The 40 articles are excluded based on the invalid measurement and 50 studies are excluded with no availability of full text based on background study 10 articles are excluded. 310 Articles were excluded due to the publication year before 2019. The 8 studies are included based on references of selected studies and at the final stage, 28 studies are selected for the synthesis phase.

4.1 Eligibility of the Studies

Although each of the selected articles in this SLR fulfilling the insertion and elimination criteria that are necessary to explain the selection of various articles. The Cough sound data is gathered from different sources including crowd-sourced and laboratory-confirmed patients and also via mobile app. excluding all situations with no prediction of COVID-19. Even though, these are included due to studies that contain crucial information for SLR. At last, neither the tables nor the article text matched the stated analysis.

4.2 Studied non-Laboratory Confirmed Data set

An overview of the work is given in (Table 2) based on the properties that were extracted (surface learning or deep learning). To recognize cough sounds in COVID-19 patients, we investigate literal characteristics (using conventional ML classifiers) and deep learning methods. We start with well-known functions like MFCC, common machine learning classifiers, and deep functions at the end, regardless of the data collection method.

Table 2. Analysis of Non-Laboratory Confirmed Datasets

Authors year	Data Type (Sample size)	ACC	AUC	SEN	SPEC
(Akman et al., 2022) [15]	Sneezing Noises (6240)	0.89	0.65	-	-
(Anandetal., 2022) [16]	Sneezing Noises (1755)	0.87	0.88	-	-

(Andreu-Perez et al., 2022) [17]	Speaking (1535)	0.83	0.79	-	
(Anupam et al., 2021) [18]	Sneezing Noises (1800)	0.74	0.55	0.90	0.35
(Bansal et al., 2020) [19]	Sneezing Noises (425)	0.92	-	0.87	0.89
(Channa et al., 2021) [20]	Cough Sounds (180)	0.99	0.99	0.98	0.99
(Dang et al., 2022) [21]	Sneezing Noises (1430)	0.98	0.98	0.96	-
(Deshpande et al., 2022) [22]	Cough (910)	0.75	-	0.79	-
(Despotovic et al., 2021)	Sneezing Noises (1520)	0.88	0.80	-	-
[23]	Sneezing Noises	-	0.90	-	-
(Erdoğan & Narin, 2021) [24]	Multi Data Set Values (8,000)	0.94	-	-	-
(Ghrabli et al., 2022)	Sneezing Noises (1207)	0.91	-	0.89	0.90
[25]	Sneezing Noises (6400)	0.86	0.87	0.88	0.90
(Hamidi et al., 2023) [26]	Sneezing Noises (230)	0.96	-	0.95	-

4.3 Studied on Laboratory Confirmed Data Set

We used the same search criteria to ensure we didn't miss any new experimental research papers. (Table 3) summarizes the outcomes of articles on laboratory confirmation data.

Table 3. Analysis of Laboratory Confirmed Datasets

Authors year	Data Type (Sample size)	Performance			
		ACC	AUC	SEN	SPEC
(Han et al., 2023) [27]	Sneezing Noises (543)	0.90	-	0.89	0.90
(Han et al., 2022) [28]	Sound Recordings (292)	0.83	-	0.83	-
(Harry et al., 2021)[29]	Multi Data Set Values (288)	-	0.92	-	-
(Hasan et al., 2023) [30]	Multi Data Set Values (828)	-	0.77	0.66	0.77

(Hemdan et al., 2022) [31]	Multi Data Set Values (430)	-	0.82	0.79	-
(Imran et al., 2020) [32]	Sneezing Noises (150)	0.88	0.86	0.79	-
(Islam et al., 2022) [33]	Sneezing Noises (640)	0.99	0.96	0.99	-
(Kumar et al., 2022) [34]	Sneezing Noises (500)	0.80	-	0.82	-
(Lella & Pja, 2022) [35]	Multi Data Set Values (2,239)	-	0.70	-	-
(Liu et al., 2021) [36]	Multi Data Set Values (1,427)	0.79	0.84	0.79	-
(Loey & Mir-jalili, 2021) [37]	Multi Data Set Values (3,718)	0.82	-	0.81	-
(Mallol-Ragolta et al., 2021)[12]	Multi Data Set Values (328)	0.96	-	0.93	0.95

(Table 3) illustrates how ensemble learning, CNNs, and/or DNNs can be used to identify COVID-19 in sneezing noises from human participants. Using lab-validated datasets, we assess the work of authors based on their findings. In the next sections, CNN-based research and novel physiological effects paradigms will be described.

CNNs have been extensively utilized to produce AI-guided solutions for a range of computer vision problems, such as COVID-19 screening using sneezing noises. The 'AI4COVID-19 software utilized by captured three seconds of sound and produced results in less than two minutes. For cough recognition, the program uses CNNs. Initial assessments of COVID-19 and three additional diseases were conducted using a deep transfer learning-based multiclass classifier and several output classifiers. To determine whether the first classifier has an overfitting problem, the second classifier employs a conventional machine learning-based multiclass classifier. The final test uses a deep transfer, learning-based binary predictor, just like the initial test, and only returns binary (yes/no) answers to potential COVID-19 infections. While testing uses 96 bronchitis, 130 pertussis, 70 COVID-19, and 247 examples of a typical cough, training employs 1838 sneezing noises and 3597 non-cough environmental noises. We deduced that the samples originated from a hospital or clinic and were thus laboratory-confirmed because they were obtained from "patients" and the authors did not specify whether they were. In this experiment, the DTL-BC classifier distinguished COVID-19-related coughs from non-COVID-19-related coughs with a sensitivity of 0.93, specificity of 0.95, and overall accuracy of 0.96.

4.4 Discussion

Using sneezing noises as primary data, we give our findings based on the most recent state-of-the-art research in this part.

4.4.1 (Q1)

Which symptoms have more effectiveness for the detection and prediction of COVID-19 using the Respiratory cough sound dataset?

Our conclusion is based on the usage of an AI-guided cough sound analysis tool for COVID-19 screening. This also applies to the general population, which makes logical given that coughing is the most common symptom of COVID-19 infection. A cough test, in addition to other clinical testing, can support the clinical diagnosis of COVID-19 positive. Cough is not the sole accurate indicator, but it can be compared to others, such as fever. Independent of cough diagnosis, an AI-guided tool can rapidly analyse sneezing noises and aid in the discovery of COVID-19. AI-guided cough screening could serve as the first line of defence against COVID-19 and other viral outbreaks, particularly in areas with limited resources.

4.4.2 (Q2)

What is the state-of-the-art method for screening covid-19 infections?

We see that laboratory-confirmed datasets are different from non-laboratory-confirmed datasets when we use cutting-edge methods for identifying COVID-19 infection. These cutting-edge methods are referred to as "AI-guided tools for COVID-19 screening using sneezing noises." On lab-confirmed datasets, AI-guided approaches scored significantly higher than unconfirmed lab data in the vast majority of the publications that were reviewed. For machine learning algorithms to function properly, appropriate training data is required (including all possible positive cases). In addition, an AI-guided system that was trained on vast quantities of data was able to accurately screen human COVID-19 participants for forced coughing, despite a slight decline in performance on unconfirmed data based in the lab. This was true regardless of the dataset. In addition, the vast majority of published works that have high metrics in the non-laboratory validation sections have significant flaws in the method descriptions that they use, or they make use of intrinsically biased models.

4.4.3 (Q3)

What sort of datasets are used for better decision-making for the screening?

Other types of data, such as respiration, speech, throat clearing, wheezing, and breathing, may help enhance decision-making.

4.4.4 (Q4)

How to adopt the A-I Model for generosity?

Deep features contain the greatest information, allowing for more precise predictions. And aid in understanding the underlying workings of data, allowing for the rapid discovery of high-value insights. Comparing shallow and deep learning (see AI-guided tools for COVID-19 screening using sneezing noises), we discovered that deep features can extend the generalization of the model without relying on past information.

4.4.5 (Q5)

What type of Deep Learning models are applied for the COVID-19 forecast for Better Results?

We observed the utilization of biomarkers and clinical data in the development of AI-guided solutions. These characteristics are merged in a CNN, which employs typical characteristics extracted from recordings. Such characteristics may affect future work. Using new methodologies, such as biomarkers, could improve COVID-19 analysis.

5. Conclusion

Artificial intelligence-based captioning is a growing and competitive field in the study of natural language processing and computer vision. As more people become interested in this area of study, more and more works are being produced. For this reason, it is important to maintain a record of all activities to determine the course of action going forward. In this SLR, we show a brief analysis of several AI models, together with datasets and automatic evaluation metrics, and the development of audio captioning over the recent years. Through the use of closed captioning, this theory is validated. It's a comprehensive overview and evaluation of various deep learning approaches, This SLR incorporates cough sound screening from both older and more recently published articles to better illustrate the year-over-year comparison of findings. Researchers with an interest in this area will now be able to quickly identify which techniques and models perform better than their predecessors. This work documents the evolution of cough sound over the past few years, which will help researchers interested in constructing improved models for deep feature extraction of cough sound data. To undertake this systematic literature review, we devised five research questions that we hope will lead us to high-quality papers; we then used these questions to guide our search across five libraries. First, duplicate papers are removed, yielding a total of 1813 of 1597 studies; next, studies are screened for redundancy based on their titles and abstracts using the inclusion and exclusion criteria laid. Finally, 25 studies are chosen for the synthesis phase. The process flow schematic for the intended SLR.

Scientists used several A-I-guided instruments to conduct their analyses of COVID-19. This might be the most promising field of study shortly. Datasets involving coughing sounds are the most popular, but speaking, breathing, and voice is also used for audio analysis. All of the content from 2020–2022 has been evaluated. This SLR provides the current state of work for the prediction of COVID-19 with inputs from Cough sound and DL techniques. The followings are the major conclusions from the twenty-eight selected articles that are reviewed: In this essay, we examine the most recent research from 2020 to 2023 sectors of COVID-19 screening and cough sound analysis.

5.1. (Q1)

According to our clinical findings, the cough was one of the most prominent symptoms of both serious and non-serious sickness. Screening for COVID-19 using sneezing noises has proven to be a potentially affordable, practical, and accessible alternative that might assist persons in deciding whether to isolate themselves or be tested. In other words, because coughing is so prevalent across diverse populations, it is possible to develop AI-guided technology that leverages coughing sounds for precise mass screening. This screening method merits additional research and uses in mobile applications.

5.2 (Q2)

The most current study on COVID-19 detection using cough sounds is detailed here. This review also revealed smartphone-based COVID-19 self-testing utilizing breathing sounds, as well as the implications for recognizing breathing difficulties by comparing certain acoustic signal patterns. Moreover, the review found that smartphone-based self-testing could be performed by the user.

5.3 (Q3)

The combination of biomarkers and clinical data with additional data types, such as sneezes, breaths, speeches, throat clearings, wheezes, breaths, and throat clear, can improve decision-making processes. Now, concluded that the addition of other data types in audio form, such as respiration, speech, throat clearing, wheezing, and breathing, can significantly improve decision-making for better prediction and screening of COVID-19 as shown in (Tables 1 and Table 2).

5.4 (Q4)

It can generalize the model and apply it to other domains. Deep features can extend the generalization of the model without relying on past information.

5.5 (Q5)

We will further our research by incorporating ensemble DNNs into multimodal learning methods. In the extent of our review article, CNN is the best model for audio data Analysis as it has been analyzed.

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Conflicts of Interest: The authors declare no conflict of interest.

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