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Original Article

Toward artificial intelligence (AI) applications in the determination of COVID-19 infection severity: considering AI as a disease control strategy in future pandemics

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Abstract

Background: To guarantees patient survival and reduce the consumption of pharmaceutical and medical resources, an accurate diagnosis and assessment of COVID-19 severity are crucial. Since the outbreak of the pandemic, researchers have evaluated, identified, and predicted the severity of COVID-19 using a range of AI techniques. Due to the lack of a systematic review in the field of analysis of these studies, the present research rigorously reviewed all the pertinent literature.

Methods: Between December 1, 2019, and January 1, 2022, 762 articles were found by searching the PubMed, Scopus, Web of Science, and Scholar databases using the search method. 34 papers were chosen from this group as the research community's representatives using inclusion and exclusion criteria.

Results: By looking at the machine learning approach used in this research, it can be seen that XGBoost and SVM algorithms were more prevalent and effective in identifying the severity of the condition, according to the results of the data analysis used in this study. A set of impressive features, including clinical, demographic, laboratory, and serology data, was used to calculate the severity of COVID-19 using ML algorithms. By calculating the performance metric, it can be concluded that the ML methods had high sensitivity and specificity in determining the severity of COVID-19.

Conclusion: Deep learning methods, as cutting-edge methods, have a significant tangible capacity for providing an accurate and efficient intelligent system for detecting and estimating the severity of COVID-19. It is recommended that in the future or other variants of COVID-19 epidemics, AI-based systems in conjunction with IoT, cloud storage, and 5G technologies be used to remove geographical problems in the rapid estimation of disease severity, immediate epidemic control before the pandemic, epidemic management, and lower treatment costs.

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1. Introduction

The coronavirus was discovered in Wuhan, China, in December 2019. Within a few months, the disease had spread to become a worldwide pandemic and one of the most lethal epidemics in history. According to the most recent WHO data, the virus's global outbreak continues to grow, with more than 671 million laboratory-confirmed cases and more than 6.72 million deaths as of January 14, 2023(1,2). However, the virus's mutation in RNA caused the birth of other variations, some of which were more hazardous and infectious, like Omicron. According to leading epidemiologists with the World Health Organization, this variety also has sub-variants, the latest of which is XBB.1.5, in which the virus's spike protein has undergone a mutation that improves its ability to connect to cells and disseminate quickly, making it highly contagious (3).

However, the virus soon shifted from one strain to another, and the immunizations employed to fend off those fresh versions quickly lost practically most of their efficacy. In such a setting, many nations' healthcare systems were unable to handle the patients' increasing demands for diagnosis and prognostication of illness severity. In order to detect the disease's infection rate using different machine-learning techniques, several studies were carried out. Each of these studies employed a unique set of clinical data and produced a unique set of findings (4–6).

Since the COVID-19 pandemic began, the severity of the COVID-19 infectious level has been assessed using a variety of diagnostic techniques, including CT scans and radiography. Although they are regarded as the time-tested and most effective methods for diagnosing COVID-19, they have drawbacks as well. The most significant of these drawbacks include high cost, false positive results, being time-consuming, low accuracy in GGO detection and involved areas in the radiography method, and radiologists' errors when dealing with numerous cases. As a result, researchers were encouraged to employ less costly and more accessible approaches (7–14).

AI has many applications in medical data as the most efficient method. AI applications have been used to control disease, boost clinical trials, and even develop vaccines, with highly promising results. A number of studies have used artificial intelligence approaches like machine learning and deep learning to diagnose and assess COVID-19 severity. In spite of these studies, there has been no comprehensive review assessing the application of these studies to the analysis of the severity of COVID-19. Hence, the present research identified and examined studies systematically that employed several AI approaches to assess the severity of COVID-19 disease (13,15,16).

2. Methods

This study is a systematic survey aiming to review various AI methods, algorithms, and features used in the prediction and determination of the severity of COVID-19.

The purpose of this systematic study was to examine research on the classification of COVID-19 severity levels using a range of AI algorithms. The primary objective was to answer the following analytical questions (AQ):

- AQ1: Which artificial intelligence methods and machine learning algorithms performed better in estimating infection rates?
- AQ2: Which artificial intelligence methods were employed more frequently?
- AQ3: What features were used to categorize the types of infection levels produced by COVID-19?
- AQ4: Which features were mostly processed by ML methods to estimate the infection of COVID-19?

The research question will be answered in this study by giving tables and graphics and discussing their properties.

2.1. Design

The Arksey and O'Malley framework was used to perform this study, which extensively reviewed the investigations that were conducted with the goal of applying artificial intelligence to identify the severity of the disease. The study is divided into five primary stages and one elective stage based on this framework, which are as follows: 1) Formulating the research question 2) Locating relevant studies 3) Determining criteria and study selection 4) Recording and classifying key outcomes 5) Summarizing and reporting the findings 6) Consulting with stakeholders It should be mentioned that the sixth stage is not covered by this research. The title of this study was also based on the rules for preferential reporting cases in systematic reviews and meta-analysis creation (PRISMA-ScR) (17,18).

2.2. Search Strategy

The keywords and inflectional combinations of these keywords were searched in the PubMed, Web of Science, Scopus, and Google databases using **Table 1**. The final article search was conducted between December 1, 2019, and January 1, 2022. One researcher (M.G) looked for and restored publications independently, and any discrepancies with the other three authors (F.A, S.A, N.G) were discussed. The article search was completed with a bibliographic review of the chosen studies.

2.3. Study Selection and Quality Assessment

The study method was chosen in two stages: 1) screening article titles and abstracts, and 2) article selection based on the entire text.

Before each stage, the senior authors (MG and FA) were trained to ensure proper selection and consistency.

The screening was then thoroughly evaluated, and the researchers received feedback from the senior author.

All of the researchers in this study independently evaluated the papers based on the inclusion and exclusion criteria, and they also assigned "include," "exclude," or "undecided" values to each article.

Before deciding on research, articles with "undecided" values were discussed with the other authors.

Qiao's proposed criteria were used in the current study for quality control and review of the selected papers in terms of eligibility criteria.

The studies were evaluated qualitatively based on five criteria: unmet need (limitations in the current non-ML approach), repeatability (feature engineering methods, platforms or packages, meta-parameters), robustness (valid methods for overcoming overfitting, result stability), generalizability (validation of external data), and clinical significance (description of predictors and proposed clinical use). A quality evaluation table was presented and measured with "yes" and "no" for the relevant items in each category.

Table 1: Search keywords and statements

Keywork	*Logical Combination of keyword*
COVID-19 Severity Disease progression Artificail Inteligence Machine Learning Deep learning Infection assessment	((“COVID-19”) AND (“Severity” OR “Disease progression”) AND (“Artificail Inteligence” OR “Machine Learning” OR “Deep learning”))

2.4. Data extraction

During the information extraction stage for each article, the year of publication, country, paper type, dataset type, employed characteristics, algorithms, and performance of the algorithms employed in the research were examined and written. Finally, the data extracted from the articles was loaded into Excel software to be classified, aggregated, and published.

3. Result

The initial number of extracted articles was 1046, which was reduced to 762 after duplicate articles were removed. 689 publications were eliminated after analyzing their titles and abstracts in compliance with the study's inclusion and exclusion criteria. The whole content of the publications was then reviewed, and 39 of them were eliminated due to the use of machine learning approaches in detecting, diagnosing, and forecasting corona mortality. This method was repeated three times to guarantee the authenticity of the search, and the last stage evaluated the quality of the articles extracted using Qiao criteria. In the end, 34 articles were chosen. **Figure 1** depicts the article selection procedure.

3.1. Characteristics of the included studies

According to a check of the year of publication of the articles, 76% were completed in 2021 and 26% in 2020. Furthermore, the geographical distribution of the publications revealed that 32% were in China, 9% in South Korea and Bangladesh, and 6% in India, Saudi Arabia, and Egypt, respectively. 97% of the research was in journal articles, and 3% was in conference papers (**Table 2** and **Figure 2**).

Since the COVID-19 pandemic first emerged in 2019, a range of AI algorithms and methods have been used to diagnose and forecast the severity of the disease. A taxonomy was developed to better organize the content and concepts related to AI applications for COVID-19 severity estimation as shown in **Figure 3**.

3.2. Overview of AI Methods in Detection and Prediction of Severity of COVID-19

By analyzing the models used to estimate the severity of the COVID-19 disease, the most commonly used techniques can be divided into two categories: conventional Machine Learning (ML) algorithms and Deep Learning (DL) algorithms.

3.2.1. Machine Learning Algorithms

Numerous studies use traditional ML to determine the severity of the infection since many of the factors used to gauge the severity of COVID-19 sickness are numerical data. Due to their age and the wide range of developers and researchers who are familiar with them, the use of ML algorithms for the analysis of laboratory and demographic data has also risen. Based on their performance, certain of them were used more frequently in studies that included ML techniques.

3.2.1.1. XGBoost algorithm

One of the most well-known and most recent ML methods is the XGBoost approach, which is based on a collection of classification and regression trees. An efficient and scalable tree-boosting method called the XGBoost algorithm was put out by Chen and Guestrin in 2016. The Gradient Boosted Decision Tree (GBDT) method is improved by this variant. Since it has proven that it does not have computational constraints, it differs from the GBDT technique. The GBDT uses the first-order Taylor expansion, whereas the loss function of the XGBoost uses the second-order Taylor expansion. Additionally, XGBoost normalizes the objective function to lessen model complexity and prevent overfitting. This method has been frequently used to diagnose and categorize diseases during the last ten years.The XGBoost method was utilized in 23% of

Table 2. **General characteristics of the included studies**

Characteristics	Number of studies (n)	Studies
Year of publication	2020: 8	(5,18–24)
	2021: 26	(25–49)
Type of publication	Journal article: 33	
	Conference article: 1	

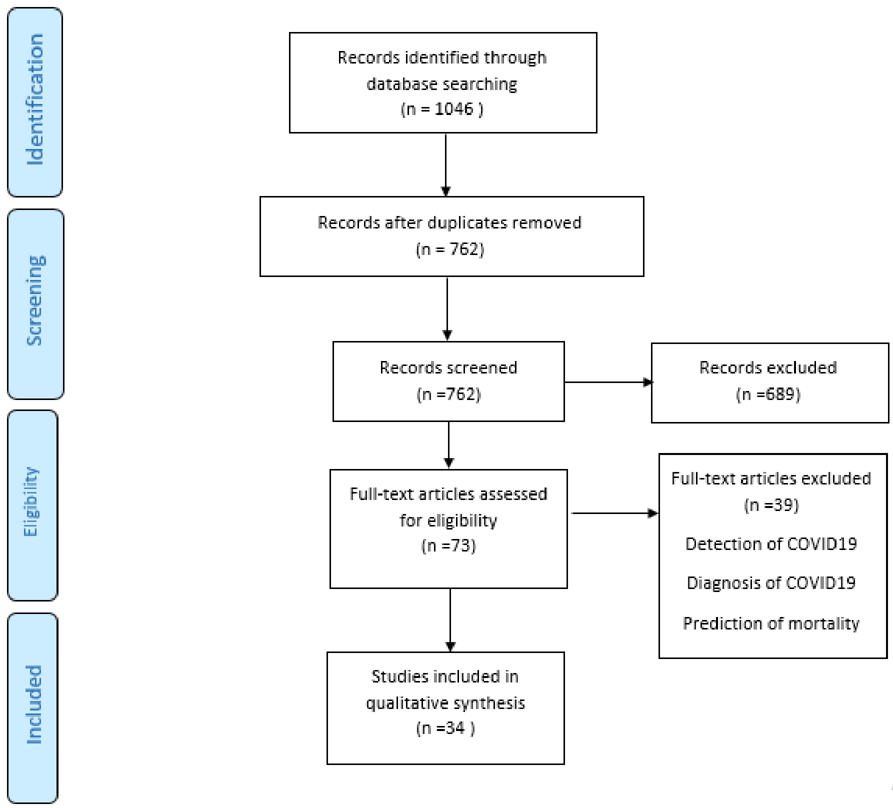

Figure 1. **PRISMA flowchart of search and exclusion process. Out of 1046 retrieved studies, 34 studies were selected for data analysis.**

the research conducted to determine the severity of COVID-19. The best performance of this algorithm was in the Blagojevic study, with 94% accuracy, 98% specificity, and 97% sensitivity. Age, gender, WBC, LY, MCHC, RDW, Hgb, Urea CRP, Creatinine, ALB, and LDH were the features employed in this study (51).

3.2.1.2. Support Vector Machine algorithm

The SVM method, which has historically played an important role in disease diagnosis, is one of the most common machine learning algorithms. In other words, SVM is a collection of supervised learning algorithms that can execute tasks using classification and regression. The key characteristic of SVM is a model estimation, in which it must design the optimal superplane capable of separating the data with the greatest margin. This characteristic enables the algorithm to be appropriate for the superplane with the maximum margins in a modified feature space. In SVM, the classifier is a superplane in the high- dimensional

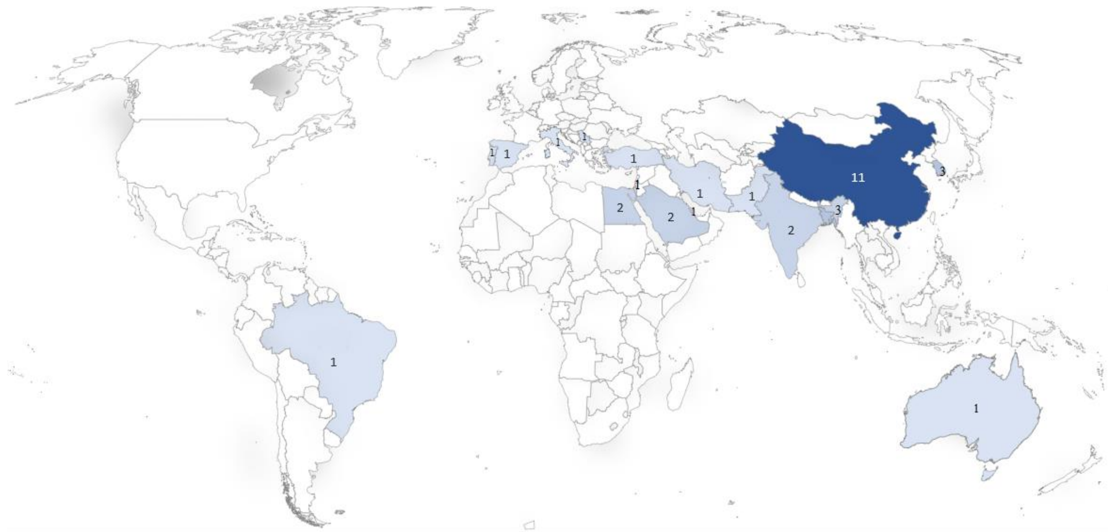

Figure 2. Application of AI in COVID-19 severity assessment publications based on place

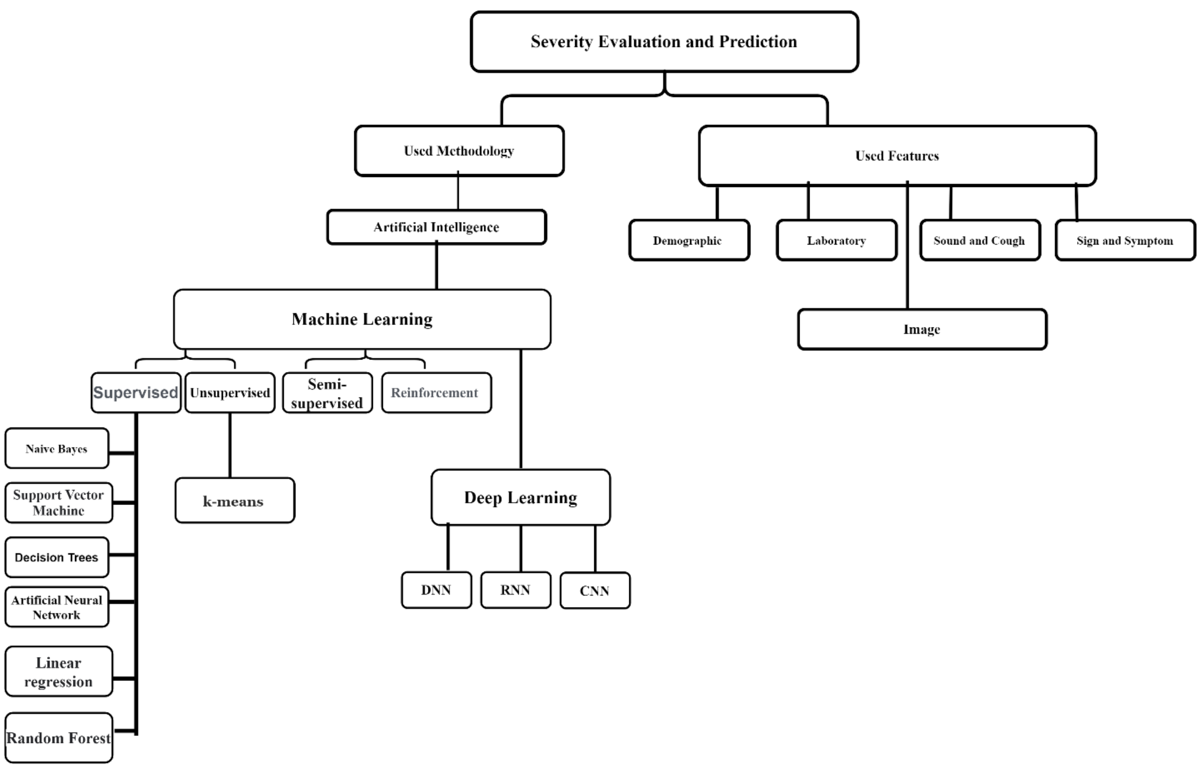

Figure 3. The taxonomy of AI Method in the COVID-19 severity estimation.

feature space, and it may also be nonlinear in the input space (52).

The SVM algorithm was utilized to predict or diagnose disease severity in 29% of the reviewed studies. This algorithm performed best in Kang et al.'s article, with 95% accuracy and 97.6% specificity. The dataset used in this paper contained CT pictures (49). Also, this algorithm was used in the Sayed et al's article with 97%

accuracy, 93.3% sensitivity, and 91% AUC. This article's dataset included radiographic images (41).

3.2.1.3 Random Forest algorithm

A technique called ensemble learning, which produces a lot of classifiers and aggregates their outputs, is what Random Forest (RF) does. Using a Bootstrap sample of the primary training data, the RF creates a number of classification and regression (CART) trees. CARTs are binary decision trees that are created regularly by splitting data into one root node and subsequent daughter nodes, each containing the whole learning instance. Each tree in the RF casts a vote for one or more of the x inputs, and the classifier's result is based on which inputs received the majority of the trees' votes. RF is capable of handling high-dimensional data and employing a large number of trees in the array. By examining all of the research community's studies, it was discovered that the RF algorithm was employed in 23% of the reviewed journals. Chen et al. achieved the best results using this algorithm with 97.22% accuracy, 99% sensitivity, and 97.4% AUC, and features such as age, gender, HTN, CVD, DIA dimerized plasmin fragment D, high-sensitivity TNI I, NE, IL-6, and LDH were used in this study (48).

3.2.1.4. Artificial Neural Network algorithm

A major part of AI technology is built on neural networks known as ANNs, which stimulate the human brain's ability to comprehend and solve complicated situations. The distinctive characteristics of ANN (such as efficient data management, low complexity, and decreased computing and storage requirements) hold significant promise for a wide range of fields, including the medical sciences. The ANN can be classified into a single-layer feedforward neural network, a multilayer feedforward network, a single node with feedback, and a recursive multilayer network. These networks are able to find hidden nonlinear patterns in the data, so they have many applications in the field of disease diagnosis (53).

ANN was one of the popular methods to analyze COVID-19 features; therefore, numerous studies using ANN to assess severity during the pandemic were conducted, and nearly 23% of the current study to determine the severity of COVID-19 disease uses ANN methods. This method performed best in the Assaf et al. study, with an accuracy of 92% and an AUC of 93.5%. Features included in this article are WBC, time from symptoms to admission, oxygen saturation, and LY(19). Kang et al used this algorithm with a sensitivity of 96.4%, F1 score of 95.3%, and AUC of 100% and the features used in this paper were GLB, BUN, age, history of lung disease, Hb, and ALB(34).

3.2.1.5. Logistic Regression algorithm

Logistic regression (LR) is a supervised learning approach that is used to solve medical binary classification problems. LR is based on a mathematical theory that models binary classification using a logistic function. In essence, LR is a regression model that predicts whether a data item or input belongs to a specific class or not. LR has numerous key characteristics, including ease of implementation, computational efficacy, training-based effectiveness, and ease of systematization. There's no need to scale input features; however, doing so addresses nonlinear problems and is prone to overfitting. The LR method was utilized in 18% of the studies, the best performance was achieved by Wu et al., with an AUC of 93%, a sensitivity of 96.9%, a specificity of 88%, and an F1 score of 78%. The data used in this paper include CT scan images and clinical data (age, LY, CRP, LDH, CK, urea, and calcium) (23).

3.2.1.6. Decision Tree algorithm

The Decision Tree (DT) is a supervised learning technique that divides data repeatedly into a certain variable to solve regression and classification issues.

The data is divided into nodes, and the tree's leaf symbolizes the final decisions. The decision tree's goal is to build a model that can predict the target variable by learning simple decision-making rules using training data. The class name is held by the leaf node, and the non-leaf node is held by the decision node. The decision tree is used to manage both categorical and numerical data. The DT algorithm was utilized in 9% of the examined studies that estimated the severity of COVID-19 disease. This algorithm performed best in the study by Cobre et al., with specificity, sensitivity, and the F1 score of 13%, 13%, and 13%, respectively. Hyperferritinaemia, hypocalcemia, pulmonary hypoxia, hypoxemia, metabolic and respiratory acidosis, low urine pH, and low LDH were the features used in this article (50).

3.2.2. Deep Learning Algorithms

One of the concepts that is growing quickly is deep learning (DL). Due to its robust capabilities, this technology has been widely used in the last five years for medical applications and the analysis of health data. Convolutional Neural Networks (CNN) are one of the most significant and extensively used methods and algorithms in deep learning.

3.2.2.1. Convolutional Neural Network Model

The convolutional neural network is one of the most important networks in deep learning. This network has multiple layers that can extract characteristics in an exceptional manner. Each of these layers has a distinct purpose. The convolution layer in these networks uses filters to accomplish the convolve operation, resulting in a matrix termed a feature map as the output of these convolve operations. The pooling layer is a critical component of CNN's architecture. By lowering the size of the features obtained in the previous stage, this layer extracts valuable features. These features are classified in the next layer of the network, known as the "fully connected layer." Because this network works with images, this technology has been employed in circumstances where the objective of processing radiological images is to diagnose the severity of the condition. In the current survey, the CNN algorithm was applied to 6% of the articles. This method performed best in the article by Li et al., with an accuracy of 95.8 (37).

In the present study, after a review of all research, a single framework was developed to carry out the processes of these studies. **Figure 4** depicts this framework.

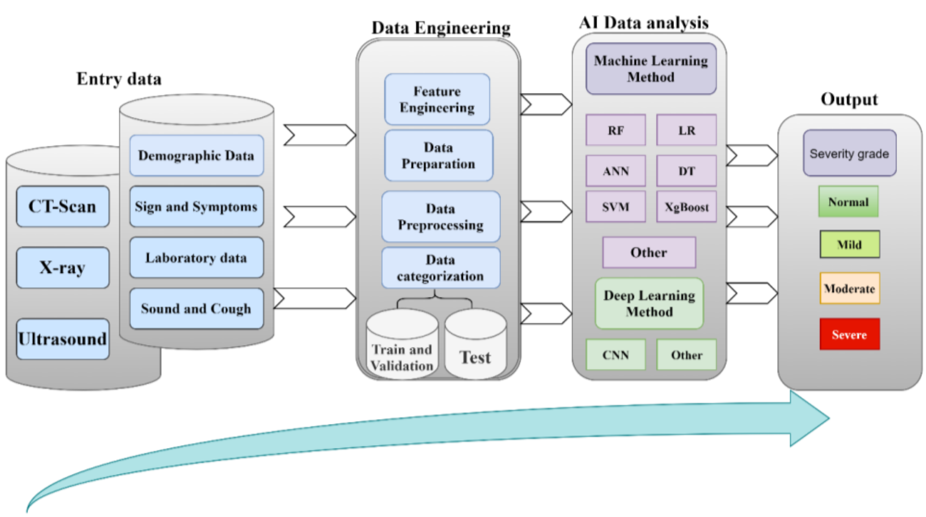

Figure 4. **A schematic view of relationships between ML approaches and prediction of COVID-19 severity reviewed in this article.**

Studies have revealed that some ML approaches are more frequently employed by researchers than others, while some machine learning techniques have never been used to estimate COVID-19 severity. An analysis of the studies demonstrates that some of these algorithms, given their great performance, were successful in persuading scientists to use COVID-19 data as the processing core to identify the intensity of COVID-19 in order to diagnose and forecast the severity of COVID-19. Since 32% of research employed machine learning methods, this represents the highest percentage of studies using machine learning algorithms. 29% of the COVID-19 severity predictions made in the investigations used the SVM classifier. Additionally, 29% of studies utilized RF to determine the severity of the disease, 23% used ANN, 18% used LR, 9% used DT, and 6% used CNN to divide the severity of COVID-19 into four categories: normal, mild, moderate, and severe.

To show the amount of use of various artificial intelligence algorithms at a glance, **Figure 5** depicts the extent and quantity of studies that have employed AI methods (including traditional ML and DL) to diagnose the severity of COVID-19. In some of the studies, more than one ML algorithm has been utilized. **Table 3** presents the classification of studies based on indicators, types of data used, features, that use ML techniques. In this table, the performance of models based on functional metrics in predicting disease severity is also displayed.

3.3. Various Features used to Predict Severity of COVID-19

In the conducted studies, a wide range of features was used, some of them were used many times and others were used less frequently. Generally, these features can be categorized into two categories: numerical data, and image data (pixels and voxels).

Numerical data that describes clinical and biomarkers in the form of numbers, formed the largest volume of used features. These features, either qualitatively or quantitatively, are finally displayed in the form of numbers.

On the other hand, radiographic images, which made up a significant portion of the data, featured a lot of high-level features. Hidden features in images can be detected as lines, corners, edges, and color differences that are not visible. **Figure 6** depicts the type and frequency of features in non-image data used to determine the severity of the COVID-19 disease.

4. Discussion

This comprehensive evaluation includes 34 papers from 17 different nations. Numerous artificial intelligence algorithms were employed, according to the literature, while ML algorithms like SVM, RF, AN, LR, DT, CNN, and XGBoost were the most often used AI techniques for determining the severity of COVID-19 disease, other algorithms were also used. The structure, topology, and parameters of machine learning algorithms were optimized to calculate the rate of design infection in several of these studies using customized models based on trial and error. In much of the research, they compared different ML techniques and chose a powerful algorithm to serve as a model for determining the severity of the infection.

In some research, their methodology was such that they compared traditional machine learning algorithms with newer algorithms such as deep learning methods and the CNN algorithm. Kivirak et al. also examined the efficacy of DL and traditional ML approaches in predicting COVID-19 mortality in 2021. In this study, 13 parameters of 1603 COVID-19 patients were analyzed using DL and ML algorithms (RF, k-nearest neighbour, and extreme gradient boosting (XGBoost)). These parameters included age, sex, chronic disease, and certain enzymes (ACE, angiotensin II receptor blockers) to estimate the severity of COVID-19. This study found that newer DL approaches (97.15%) can outperform traditional

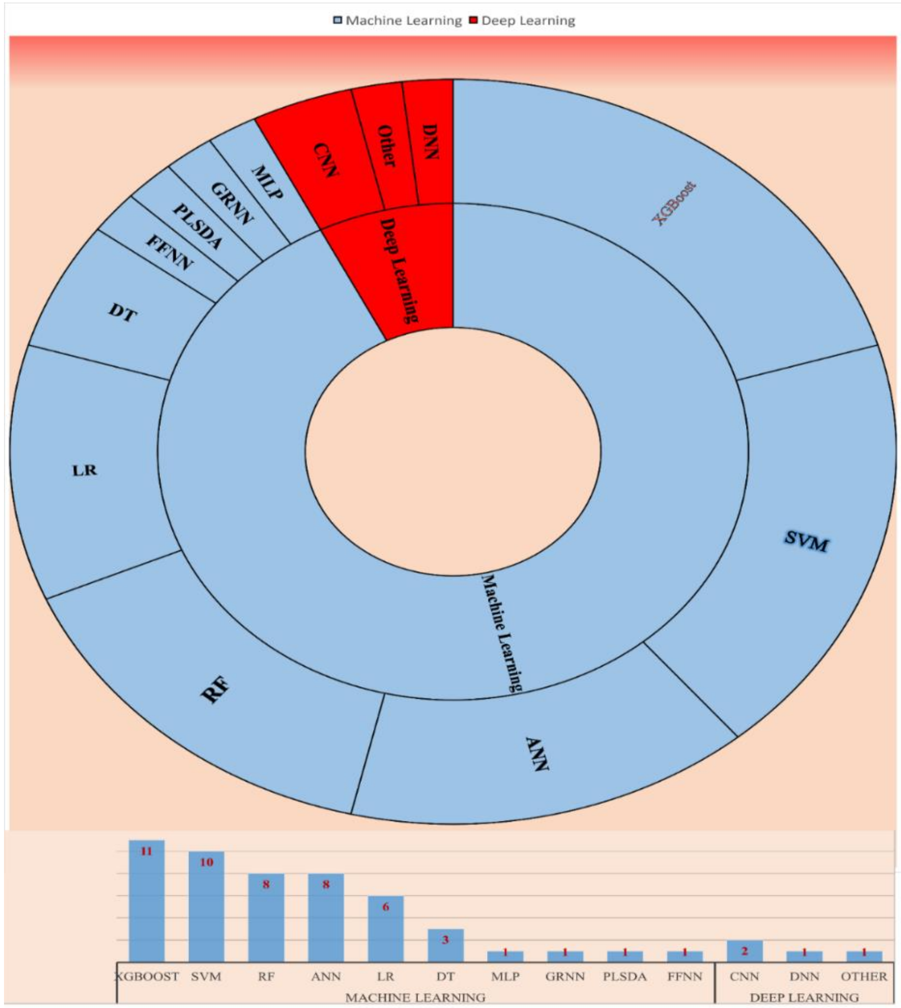

Figure 5. **Frequently reported machine learning approaches for predicting the severity COVID-19**

ML methods in terms of accuracy. As a result, XGBoost can be introduced as one of the most well-known approaches for predicting COVID-19 patient death (35). In a number of studies, AI techniques were applied to offer a decision-support tool to physicians. such that a decision support system using a rule-based inference engine was developed for COVID-19 severity prediction. In this study, supervised ML types were used to assess data related to demographic variables, clinical signs, and the pattern of areas where the patient was present (27). Some ML algorithms outperformed the others in terms of performance. GXBoost and SVM thus displayed the best performance in the interim. By comparing and analyzing the performance metrics of different ML algorithms, it can be said that the XGBoost algorithm had the best accuracy performance, with an accuracy of 97.6% in terms of determining the COVID-19 disease's level of infection. The SVM algorithm's best result, at 97%, was likewise considered satisfactory by the standards set by its classification process. On average, the performance of these two algorithms outperformed the rest of the algorithms. The average performance of these two ML algorithms was higher

than that of the remaining traditional ML algorithms, as demonstrated. Furthermore, the CNN network algorithm from the category of deep learning methods achieved excellent performance results.
The average performance metrics for these three algorithmic classes are shown in the **Table 4** to calculate the estimation of COVID-19 infection in these studies. The other effective ML method for finding complex hidden patterns in data is the ANN, which is extremely important in medical pattern recognition. This method has been used to analyze all types of clinical and demographic data and images and has been successful in classifying different levels of the severity of the infection caused by COVID-19. The sensitivity of this method in the analysis of different types of experimental data combined with age reached its maximum value (100%) in this study. However, in some studies, this method did not produce satisfactory results. As a result, it is not included in the category of the best-determining algorithms for the diagnosis of Covid-19 infection. (55).

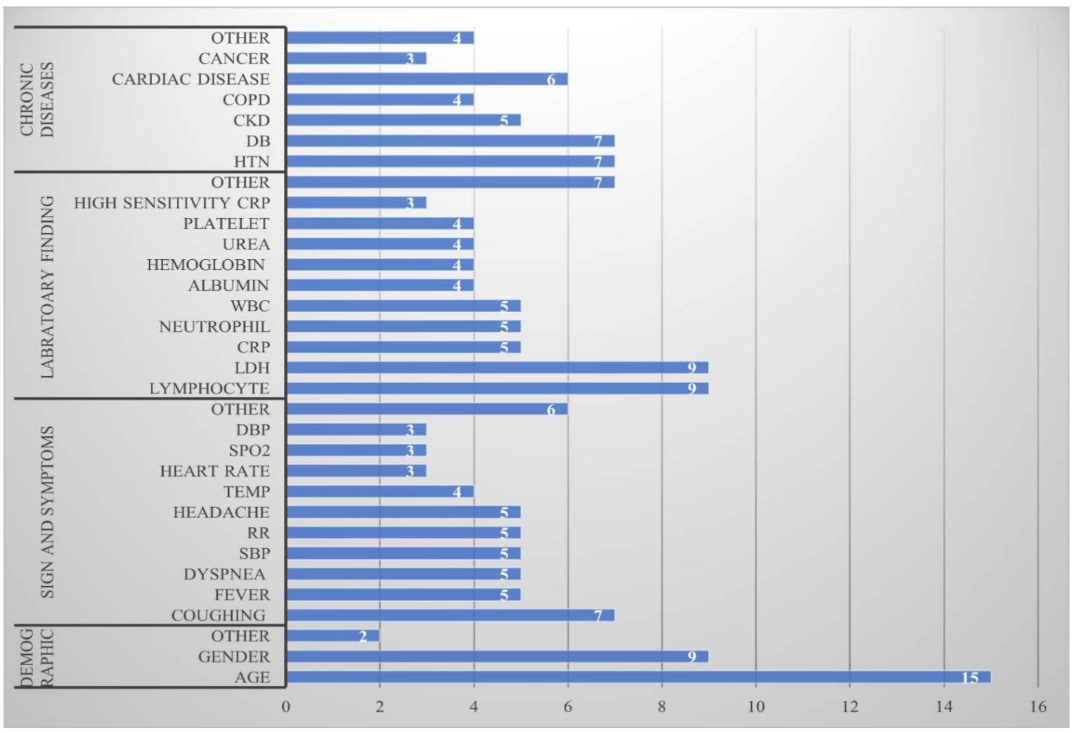

Figure 6. Frequently reported features for predicting the severity of COVID-19.

Table 3. Average accuracy for the best performing AI algorithms.

Algorithm	Category	Accuracy
SVM	Traditional ML	97%
XGBoost	Traditional ML	97.6%
CNN	DL	96%

Table 4. Studies evaluating ML for the determination of COVID-19 infection severity

Reference	Dataset Type	Highest-weighted features	ML approaches	Performance					
				Accuracy%	F1 Score%	Specificity%	Sensitivity%	Precision%	AUC%
(18)	Laboratory	WBC, Symptoms, Oxygen Saturation, LY	ANN	92.0		92.7	88		93.5
(19)	Chest CT image	-	ANN	82	85	86	80		90
(20)	-	Age and gender, FEV, tiredness, SOR, Pains, Congestion,	SVM	60					
(53)	-	Age, hsCRP, LY and D-Dimer level	LR			79.4	83.9%		88.1
(24)		Age, GHSs, immune feature cluster of differentiation 3 (CD3) percentage, total protein	SVM	77.5					97.5
(5)	Chest CT image	LY, NE, monocyte, eosinophil; RBC distribution width; HGB, PCT, PLT.	XGBoost	88	81				81
(23)		LDH, LY, and hsCRP	XGB	90	94				
(22)	Chest CT image	Age, LY, CRP, LDH, CK, Urea	LR	87		88	96.9		93
(25)	Chest CT image		ResNet-50 DenseNet-201	99.04	97.78	99.39	97.78		
(26)		LDH, LY, and CRP	SVM	87.3		89.7	69.2		
			DT	91.8		92.8	84.6		
			LR	85.5		88.7	61.5		
			ANN	89.1		90.7	76.9		
(37)		Respiratory Rate, DBP, HGB, HCT, Venous Base Excess, leukocytes, NE, ALB, arterial base excess, urea, PLT, potassium, and SBP	RF	89	90			90	89
			SVM	84	86			84	84
			DT	82	83			83	82
			XGBoost	88	91			86	88
			KNN	84	86			81	84
			ANN	83	79			92	82
(43)		Age, gender,HTN, CVD, CKD, TEMP, last body TEMP, Pulse rate, respiratory rate, SBP, DBP, FEV, COU, SOB, dyslipidemia	LR	84.9	85.5	83.1	86.7		
			RF	92.5	93.3	98.3	88.4		
			XGBoost	89	90.4	96.5	84.3		
(44)		Gender, HTN, DIA, heart disease, COPD	RF	81.6	71.1	81.3	83.3		
			MLP	90	84.7	97.85	79.7		
			SVM	86.6	69.4	92.7	69.6		

		HBV infection, CL, PTT, MAM, DIR, FEV, SBP, sputum, COU, history of surgery, FTG, HED, nasal congestion	GRNN	83.3	56.6	97.8	46.8		
(45)	Chest CT image	-	RF	90.95					
(46)		Age, Gender,WBC,Ly,MCHC,RDW, Hgb,Urea,CRP ,Ceatinine,ALB LDH	XGBoost	94	96	98	97	95	
			KNN	88	90	94	89	92	
			SVM	82	83	93	88	83	
			ANN	76	77	91	85	73	
			RNN	56	37	77	37	51	
(47)		Age, gender, HTN, CVD, DIA dimerized plasmin fragment D, high sensitivity TNI I, NE, IL 6, LDH	RF	97.22	97.78	94.44	99		97.40
(48)		Age, ACC, CCD, CKD, CLD, COPD, DEMEN, DIA, DBP, DIARR, FM, HCT, HED, HF, HGB, HR, HTN, LY, MAM, PLT, Preg, PregWk, RDAD, RNR, SBP, SOB, SOR, Temp, VN, WBC, BMI,	DNN	90.4		90.4	90.2		96
			RF	89.3		89.2	90		95.9
			SVM	89.3		89.2	90		95.8
			XGBoost	88.3		88.3	88.2		95.5
(49)		Hyperferritinaemia, Hypocalcaemia, Pulmonary Hypoxia, Hypoxemia, Metabolic and Respiratory Acidosis, low urinary Ph, LDH	ANN	98		97	99		
			DT	92		94	90		
			PLS-DA	88		88	87		
			KNN	86		88	82		
(27)	Lung Ultrasound	-	CNN	79.1	78.6	90	79.1		
(28)		LDH activity, CRP, NE, urea levels.	XGBoost	94	77	91	93	86	97
(29)		Age, Disease severity, hs-CRP, LDH, ferritin, and Interleukin	XGBoost	90	90		90	85	
(30)	Chest CT image	Age, gender DIA, HTN, COPD, CKD, CAC, SMK, FEV, COU, SOB, HED, SBP, CRP, HR, WBC, Respiratory Rate, Oxygen Saturation	ResNet50	93.3	76.6	96.5	78.3	75.3	90
			InceptionV3	91.9	67.2	93.6	59.4	78.4	81.4
			DenseNet121	91.6	63	93.5	56.1	88.7	82.6

(31)	Chest CT image		Modified NormVGG	96.64	97.2	95.26	93.65	96.92	
			Xception	94.89	92.58	96.58	90.63	94.00	
			ResNet-50	92.80	90.03	94.98	88.00	92.50	
			MobileNet-	92.72	89.80	95.80	88.00	92.77	
			Inception-v3	90.58	85.98	95.63	85.23	86.89	
(32)		Age, gender,HTN, KID, CCD,SMK, oxygen saturation, respiratory rate, SOB, FEV, COU,HED	FFANN	91	98			91	
			LR	80	68			79	
			XGB	69	63			70	
			SVM	71	65			71	
(33)		Age, History of lung disease, Hb, ALB, GLB, BUN	ANN		96.4	85.7	100		95.3
(48)	Chest CT image		SVM	95		97.06	83.3		
(34)		Age, gender CKD, HTN, DIA, CNC, CVD ACE 2, Angiotensin II Receptor Blockers	RF	92.15		85.9	98.3	99.7	
			K-NN	93.4		71.2	95.1	97.7	
			XGBoost	99.7		1.00	99.7	99.7	
(35)	Lung Ultrasound		ResNet50	97.73	93.73			94.71	99.78
(36)	Chest CT image		CNN	95.8	89.5	96.4	93.6		98.1
(38)	Chest CT image		DenseNet201	97.05	94	95.53	94.05	94.18	
(39)	Chest CT image	Age, gender,CVD , CNC, DIA, CKD, COPD,body TEMP, HR, COU, SOB, HED,VN,DIR,WBC, NE, LY, HGB, PLT , PT, Thromboplastin Time, D-dimer, CRP, ALB, ALT, AST, total	LR		60.4	91.9	76.4	95	
			XGBoost		52	96.5	47.3	90.2	

		bilirubin, potassium, sodium, creatinin, creatine kinase,LDH	ANN		41.3	90.7	48.3	78.2	
(40)	X-ray image		XGBoost	97	96			98	100
			SVM	97	95			96	99
(41)	Chest CT image		RF	87.5		74.5	93.3		91
(42)		Age, number of drugs taken, cystatin C (reflecting renal function), waist-to-hip ratio, Townsend deprivation index	XGBoost	71.2					

Machine learning abbreviation: AUC: area under the curve; CNN: Convolutional Neural Network; RF: Random Forest; SVM: Support Vector Machines; LR: logistic regression; DT: decision tree; XGBOOST: extreme gradient boosting; ANN; artificial neural network; MLP: multi-layer perceptron; GRNN: General Regression Neural Network; DNN: Deep Neural Network; PLS-DA: partial least squares discriminant analysis; FFANN: Feed-Forward Artificial Neural Networks
Chronic disease abbreviation: DEMEN: dementia; CAC: coronary artery calcification; HTN: hypertension; KID: renal disease; CCD: chronic cardiac disease; CKD: chronic kidney disease; CLD: chronic liver disease; COPD: chronic obstructive pulmonary disease; CVD: cardiovascular disease; CNC: cancer; RDAD: rheumatism/autoimmune disease; DIA: diabetes; FEV: fever; FTG: fatigue; HED: headache; SMK: history of smoking; SOR: sore throat; VN: vomiting/nausea; Temp: temperature; ; DIR: diarrhea; SOB: shortness of breath/dyspnea; MAM: muscle aches/myalgia; Preg: pregnancy; PregWk: pregnancy weeks; RNR: runny nose/rhinorrhea; SBP: systolic blood pressure; FM: fatigue/malaise; HEADA: headache; HF: heart failure; HR: heart rate; COU: coughing; ACC: altered consciousness/confusion; BMI: body mass index; DBP: diastolic blood pressure;
Laboratory finding abbreviation: ALB: albumin; CK: creatine kinase; HCT: hematocrit; ; HGB: hemoglobin; CRP: C-reactive protein; hsCRP: high-sensitivity C-reactive protein; TNI: troponin I; IL6: interleukin 6; LDH: lactate dehydrogenase; LY: lymphocyte; NE: neutrophil; PCT: procalcitonin; PLT: platelet; WBC: white blood cell; GHS: growth hormone secretagogues; GLB: globulin: BUN: blood urea nitrogen; ACE 2: Angiotensin-Converting Enzyme 2; MCHC: mean cell hemoglobin concentration; RDW: red cell .distribution width

In some studies, multiple datasets were used to test their models. In a research study, difference regression, difference time, and different space models are developed based on Chinese patient data and verified using other data samples, such as those from India. As expected, this model is one of the most accurate methods for predicting the number of positive instances and can be used in the future for classifying the patient's severity of infection (56). On the other hand, Cobre et al. reported the best performance of this algorithm using a similar method, with an F1 score of 92%, a specificity of 90%, and a sensitivity of 94%. The characteristics employed in this study are hyperferritinemia, hypocalcemia, pulmonary hypoxia, hypoxemia, metabolic and respiratory acidosis, low urinary pH, and high LDH (50).

In other studies, researchers concluded that using radiographic images such as a CT scan or X-ray could better grade the intensity of the COVID-19 infection. In most of these studies, due to the high efficiency of transfer learning methods, pre-trained models were used. In one of the studies, the pre-trained model GoogleNet, which is part of CNN's architecture and is known as InceptionV1, was successfully used. The 99% training accuracy and 98.5% test accuracy obtained in COVID prediction using GoogleNet highlight the applicability of transfer learning models in disease prediction (56).

5. Conclusion

As previously discussed, accurate detection of COVID-19 disease severity can improve patient survival and prompt treatment of COVID-19. Many studies have been conducted in the field of diagnosis and estimation of the intensity of infection using artificial intelligence methods, and it seems that the diagnosis of COVID-19 severity using AI approaches with the least cost and complexity is one of the fundamental elements in curing the disease and slowing the spread of the pandemic. This study, as a comprehensive survey, has answered these four analytical questions: Which machine learning methods and to what extent have they been used with the aim of detecting the rate of COVID-19 infection? Which features and to what extent have they been used to estimate the rate of infection caused by COVID-19? By examining the performance of ML algorithms, it was found that some of them can be used as a tool in the hands of clinical experts in radiology applications and modalities to detect the level of infection, and maybe with the introduction of ML algorithms into facilities and laboratories in the near future, disease diagnosis will be faster, cheaper, and safer. The application of these methodologies in assessing COVID-19 severity can be a powerful tool for radiologists and laboratories to eliminate human error and assist them in making judgments under critical conditions and at the peak of the disease.

This study backs up the notion that machine learning algorithms are a viable technique to optimize healthcare and improve the outcomes of diagnostic and therapeutic operations. Although ML is one of the most powerful computing tools for calculating involved lung area, particularly COVID-19, developers must exercise caution to avoid model overfitting and maximize the generalizability and usefulness of ML models that deal with COVID-19; these models must be trained on large, heterogeneous datasets to cover all available data space. It is suggested that in future research, ML methods be used in portable devices such as mobile applications so that they are available everywhere and that these applications can be used as suitable services in clinical expert authority by using 5G technologies and data transfer based on the cloud platform.

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Conflict of interests

The authors declare that there is no conflict of interest.

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