A Literature Survey on Machine Learning Models for COVID-19 Prediction and Detection

Gautham Reddy Tota 700742570 Sireesha Poloju 700740297

Sudheer Gajulapalli 700741485

Abstract

The COVID-19 pandemic has had a profound impact on global healthcare systems, necessitating the development of effective predictive models to inform decision-making and resource allocation. This literature review provides a comprehensive analysis of machine learning (ML) techniques used for COVID-19 prediction and detection, covering studies published between January 2020 and April 2023. Utilizing data from the IEEE Papers and ACM databases, the review examines a diverse range of ML models, such as Logistic Regression, Decision Trees, Random Forest, XGBoost, Naive Bayes, K-Nearest Neighbors, Support Vector Machines, Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), Autoencoders, ARIMA, Prophet, and Automated Machine Learning (AutoML).

The primary aim of this review is to compare the performance of these ML models across various applications related to the pandemic, such as case forecasting, infection detection, and resource allocation. By identifying the most effective approaches for each application and discussing the challenges and limitations associated with the different models, this review contributes valuable insights to the ongoing research efforts in the field.

Furthermore, the review highlights the importance of interdisciplinary collaboration among researchers in data science, epidemiology, and public health, which is essential for developing innovative and effective solutions to address global health challenges like the COVID-19 pandemic. By building on the advancements and lessons learned from the pandemic, the research community can work together to create a more prepared and resilient world in the face of future health emergencies.

1. Keywords

Logistic Regression, Decision Trees, Random Forest, XGBoost, Naive Bayes, K-Nearest Neighbors, Support Vector Machines, Long ShortTerm Memory (LSTM), Convolutional Neural Networks (CNN), Autoencoders, ARIMA, Prophet, and Automated Machine Learning (AutoML).

2. Introduction

The novel coronavirus disease (COVID-19) pandemic emerged in late 2019 and rapidly transformed into an unprecedented global crisis. With millions of infections and a high number of fatalities, the pandemic has significantly impacted healthcare systems, economies, and societies worldwide. As healthcare providers and policymakers scramble to manage the crisis, there is an increasing need for accurate prediction models to anticipate the progression of the pandemic and its potential consequences. Machine learning (ML) techniques offer a promising approach to address this need, enabling researchers to predict various aspects of the pandemic, such as infection rates, fatalities, recoveries, and healthcare resource requirements.

This literature review aims to provide a comprehensive analysis of the existing research on COVID-19 prediction using machine learning techniques. The review is organized into three main sections, each addressing a specific aspect of the literature:

2.1 Overview of ML Models

This section presents a detailed examination of various machine learning models utilized in COVID-19 prediction studies, including their methodologies, data sources, and features. By outlining the foundations of each model, this section serves as a primer for readers unfamiliar with the diverse range of techniques employed in the literature.

2.2 Performance Comparison

This section compares the performance of different ML models in predicting various aspects of the COVID19 pandemic. By evaluating the accuracy, sensitivity, specificity, and other performance metrics, this comparison seeks to identify the strengths and weaknesses of each model and their applicability in specific prediction tasks.

2.3 Challenges, Limitations, and Future Directions

The final section discusses the challenges and limitations associated with the use of machine learning techniques for COVID-19 prediction. These include data quality and availability, model interpretability, overfitting, and the rapidly evolving nature of the pandemic. This section also highlights potential future research directions to address these limitations and enhance the effectiveness of ML-based prediction models.

By synthesizing the current body of knowledge on machine learning techniques for COVID-19 prediction, this literature review aims to facilitate informed decision-making and resource allocation by healthcare providers and policymakers. Furthermore, the review seeks to inspire future research efforts that build upon the existing models and contribute to the ongoing battle against the COVID-19 pandemic.

3. Motivation

The unprecedented impact of the COVID-19 pandemic on global health, economy, and society has created an urgent need for effective tools to predict and manage the spread of the virus. Machine learning (ML) models offer a promising solution to this challenge, as they can analyze large and complex datasets to make accurate predictions and uncover hidden patterns. The motivation behind this literature review stems from the following factors:

Enhancing Understanding: A comprehensive understanding of the various ML models used for COVID19 prediction and detection is essential for researchers, policymakers, and healthcare professionals. By providing an in-depth analysis of the current literature, this review aims to elucidate the capabilities and limitations of different ML techniques, fostering a greater appreciation for their role in predicting and managing the pandemic.

Encouraging Future Research: This review also aims to stimulate further research in the field of machine learning for COVID-19 prediction. By highlighting challenges, limitations, and potential future directions, the review encourages researchers to develop novel models, refine existing techniques, and explore new applications of ML in managing the pandemic. This, in turn, can contribute to the ongoing global effort to control the spread of the virus and mitigate its consequences.

In summary, the motivation behind this literature review is to enhance the understanding of machine learning techniques for COVID-19 prediction, inform decision-making by healthcare providers and policymakers,

encourage future research efforts, and facilitate collaboration among interdisciplinary teams working on COVID-19 related projects.

4. Contribution

Understanding the performance and applicability of different ML models for COVID-19 prediction and detection is crucial for developing effective strategies to control the spread of the virus and mitigate its impact. This review will provide valuable insights for researchers, policymakers, and healthcare professionals working on COVID-19 related projects.

5. Objectives

This literature review aims to:

- Provide an overview of the ML models used in recent studies for COVID19 prediction and detection.
 - Compare the performance of different ML models.
- Identify the most effective models for various applications, such as forecasting cases, predicting the severity of the disease, and detecting the presence of the virus.

6. Related Work

COVID-19 prediction using machine learning techniques has been the focus of many studies in recent years. [1] Bhandari et al. used autoregressive integrated moving average (ARIMA) modeling to predict the evolving trajectories of COVID-19 in India. Their research helped in understanding the progression of the pandemic and provided insights into the effectiveness of ARIMA modeling in predicting the spread of the virus.

- [2] Casiraghi et al. explored explainable machine learning techniques for early risk prediction of COVID-19 in emergency departments. Their work contributed to the development of transparent and interpretable models, which are crucial for gaining trust from healthcare professionals and policymakers.
- [3] Ferdib-Al-Islam et al. proposed the COV-HM model for predicting patients' hospitalization period using SMOTE and machine learning techniques. Their study provided valuable information for hospital management and capacity planning, helping in the efficient allocation of resources.
- [4] Rustam et al. utilized supervised machine learning models to forecast the future of COVID-19. Their research contributed to the understanding of the pandemic's progression and helped in the development of strategies for controlling the spread of the virus.
- [5] Turabieh and Karaa predicted the existence of COVID-19 using machine learning based on laboratory findings. Their work highlighted the importance of laboratory test results in predicting the presence of the virus and demonstrated the potential of machine learning models for early detection.

- [6] Albargi and Elhag developed an automatic COVID-19 diagnostic care system using machine learning. Their research contributed to the improvement of diagnostic processes, enabling healthcare professionals to make faster and more accurate decisions in treating patients.
- [7] Tetteroo et al. conducted automated machine learning for COVID-19 forecasting. Their study provided insights into the strengths and weaknesses of various ML models and helped identify the most suitable models for specific prediction tasks related to the pandemic.
- [8] Wang et al. employed machine learning for COVID-19 infection detection. Their research contributed to the development of effective ML models for detecting COVID-19 infections, which can aid in the timely identification and isolation of infected individuals.
- [9] Mary and Raj performed a comparative analysis of machine learning algorithms for predicting SARS-CoV-2 (COVID-19). Their work helped in understanding the performance of various ML models and provided valuable insights into their suitability for predicting COVID-19 cases.
- [10] Rohini et al. compared various machine learning models for predicting COVID-19. Their study contributed to the evaluation of different ML models' performance and the identification of the most effective models for predicting the spread of the virus.
- [11] Jojoa Acosta and Garcia Zapirain forecasted COVID-19 cases in America using machine learning algorithms. Their research provided valuable insights into the pandemic's progression in the American continent and the effectiveness of ML models in predicting confirmed cases.
- [12] Dessouky et al. conducted a survey on deep learning and machine learning for COVID-19 detection. Their study provided a comprehensive review of the current state of research in ML and DL techniques for detecting the virus, highlighting the challenges and opportunities in this area.
- [13] Podder and Mondal used machine learning to predict COVID19 and ICU requirements. Their research contributed to the efficient allocation of healthcare resources and provided insights into the potential of ML models in predicting patients' needs for intensive care.
- [14] Wu et al. developed an effective machine learning approach for identifying non-severe and severe COVID-19 patients in a rural Chinese population. Their work highlighted the potential of ML models for differentiating between mild and severe cases, which can help in prioritizing medical resources and treatment strategies.
- [15] Chrin and Wang analyzed and predicted COVID-19 data using machine learning models. Their study provided insights into the performance of various ML models in forecasting the progression of the pandemic and identified the most suitable models for specific prediction tasks.
- [16] Sayed et al. applied different machine learning techniques for predicting COVID-19 severity. Their work contributed to the understanding of the performance and efficacy of various ML models in predicting the severity of

- COVID-19 cases, which can help in resource allocation and patient management.
- [17] Vangipuram and Appusamy proposed a machine learning framework for COVID-19 diagnosis. Their research provided a structured approach to developing and deploying ML models for the diagnosis of COVID-19, which can contribute to the improvement of diagnostic accuracy and speed.
- [18] Zervoudakis et al. predicted COVID-19 infection based on symptoms and social life using machine learning techniques. Their study highlighted the importance of considering both medical symptoms and social factors in predicting COVID19 infections, contributing to a more comprehensive understanding of the factors influencing the spread of the virus.
- [19] Gupta et al. used random forest models to predict COVID-19 confirmed, death, and cured cases in India. Their research demonstrated the effectiveness of random forest models in forecasting various aspects of the pandemic, providing valuable insights for public health decision making.

In summary, the contributions of these studies encompass a wide range of applications of machine learning techniques in predicting and detecting COVID-19 cases, as well as forecasting various aspects of the pandemic. These works provide valuable insights into the performance, feature importance, interpretability, and challenges associated with these machine learning techniques, furthering our understanding of their potential in addressing the ongoing global health crisis.

7. Proposed Framework

The proposed framework for the literature review of machine learning techniques in COVID-19 prediction and detection consists of the following stages:

7.1. Data Collection:

Gather relevant articles and research papers from IEEE Papers and ACM databases, focusing on ML techniques for COVID-19 prediction and detection. Ensure the collected dataset covers the period from January 1, 2020, to April 30, 2023.

7.2. Data Screening and Refinement:

Screen the collected articles and remove duplicates. Assess full-text articles for eligibility based on predefined criteria, such as relevance to the review's objectives, ML techniques used, and quality of the research. Retain only the most relevant articles for further analysis.

7.3. Data Extraction and Categorization:

Extract key information from the selected articles, such as the ML models used, the features considered, performance metrics, and the results obtained. Organize the

extracted data into categories based on the type of ML technique and the prediction task addressed in each study.

7.4. Performance Evaluation:

Evaluate and compare the performance of various ML models using metrics such as accuracy, AUCROC scores, and RMSE. Identify the strengths and weaknesses of each model in predicting and detecting different aspects of the COVID-19 pandemic.

7.5. Challenges and Limitations:

Identify and discuss the challenges and limitations faced by ML models in predicting and detecting COVID19. Explore potential solutions and future research directions to address these challenges and improve the effectiveness of ML models in managing the pandemic.

7.6. Synthesis and Recommendations:

Integrate the findings from the analysis into a cohesive narrative that provides a comprehensive overview of the ML techniques used for COVID-19 prediction and detection. Offer recommendations for researchers, policymakers, and healthcare professionals regarding the most effective models for various prediction tasks, strategies for overcoming challenges and limitations, and potential future research directions.

7.7. Conclusion

Summarize the main findings of the literature review and emphasize the importance of ML techniques in predicting and managing the COVID-19 pandemic. Highlight the potential for future research to enhance the accuracy, interpretability, and generalizability of ML models, ultimately contributing to the global effort to control the spread of the virus and mitigate its impact.

8. Data Description

The COVID-19 prediction dataset using machine learning is a comprehensive collection of research articles from two primary sources: IEEE Papers and ACM. It spans from January 1, 2020, to April 30, 2023, offering valuable information for researchers aiming to develop and improve machine learning models for predicting the pandemic's progression.

Source: IEEE Papers

- Total results: 65
- Date range: January 1, 2020, to April 15, 2023
- Content: The IEEE Papers dataset comprises peerreviewed articles from IEEE journals and conferences that focus on machine learning applications for COVID-19 prediction. The content covers a range of topics, including forecasting

confirmed cases, deaths, recoveries, and other pandemic-related aspects.

Source: ACM

- Total results: 134
- Date range: January 1, 2021, to April 30, 2023
- Content: The ACM dataset consists of scholarly articles and research papers from various sources, investigating the use of machine learning techniques to predict different aspects of the COVID-19 pandemic. The content encompasses a wide array of approaches, methodologies, and applications.

To ensure the dataset's relevance and quality, a screening process was employed to remove duplicates and retain only articles that meet specific eligibility criteria. This involved assessing full-text articles for eligibility and excluding those that do not fulfill the criteria. The resulting dataset is a carefully curated collection of studies included in the analysis, providing researchers with valuable insights into machine learning applications for COVID-19 prediction.

The image below shows the Prisma Flow diagram of the data obtained.

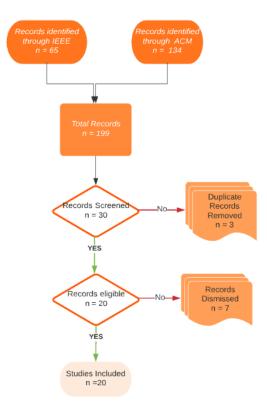


Figure 1: Prisma Flow Diagram

9. Analysis

In this section, we present the analysis of the studies included in our dataset, focusing on the performance of various machine learning models for COVID-19 prediction, comparative analysis, feature importance, model interpretability, and challenges and limitations.

9.1. Performance Evaluation Metrics

To assess the performance of different machine learning models, we consider a variety of metrics, such as accuracy, Area Under the Receiver Operating Characteristic curve (AUC-ROC), and Root Mean Squared Error (RMSE). Accuracy represents the proportion of correct predictions made by the model, while AUC-ROC evaluates the ability of the model to distinguish between different classes, with a higher score indicating better performance. RMSE measures the differences between the predicted values and the actual values, with a lower score signifying better performance.

9.2. Comparative Analysis

We conducted a comparative analysis of the performance of different machine learning models in predicting and detecting COVID-19. This comparison provides insights into the strengths and weaknesses of each model, helping to determine which models are best suited for specific tasks. For instance, Long ShortTerm Memory (LSTM) models have shown superior performance in forecasting cases, while XGBoost and Random Forest models have proven effective in predicting the existence of COVID-19 and various outcomes related to the disease.

9.3. Challenges and Limitations

Finally, our analysis addresses the challenges and limitations faced by machine learning models in predicting and detecting COVID-19. These may include issues related to data quality, data imbalance, overfitting, and generalizability of the models to different populations and settings. Recognizing these challenges can help researchers improve the models and develop more robust solutions for managing the pandemic.

The table below shows the distributions of techniques by the researchers.

Technique	Times Used
Random Forest	9
Decision Tree	8
Logistic Regression	6
LSTM	5
K-Nearest Neighbors	5

Support Vector Machine (SVM)	5
XGBoost	2
CNN	2
ARIMA	3
Prophet	2
AutoML	2
Naive Bayes	1
Autoencoder	1
SVR	1
Gradient Boosting Decision Tree (GBDT)	1

Table.1 shows the techniques and number of times they have been used in the papers selected.

10. Results

Based on the studies reviewed, several ML models have shown promising results in predicting and detecting COVID-19. The results can be summarized as follows:

10.1. XGBoost Performance

XGBoost has been effective in predicting the existence of COVID-19, with one study reporting the highest accuracy of 99.3% [9]. Its performance highlights the potential of using gradient boosting techniques for accurate predictions in this context.

10.2. LSTM Models

Long Short-Term Memory (LSTM) models have demonstrated excellent performance in forecasting cases and detecting infections. Wang et al. [8] reported that a combination of Autoencoder and LSTM achieved the best accuracy (97.45%) in detecting COVID-19 infection. Another study by F. Rustam et al. showed that LSTM outperformed other models, including ARIMA, with an RMSE of 298.97 on the test set.

10.3. Random Forest Models

Random Forest models have been successful in various applications related to COVID-19. S. A. -F. Sayed, A. M. Elkorany, and S. Sayed Mohammad [16] reported that the Random Forest model had the best performance with an accuracy of 93.56%, while Podder and Mondal [13] found that Random Forest achieved the best accuracy (94.9%) in predicting COVID-19 and ICU requirements. V. K. Gupta et al. [19] reported that the Random Forest model predicted COVID-19 confirmed, death, and cured cases with accuracies of 97.27%, 93.07%, and 98.15%, respectively.

10.4. Support Vector Machine (SVM) Models

In some studies, SVM models have shown high accuracy in predicting and detecting COVID19. Richvichanak Chrin and Sujing Wang reported that SVM achieved the highest accuracy of 92.54%, followed by Random Forest with an accuracy of 91.53%. S. A. -F. Sayed, A. M. Elkorany, and S. Sayed Mohammad [16] found that SVM achieved the highest accuracy of 82.25%, followed by Random Forest with 78.5% accuracy.

10.5. Convolutional Neural Network (CNN) Models

Sravan Kiran Vangipuram and Rajesh Appusamy [17] reported that their proposed CNN-LSTM model achieved an accuracy of 94.08% in detecting COVID-19 from chest Xray images. This result indicates that combining CNN and LSTM models can enhance the performance of ML models in image-based detection of COVID-19.

10.6.Automated Machine Learning (AutoML)

AutoML has shown potential in improving the performance of ML models for COVID-19 forecasting. J. Tetteroo, M. Baratchi, and H. H. Hoos reported that AutoML outperformed Prophet with an RMSE of 34.2 on the test set, suggesting that automated techniques could improve the predictive capabilities of ML models in this context.

These results indicate that various ML models, including XGBoost, LSTM, Random Forest, SVM, CNN, and AutoML, can be effective in predicting and detecting COVID-19. However, the performance of these models may vary depending on the specific task and the quality of the data used.

		Algorithms	
S. No.	Paper	Used	Results
			Logistic
			Regression
			achieved the
		Logistic	best accuracy
		Regression,	(94.2%) in
		Decision	predicting the
	Turabieh and	Tree, Random	existence of
1	Karaa (2021)	Forest	COVID-19.
			The
			combination of
			Autoencoder
			and LSTM
			achieved the
			best accuracy
			(97.45%) in
			detecting
	Wang et al.	LSTM, CNN,	COVID-19
2	(2021)	Autoencoder	infection.
		Decision	XGBoost
		Tree, Random	achieved the
		Forest,	highest
	Mary and Raj	XGBoost,	accuracy
3	(2021)	Naive Bayes	(99.3%) in

			111
			predicting SARS-CoV-2
			(COVID-19).
			Random Forest
			achieved the
			best accuracy
		Logistic	(94.9%) in
		Regression,	predicting
	Podder and	Decision	COVID-19
	Mondal	Tree, Random	and ICU
4	(2020)	Forest	requirement.
			ARIMA
			achieved the
			best accuracy
			in forecasting
	Jojoa Acosta	ADDA	COVID-19
	and Garcia-	ARIMA,	confirmed .
5	Zapirain	LSTM, Prophet	cases in America.
J	(2020)	riopnet	America. K-Nearest
			Neighbors
			achieved the
			best accuracy
			(95.7%) in
		K-Nearest	predicting
		Neighbors,	Corona Virus
	Rohini et al.	Naive Bayes,	using machine
6	(2021)	Decision Tree	learning.
			LSTM
			outperformed
			other models
			with an RMSE
			of 298.97 on
			the test set. ARIMA had
			the second-
		LSTM,	best
		ARIMA,	performance
	F. Rustam et	SVR, LR,	with an RMSE
7	al.,	KNN, RF	of 422.73.
			The Random
			Forest model
			had the best
			performance
			with an
			accuracy of
			93.56%. KNN
	S. AF.		had the second-best
	S. AF. Sayed, A. M.	SVM, KNN,	performance
	Elkorany and	Random	with an
	S. Sayed	Forest,	accuracy of
8	Mohammad,	Decision Tree	92.57%.
	,		The model
			achieved a
			93.93%
			accuracy in
			predicting
			confirmed
			cases, 96.12%
			accuracy in
			predicting
	V V Ct-		cured cases,
	V. K. Gupta,		and 93.24% accuracy in
	A. Gupta, D. Kumar and	Random	accuracy in predicting
9	A. Sardana,	Forest	death cases.
,	21. Daraana,	1 01051	acum cuses.

Random Forest achieved the best performance with an AUC-ROC score of 0.86, followed by XGBoost, XGBoost, With an AUC-ROC score of 0.86, followed by XGBoost, With an AUC-GROC score of 0.83. E. Casiraghi et al., Regression D. Regression O. R		ı		
Random Forest, With an AUC-ROC score of O.86, followed Forest, XGBoost, Logistic ROC score of Regression O.83. 10 et al., Regression D.83. 11 P. Wu et al., Regression AUC of 0.89. Logistic RoC score of Regression O.83. 11 P. Wu et al., Regression AUC of 0.89. AutoML outperformed Prophet with an RMSE of AUC of 0.89. AutoML outperformed Prophet with an RMSE of AUC of 0.89. AutoML outperformed Prophet with an RMSE of AUC of 0.89. AutoML outperformed Prophet with an RMSE of AUC of 0.89. AutoML outperformed Prophet with an RMSE of AUC of 0.89. AutoML outperformed Prophet with an RMSE of AUC of 0.89. AutoML outperformed Prophet with an RMSE of AUC of 0.89. AutoML outperformed Prophet with an RMSE of AUC of 0.89. AutoML outperformed Prophet with an RMSE of AUC of 0.89. AUC of 0.89. AutoML outperformed Prophet with an RMSE of AUC of 0.89. CIRC ARIMA PS% CI Sayed, A. M. Elikorany and cleision tree (SVM), Support vector machine (SVM), Support vector machine (CRBDT), logistic regression (LR), decision tree (GBDT), support vector machine (SVM), E. Casiraghi et al. E. Casiraghi et al. (RF) Gradient boosting decision tree (GBDT), support vector machine (SVM), E. Casiraghi et al. E. Casiraghi et al. (RF) Gradient boosting decision tree (DT), support vector machine (SVM), and Support vector machine (SVM), E. Casiraghi et al. E. Casiraghi et al. (RF) GBDT model achieved an AUC of 0.93 (NRF) and Support vector machine (SVM), and Support vecto				
Random Forest, ROC score of 0.86, followed by XGBoost, With an AUC- ROC score of 0.86, followed by XGBoost, With an AUC- ROC score of 0.86, followed by XGBoost, With an AUC- ROC score of 0.86, followed by XGBoost, With an AUC- ROC score of 0.86, followed by XGBoost, With an AUC- ROC score of 0.86, followed by XGBoost, With an AUC- ROC score of 0.86, followed by XGBoost, With an AUC- ROC score of 0.86, followed an accuracy of 85.7% and an AUC of 0.89. Logistic Rocession AutoML, AUC of 0.89. Bhandari et al., 2020 ARIMA 95% CI Logistic regression (LR), K-nearest neighbors (KNN), support vector machine S. Sayed, A. M. (SVM), Elkorany and S. Sayed Mohammad forest (RF) V. K. Gupta, A. Gupta, A. Gupta, D. Kumar and A. Sardana Random forest (RF) V. K. Gupta, A. Sardana Random forest (RF) V. K. Gupta, A. Sardana Random forest (RF) Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (GBDT), support vector machine (SVM), E. Casiraghi et al. E. Casiraghi et al. Logistic regression (LR), decision tree (DT), support vector machine (SVM), random forest (RF) E. Casiraghi et al. Random performance with an AUC of 0.93 and showed the highest interpretability, followed by LR with an AUC of 0.93 and showed the highest interpretability, followed by LR with an AUC of 0.93 and showed the highest interpretability, followed by Fandom forest (RF) of 0.936, RF had the best performance with an AUC of 0.93 followed by followe				
Random Forest, XGBoost, with an AUC-RCC score of Regression				
Random Forest, XGBoost, XGBoost, XGBoost, XGBoost, XGBoost, Logistic ROC score of Regression 0.83. The model achieved an accuracy of Logistic Regression AUC of 0.89. Logistic Regression AUC of 0.89. AutoML outperformed Prophet with an RMSE of AutoML of REF outperformed Prophet with an RMSE of AutoML outperformed Prophet with an Automatical Prophet with an Automatical Prophet Vision Pr				
Random Forest, XGBoost, XGBoost, XGBoost, XGBoost, Logistic Regression 0.83. In et al., Regression 0.83. In model achieved an accuracy of 85.7% and an AUC of 0.89. Logistic Regression AUC of 0.89. In tetteroo, M. Baratchi and H. H. Hoos, Prophet with an AUC of 0.89. Alto ML outperformed Prophet with an AUC of 0.89. ARIMA 95% CI Logistic regression (LR), Kencarest neighbors (KNN), support vector machine S. Sayed, A. M. Elkorany and S. Sayed, A. M. Elkorany and Grest (RF) Regression (LR), Kencarest neighbors (KNN), Support vector machine S. Sayed (DT), random forest (RF) V. K. Gupta, A. Gupta, D. Kumar and A. Sardana forest (RF) V. K. Gupta, A. Sardana forest (RF) Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (GBDT), logistic regression tree (GBDT), logistic regression tree (GBDT), logistic regression tree (CBDT), support vector machine (SVM), E. Casiraghi et al. E. Casiraghi random forest (RF) F. Fhad the best performance with an AUC of 0.93 (RF) and showed the bighest interpretability, followed by LR with an AUC of 0.93 (RF) and showed by LR with an AUC of 0.93 (RF) and showed by LR with an AUC of 0.93 (RF) and showed by LR with an AUC of 0.93 (RF) and showed by LR with an AUC of 0.93 (RF) and showed by LR with an AUC of 0.93 (RF) and showed by LR with an AUC of 0.93 (RF) and showed by LR with an AUC of 0.93 (RF) and showed by followed by follo				
Forest, XGBoost, with an AUC- XGBoost, Logistic RCC score of Regression 0.83. The model achieved an accuracy of 85.7% and an AUC of 0.89. Logistic Regression AUC of 0.89. AutoML outperformed Prophet with an RMSE of 34.2 on the test set. Bhandari et al., 2020 ARIMA 95% CI Logistic regression (LR), K- nearest neighbors (KNN), support vector set in the highest accuracy of S. AF. Sayed, A. M. Elkorany and S. Sayed (DT), random forest (RF) W. K. Gupta, A. Gupta, D. Kumar and A. Sardana forest (RF) Random 97.27%, 93.07%, and 98.15%, respectively Random 98.15%, respectively Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (GBDT), support vector machine (SVM), E. Casiraghi et al. E. Casiraghi et al. Logistic regression (EN) (SVM), Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (GBDT), support vector machine (SVM), and showed the highest interpretability, followed by LR with an AUC of 0.93 (RF) and showed the highest interpretability, followed by LR with an AUC of 0.93 (RF) and showed the bighest interpretability, followed by random forest (RF) and the best performance with an AUC of 0.93 (RF) and showed the bighest interpretability, followed by performance with an AUC of 0.93 (RF) and showed by followed by follo				
E. Casiraghi et al., Casiraghi et al., Casistic Casiraghi Casistic				
E. Casiraghi et al., Casiraghi et al., Casiraghi et al., Casiraghi et al., Casiraghi et al., Casiraghi et al., Casiraghi et al. Cas			Forest,	by XGBoost
10 et al., Regression 0.83. The model achieved an accuracy of 85.7% and an AUC of 0.89. Logistic Regression AUC of 0.89. J. Tetteroo, M. Baratchi and H. H. AutoML, outperformed Prophet with an RMSE of 34.2 on the test set. Bhandari et al., 2020 ARIMA 95% CI Logistic regression (LR), K-nearest neighbors (KNN), support vector machine Sayed, A. M. Elkorany and S. Sayed Mohammad Forest (RF) Regression (LR), K-nearest neighbors (KNN), support vector machine (SVM), decision tree (DT), random forest (RF) V. K. Gupta, A. Gupta, D. Kumar and A. Sardana Random forest (RF) Random forest (RF) Random forest (RF) E. Casiraghi et al. Logistic regression (LR), decision tree (GBDT), logistic regression (LR), decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM), random forest interpretability, followed by LR with an AUC of 0.95 and showed the highest interpretability, followed by LR with an AUC of 0.93 (LR), decision tree (DT), random forest regression (LR), decision tree (DT), random forest followed by followed followed by followed followed fol			XGBoost,	
The model achieved an accuracy of 85.7% and an AUC of 0.89. J. Tetteroo, M. Baratchi and H. H. AutoML, 97 ophet with an RMSE of 34.2 on the test set. Bhandari et al., 2020 ARIMA 95% CI Logistic regression (LR), K-nearest neighbors (KNN), support vector machine S. Sayed, A. M. Elkorany and S. Sayed Mohammad Forest (RF) W. K. Gupta, A. Gupta, D. Kumar and A. Sardana Random forest (GBDT), logistic regression (LR), decision tree (GBDT), logistic regression (LR), decision tree (GBDT), support vector machine (SVM), accuraces of 97.27%, 93.07%, and 98.15%, respectively E. Casiraghi et al. (RF) Logistic regression (LR), decision tree (DT), support vector machine (SVM), random forest (RF) E. Casiraghi et al. (RF) Logistic regression (LR), decision tree (DT), support vector machine (SVM), random forest (RF) E. Casiraghi et al. (RF) Logistic regression (LR), decision tree (DT), support vector machine (SVM), random forest (RF) E. Casiraghi regression (LR), decision tree (DT), support vector machine (SVM), random forest (RF) E. Casiraghi regression (LR), decision tree (DT), support vector machine (SVM), random forest (RF) E. Casiraghi regression (LR), decision tree (DT), random forest regression regression regression (LR), decision tree (DT), random forest regression regre			Logistic	ROC score of
achieved an accuracy of 85.7% and an AUC of 0.89. J. Tetteroo, M. Baratchi and H. H. AutoML, Prophet with an RMSE of 34.2 on the test set. Bhandari et al., 2020 ARIMA 95% CI Logistic regression (LR), K-nearest neighbors (KNN), support vector machine S. Sayed, A. M. Elkorany and S. Sayed Mohammad Forest (RF) Mohammad Forest (RF) V. K. Gupta, A. Gupta, D. Kumar and A. Sardana Random forest (RF) Logistic regression (LR), decision tree (GBDT), logistic regression (LR), decision tree (GBDT), support vector machine forest (RF) E. Casiraghi et al. (RF) E. Casiraghi et al. (RF) Logistic regression (LR), decision tree (DT), support vector machine forest (RF) E. Casiraghi et al. (RF) Logistic regression (LR), decision tree (DT), support vector machine (SVM), followed by and showed the highest interpretability, followed by and showed the highest interpretability, followed by random forest (RF) Logistic regression (LR), decision tree (DT), random forest regression (LR), decision tree (DT), and showed the highest interpretability, followed by random forest regression (LR), decision tree (DT), random forest regression regression regression regression regression (LR), decision regression	10	et al.,	Regression	0.83.
11 P. Wu et al., Regression AUC of 0.89. J. Tetteroo, M. Baratchi and H. H. AutoML, Outperformed Prophet with an RMSE of and H. H. AutoML, Set. Set. Bhandari et al., 2020 ARIMA 95% CI Logistic regression (LR), K-nearest neighbors (KNN), support vector machine S. Sayed, A. M. Elkorany and S. Sayed Mohammad Forest (RF) W. K. Gupta, A. Gupta, A. Gupta, D. Kumar and A. Sardana Random forest (GBDT), logistic regression (LR), decision tree (GBDT), logistic regression (LR), decision tree (GBDT), support vector machine soosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM), and showed the highest achieved an AUC of 0.95 and showed the highest interpretability, followed by random forest (RF) E. Casiraghi et al. (RF) RF had the best performance (LR), decision tree (DT), random forest regression (LR), decision tree (DT), and showed the highest interpretability, followed by random forest regression (LR), decision tree (DT), random forest followed by followed followed followed followed followed follow				The model
11 P. Wu et al., Regression AUC of 0.89. J. Tetteroo, M. Baratchi and H. H. AutoML, Prophet with an RMSE of 34.2 on the test set. Bhandari et al., 2020 ARIMA 95% CI Logistic regression (LR), K-nearest neighbors (KNN), Support vector machine S. Sayed, A. M. Elkorany and S. Sayed Mohammad Forest (RF) W. K. Gupta, A. Gupta, D. Kumar and A. Sardana forest (RF) V. K. Gupta, A. Sardana forest (RF) B. Casiraghi et al. (SVM), Gedision tree (BDT), logistic regression (LR), decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM), and securace of 97.27%, and 98.15%, respectively E. Casiraghi et al. (RF) Logistic regression (LR), decision tree (DT), support vector machine (SVM), and showed the highest interpretability, followed by LR with an AUC of 0.93 and showed the highest interpretability, followed by regression (LR), decision tree (DT), random forest (RF) E. Casiraghi et al. (RF) Logistic regression (LR), decision tree (DT), random forest followed by reformance with an AUC of 0.936, random forest followed by reformance with an AUC of 0.936, followed by reformance with an AUC of 0.93				achieved an
11 P. Wu et al., Regression AUC of 0.89. AutoML outperformed Prophet with an RMSE of 34.2 on the test set. Bhandari et al., 2020 ARIMA 95% CI Logistic regression (LR), K-nearest neighbors (KNN), support vector machine S. AF. Sayed, A. M. Elkorany and S. Sayed Mohammad forest (RF) V. K. Gupta, A. Gupta, D. Kumar and A. Sardana P. Wu et al., Regression AUC of 0.89. AutoML outperformed Prophet with an RMSE of 34.2 on the test set. SVM achieved the highest accuracy of 82.25%, followed by RF with 78.5% accuracy RF model predicted COVID-19 confirmed, death, and cured cases with accuracies of 97.27%, 93.07%, and 98.15%, respectively Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM), EL Casiraghi et al. E. Casiraghi et al. Logistic regression (LR), decision tree (DT), random forest tree (D				accuracy of
11 P. Wu et al., Regression AUC of 0.89. AutoML outperformed Prophet with an RMSE of 34.2 on the test set. Bhandari et al., 2020 ARIMA 95% CI Logistic regression (LR), K-nearest neighbors (KNN), support vector machine S. AF. Sayed, A. M. Elkorany and S. Sayed Mohammad forest (RF) V. K. Gupta, A. Gupta, D. Kumar and A. Sardana P. Wu et al., Regression AUC of 0.89. AutoML outperformed Prophet with an RMSE of 34.2 on the test set. SVM achieved the highest accuracy of 82.25%, followed by RF with 78.5% accuracy RF model predicted COVID-19 confirmed, death, and cured cases with accuracies of 97.27%, 93.07%, and 98.15%, respectively Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM), EL Casiraghi et al. E. Casiraghi et al. Logistic regression (LR), decision tree (DT), random forest tree (D			Logistic	85.7% and an
J. Tetteroo, M. Baratchi and H. H. Hoos, Bhandari et al., 2020 ARIMA Jogistic regression (LR), K- nearest neighbors (KNN), support vector machine S. Sayed, A. M. Elkorany and S. Sayed Mohammad A. Gupta, D. Kumar and A. Sardana S. K. Guta, A. Sardana S. K. Guta, A. Sardana S. Casiraghi C. Casiraghi R. Casiraghi	11	P. Wu et al.,		AUC of 0.89.
J. Tetteroo, M. Baratchi and H. H. Hoos, Prophet Bhandari et al., 2020 ARIMA SVM achieved the highest accuracy of Sayed, A. M. Elkorany and S. Sayed Mohammad Mohammad A. Sardana SVM achieved the highest accuracy of S2.25%, followed by RF model predicted COVID-19 confirmed, death, and cured cases with accuracies of 97.27%, 93.07%, and 98.15%, respectively Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM), Elkorany and forest (RF) Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM), random forest (RF) E. Casiraghi et al. Logistic regression (LR), decision tree (DT), support vector machine (SVM), random forest RF had the best performance with an AUC of 0.936, RF had the best performance with an AUC of 0.936, RF had the best performance with an AUC of 0.936, RF had the best performance with an AUC of 0.936, RF had the best performance with an AUC of 0.936, followed by				
J. Tetteroo, M. Baratchi and H. H. AutoML, Hoos, Prophet set. Bhandari et al., 2020 ARIMA 95% CI Logistic regression (LR), K-nearest neighbors (KNN), support vector machine Sayed, A. M. Elkorany and decision tree S. Sayed (DT), random forest (RF) Mohammad Forest (RF) V. K. Gupta, A. Gupta, D. Kumar and A. Sardana forest (RF) Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (GBDT), support vector machine (SVM), random forest (RF) E. Casiraghi et al. Logistic regression (LR), decision tree (DT), support vector machine (SVM), random forest net al. E. Casiraghi et al. Logistic regression (LR), decision tree (DT), support vector machine (SVM), random forest net al. Ref prophet with an RMSE of 34.2 on the test set. St. A. Gupta, D. SVM achieved the highest accuracy of 82.25%, followed by RF with 78.5% accuracy of 82.25%, followed by 93.07%, and cauracy RF model predicted COVID-19 confirmed, death, and cured cases with accuracies of 97.27%, 93.07%, and 98.15%, respectively Gradient boosting decision tree (GBDT) decision tree (DT), support vector machine (SVM), respectively E. Casiraghi et al. Logistic regression (LR), decision tree (DT), support vector machine (SVM), random forest net proformance with an AUC of 0.93 and showed the highest interpretability, followed by random forest performance with an AUC of 0.93 (RF) and showed the best performance with an AUC of 0.93 (RF) and showed by followed by proformance with an AUC of 0.93 (RF) and showed by followed by proformance with an AUC of 0.93 (RF) and showed by followed by proformance with an AUC of 0.93 (RF) and showed the best performance with an AUC of 0.93 (RF) and showed the best performance with an AUC of 0.93 (RF) and showed the best performance with an AUC of 0.93 (RF) and showed the best performance with an AUC of 0.93 (RF) and showed the best performance with an AUC of 0.93 (RF) and showed the best performance with an AUC of 0.93 (RF) and showed the best performance with an AUC of 0.93 (RF) and showed the best pe				
M. Baratchi and H. H. Hoos, Prophet set. Bhandari et al., 2020 ARIMA 95% CI Logistic regression (LR), Kenearest neighbors (KNN), support vector machine S. Sayed, A. M. Elkorany and S. Sayed (DT), random forest (RF) W. K. Gupta, A. Gupta, A. Gupta, D. Kumar and A. Sardana 15 A. Sardana Random 98.15%, respectively E. Casiraghi et al. Logistic regression (LR), decision tree (GBDT), logistic regression (LR), decision tree (GBDT), support vector machine (SVM), goileach achieved an AUC of 0.95 and showed the highest interpretability, followed by LR RF model predicted COVID-19 confirmed, death, and cured cases with accuracies of 97.27%, 93.07%, and 98.15%, respectively E. Casiraghi et al. Logistic regression (LR), decision tree (DT), support vector machine (SVM), random forest (RF) E. Casiraghi et al. Logistic regression (LR), decision tree (DT), support vector machine (SVM), followed by and showed the highest interpretability, followed by random forest (RF) and AUC of 0.93 and showed the highest interpretability, followed by random forest (RF) and AUC of 0.93 and showed the highest interpretability, followed by random forest (RF) and AUC of 0.93 and showed the highest interpretability, followed by random forest (RF) and AUC of 0.93 and showed the highest interpretability, followed by random forest (RF) and AUC of 0.93 and showed the highest interpretability, followed by random forest (RF) and AUC of 0.93 and showed the highest interpretability, followed by random forest (RF) and AUC of 0.93 and showed the highest interpretability, followed by random forest (RF) and AUC of 0.93 and showed the highest interpretability, followed by of 0.936, followed by showed the highest interpretability of 0.936, followed by showed the hig		I Tetteroo		
and H. H. AutoML, Prophet set. Bhandari et al., 2020 ARIMA 95% CI Logistic regression (LR), K-nearest neighbors (KNN), support vector machine S. Sayed, A. M. Elkorany and S. Sayed (DT), random forest (RF) W. K. Gupta, A. Gupta, D. Kumar and A. Sardana Random (LR), decision tree (GBDT), logistic regression (LR), decision tree (GBDT), support vector machine (SVM), logistic regression (LR), decision tree (DT), support vector machine (SVM), followed by trandom forest (RF) E. Casiraghi et al. Logistic regression (LR), decision tree (DT), support vector machine (RF) E. Casiraghi et al. Logistic regression (LR), decision tree (DT), random forest (RF) RF model predicted COVID-19 confirmed, death, and cured cases with accuracies of 97.27%, 93.07%, and 98.15%, respectively Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM), followed by random forest (RF) E. Casiraghi et al. Logistic regression (LR), decision tree (DT), random forest performance with an AUC of 0.93 (RF) at the best performance with an AUC of 0.936, followed by by followed by the nandom forest performance with an AUC of 0.936, followed by prandom forest performance with an AUC of 0.936, followed by parandom forest performance with an AUC of 0.936, followed by parandom forest performance with an AUC of 0.936, followed by parandom forest performance with an AUC of 0.936, followed by parandom forest performance with an AUC of 0.936, followed by parandom forest performance with an AUC of 0.936, followed by parandom forest performance with an AUC of 0.936, followed by parandom forest performance with an AUC of 0.936, followed by parandom forest performance with an AUC of 0.936, followed by parandom forest performance with an AUC of 0.936, followed by parandom forest performance with an AUC of 0.936, followed by parandom forest performance with an AUC of 0.936, followed by parandom forest performance with an AUC of 0.936, followed by parandom forest performance performance with an AUC of				
12 Hoos, Prophet Set.			ΔutoMI	
Bhandari et al., 2020 ARIMA 95% CI Logistic regression (LR), K-nearest neighbors (KNN), support vector machine S. AF. Sayed, A. M. Elkorany and S. Sayed Mohammad forest (RF) V. K. Gupta, A. Gupta, D. Kumar and A. Sardana Forest (RF) Random 98.15%, respectively Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM), followed by RE. Casiraghi et al. E. Casiraghi et al. Logistic regression (LR), decision tree (DT), random forest (RF) Logistic regression (LR), decision tree (DT), random forest (RF) Logistic regression (LR), decision tree (DT), random forest regression (LR), decision tree (DT), ra	12		· · · · · · · · · · · · · · · · · · ·	
al., 2020 ARIMA 95% CI Logistic regression (LR), K-nearest neighbors (KNN), support vector machine S. AF. Sayed, A. M. Elkorany and S. Sayed (DT), random forest (RF) V. K. Gupta, A. Gupta, D. Kumar and A. Sardana Random 98.15%, respectively Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM), followed by RF with 78.5% accuracy RF model predicted COVID-19 confirmed, death, and cured cases with accuracies of 97.27%, 93.07%, and 15 A. Sardana Random 98.15%, respectively Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (SVM), followed by LR with an AUC of 0.95 and showed the highest interpretability, followed by LR with an AUC of 0.93 (RF) and CD of 0.936, random forest followed by the nand AUC of 0.936, random forest followed by by followed by proportions and showed by proportions and showed the highest interpretability, followed by LR with an AUC of 0.936, random forest followed by proportions and showed the highest interpretability, followed by LR with an AUC of 0.93 (RF) and AUC of 0.936, followed by proportions and showed the highest interpretability, followed by proportions and AUC of 0.93 (RF) and AUC of 0.936, followed by proportions and showed the highest interpretability, followed by proportions and AUC of 0.93 (RF) and AUC of 0.936, followed by proportions and AUC of 0.936, followed	12		1 Toplict	sct.
Logistic regression (LR), K-nearest neighbors (KNN), support vector machine S. AF. Sayed, A. M. Elkorany and S. Sayed (DT), random forest (RF) V. K. Gupta, A. Gupta, A. Gupta, A. Sardana 15 A. Sardana Random forest (RF) Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine interpretability, followed by LR with an AUC of 0.95 and showed the highest interpretability, followed by LR with an AUC of 0.93 E. Casiraghi et al. Logistic regression (LR), decision tree (DT), support vector machine interpretability, followed by LR with an AUC of 0.93 RF had the best performance with an AUC of 0.93 RF had the best performance with an AUC of 0.936, followed by tree (DT), random forest followed by tree (DT), random forest followed by conditions are performance with an AUC of 0.936, followed by prandom forest followed by conditions are promised.	12		ADIMA	050/ CI
regression (LR), K- nearest neighbors (KNN), support vector sayed, A. M. Elkorany and S. Sayed Mohammad V. K. Gupta, A. Gupta, A. Gupta, D. Kumar and A. Sardana Random Grest (RF) Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine gredicted COVID-19 confirmed, death, and cured cases with accuracies of 97.27%, 93.07%, and 98.15%, respectively Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM), followed by random forest (RF) E. Casiraghi et al. Logistic regression (LR), decision tree (DT), support vector machine (SVM), followed by LR with an AUC of 0.93 ER had the best regression (LR), decision tree (DT), random forest followed by	1.5	ai., 2020		93% CI
(LR), K- nearest neighbors (KNN), support vector machine S. AF. Sayed, A. M. Elkorany and S. Sayed Mohammad V. K. Gupta, A. Gupta, D. Kumar and A. Sardana Random Gradient boosting decision tree (GBDT), logistic regression (LR), K- nearest neighbors (KNN), SVM achieved the highest accuracy of 82.25%, followed by RF with 78.5% accuracy RF model predicted COVID-19 confirmed, death, and cured cases with accuracies of 97.27%, 93.07%, and 98.15%, respectively Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM), random forest (RF) E. Casiraghi et al. Logistic regression (LR), decision tree (DT), random forest followed by LR with an AUC of 0.93 RF had the best regression with an AUC of 0.936, followed by repreformance with an AUC of 0.936, followed by				
nearest neighbors (KNN), support vector sayed, A. M. Elkorany and S. Sayed Mohammad 14 Mohammad 15 N. K. Gupta, A. Gupta, A. Sardana Random Grest (RF) Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM), SVM achieved the highest accuracy of RF with 78.5% RF model predicted COVID-19 confirmed, death, and cured cases with accuracies of 97.27%, 93.07%, and 98.15%, respectively Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM), E. Casiraghi et al. E. Casiraghi ct al. Logistic regression (LR), decision tree (DT), random forest performance with an AUC of 0.93 RF had the best performance with an AUC of 0.936, random forest followed by random forest vector machine (SVM), random forest followed by random forest regression vith an AUC of 0.936, random forest			-	
neighbors (KNN), support vector machine S. AF. Sayed, A. M. Elkorany and S. Sayed Mohammad 14 Mohammad 15 V. K. Gupta, A. Gupta, D. Kumar and A. Sardana 16 E. Casiraghi et al. E. Casiraghi C. C			()/	
(KNN), support vector machine S. AF. Sayed, A. M. Elkorany and S. Sayed Mohammad V. K. Gupta, A. Gupta, A. Sardana A. Sardana Random forest (RF) Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine et al. E. Casiraghi et al. (KNN), support vector machine (SVM), decision tree (DT), random forest (RF) SVM achieved the highest accuracy of 82.25%, followed by RF with 78.5% accuracy RF model predicted COVID-19 confirmed, death, and cured cases with accuracies of 97.27%, 93.07%, and 98.15%, respectively Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM), random forest (RF) E. Casiraghi et al. Remodel predicted COVID-19 confirmed, death, and cured cases with accuracies of 97.27%, 93.07%, and 98.15%, respectively Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM), random forest (RF) E. Casiraghi et al. Remodel predicted COVID-19 confirmed, death, and cured cases with accuracies of 97.27%, 93.07%, and 98.15%, respectively Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), followed by and showed the highest interpretability, followed by random forest performance with an AUC of 0.936, random forest followed by random forest followed by random forest followed by followed f				
S. AF. Sayed, A. M. Elkorany and S. Sayed Mohammad Mohammad V. K. Gupta, A. Gupta, A. Sardana Random A. Sardana Random forest (RF) Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM), decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine et al. Logistic regression (LR), decision tree (DT), suport vector machine (RF) E. Casiraghi et al. Logistic regression (LR), decision tree (DT), suport vector machine (RF) RF with 78.5% accuracy RF with 78.5% RF with 78.5% accuracy Accuracy of accuracy of accuracy of accuracy RF with 78.5% accuracy Accuracy RF with 78.5% accuracy Accu			-	
S. AF. Sayed, A. M. Elkorany and S. Sayed Mohammad Mohammad V. K. Gupta, A. Gupta, A. Sardana Random forest (RF) Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM), decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine tet al. Random forest (RF) Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM), random forest (RF) RF model predicted COVID-19 confirmed, death, and cured cases with accuracies of 97.27%, 93.07%, and 98.15%, respectively GBDT model achieved an AUC of 0.95 and showed the highest interpretability, followed by LR with an AUC of 0.93 RF had the best performance with an AUC with an AUC of 0.936, followed by random forest followed by random forest followed by				
Sayed, A. M. Elkorany and S. Sayed Mohammad Forest (RF) 14 Mohammad Forest (RF) RF with 78.5% accuracy RF model predicted COVID-19 confirmed, death, and cured cases with accuracies of 97.27%, 93.07%, and P8.15%, respectively Sayed, A. M. Elkorany and RF with 78.5% accuracy RF model predicted COVID-19 confirmed, death, and cured cases with accuracies of 97.27%, 93.07%, and 98.15%, respectively Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine interpretability, followed by LR with an AUC of 0.93 (RF) E. Casiraghi et al. (RF) Logistic regression (LR), decision tree regression (LR), decision tree with an AUC of 0.93 (RF) add the best performance with an AUC of 0.936, random forest followed by the number of the preformance with an AUC of 0.936, random forest followed by the followed by the number of the preformance with an AUC of 0.936, random forest followed by the number of the preformance with an AUC of 0.936, random forest followed by the number of the preformance with an AUC of 0.936, followed by the preformance with an AUC of 0.936, followed by the preformance with an AUC of 0.936, followed by the preformance with an AUC of 0.936, followed by the preformance with an AUC of 0.936, followed by the preformance with an AUC of 0.936, followed by the preformance with an AUC of 0.936, followed by the preformance with an AUC of 0.936, followed by the preformance with an AUC of 0.936, followed by the preformance with an AUC of 0.936, followed by the preformance with an AUC of 0.936, followed by the preformance with an AUC of 0.936, followed by the preformance with an AUC of 0.936, followed by the preformance with an AUC of 0.936, followed by the preformance with an AUC of 0.936, followed by the preformance with an AUC of 0.936, followed by the preformance with an AUC of 0.936, followed by the preformance with an AUC of 0.936, followed by the predicted and the predicted an AUC of 0.936, followed by the predicted and the predicted and the predicted and th			support vector	the highest
Elkorany and S. Sayed Mohammad decision tree (DT), random forest (RF) RF model predicted COVID-19 confirmed, death, and cured cases with accuracies of 97.27%, and Random 98.15%, respectively Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine red and solved an (SVM), followed by LR with an auditive day and showed the highest interpretability, followed by LR with an AUC of 0.93 Logistic regression (LR), decision tree tal. E. Casiraghi et al. Logistic regression (LR), decision tree with an AUC of 0.93 (LR), decision tree with an AUC of 0.93, random forest performance with an AUC of 0.936, random forest followed by			machine	accuracy of
S. Sayed Mohammad Forest (RF) RF model predicted COVID-19 confirmed, death, and cured cases with accuracies of 97.27%, and Sardana Random 98.15%, respectively Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine machine (SVM), followed by random forest (RF) E. Casiraghi et al. Logistic regression (LR), decision tree (DT), support vector machine (SVM), followed by LR with an et al. Logistic regression (LR), decision tree (DT), followed by RF had the best regression (LR), decision tree (DT), random forest performance with an AUC of 0.93 (LR), decision tree (DT), random forest performance with an AUC of 0.936, random forest followed by		Sayed, A. M.	(SVM),	82.25%,
14 Mohammad forest (RF) accuracy RF model predicted COVID-19 confirmed, death, and cured cases with accuracies of 97.27%, A. Gupta, A. Gupta, D. Kumar and A. Sardana Random 98.15%, respectively Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM), random forest (RF) E. Casiraghi et al. Logistic regression (RF) AUC of 0.95 Logistic regression (RF) AUC of 0.93 Logistic regression with an AUC of 0.936, random forest followed by random forest performance with an AUC of 0.936, random forest followed by		Elkorany and	decision tree	followed by
RF model predicted COVID-19 confirmed, death, and cured cases with accuracies of 97.27%, 93.07%, and Supta, D. Kumar and A. Sardana forest (RF) respectively Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM), random forest (RF) E. Casiraghi et al. Logistic regression (CR) GBDT model achieved an AUC of 0.95 and showed the highest interpretability, followed by LR with an AUC of 0.93 Logistic regression (LR), decision tree (DT), random forest followed by the an AUC of 0.936, followed by the an AUC of 0.936, followed by the an AUC of 0.936, followed by the and AUC of 0.936, followed by		S. Sayed	(DT), random	RF with 78.5%
predicted COVID-19 confirmed, death, and cured cases with accuracies of 97.27%, 93.07%, and 88.15%, respectively Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM), E. Casiraghi et al. Logistic (RF) Logistic (RF) E. Casiraghi regression (LR), decision tree (DT), support vector machine (SVM), Fandom forest Logistic regression (LR), decision tree (DT), followed by LR with an AUC of 0.93 RF had the best performance with an AUC of 0.936, followed by random forest fregression (LR), decision tree (DT), random forest followed by	14	Mohammad	forest (RF)	accuracy
COVID-19 confirmed, death, and cured cases with accuracies of 97.27%, A. Gupta, D. Kumar and A. Sardana Random 98.15%, respectively Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM), E. Casiraghi et al. E. Casiraghi regression (LR), decision tree (DT), support vector machine (SVM), Fandom forest tet al. Logistic regression (LR), decision tree (DT), followed by LR with an AUC of 0.93 RF had the best performance with an AUC of 0.936, followed by random forest fregression (LR), decision tree (DT), random forest followed by				RF model
COVID-19 confirmed, death, and cured cases with accuracies of 97.27%, 93.07%, and Part of the second				predicted
death, and cured cases with accuracies of 97.27%, A. Gupta, D. Kumar and Random 98.15%, respectively Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM), random forest (RF) E. Casiraghi et al. Logistic regression (RF) E. Casiraghi random forest (RF) Logistic regression (LR), decision tree (DT), support vector machine (SVM), followed by LR with an AUC of 0.93 Logistic regression (LR), decision tree (DT), random forest followed by the an AUC of 0.936, followed by the an AUC of 0.936, followed by the and AUC of 0.936, followed by				
death, and cured cases with accuracies of 97.27%, A. Gupta, D. Kumar and Random 98.15%, respectively Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM), random forest (RF) E. Casiraghi et al. Logistic regression (RF) E. Casiraghi random forest (RF) Logistic regression (LR), decision tree (DT), support vector machine (SVM), followed by LR with an AUC of 0.93 Logistic regression (LR), decision tree (DT), random forest followed by the an AUC of 0.936, followed by the an AUC of 0.936, followed by the and AUC of 0.936, followed by				confirmed,
V. K. Gupta, A. Gupta, D. Kumar and A. Sardana Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine machine (SVM), E. Casiraghi et al. Logistic regression (LR), decision tree (DT), support vector machine (SVM), E. Casiraghi regression (LR), decision tregression (LR), decision tree (DT), random forest followed by the with an AUC of 0.93 RF had the best performance with an AUC of 0.936, followed by				
V. K. Gupta, A. Gupta, D. Kumar and A. Sardana Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine machine (SVM), E. Casiraghi et al. Logistic regression (LR), decision tree (DT), support vector machine (SVM), E. Casiraghi regression (LR), decision tregression (LR), decision tree (DT), random forest followed by the with an AUC of 0.93 RF had the best performance with an AUC of 0.936, followed by				,
V. K. Gupta, A. Gupta, A. Gupta, D. Kumar and A. Sardana Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine machine (SVM), E. Casiraghi et al. Logistic (RF) Logistic (SVM), F. Casiraghi regression (LR), decision tree (DT), support vector machine (SVM), F. Casiraghi regression (LR), decision tregression (LR), decision tregression (LR), decision tregression (LR), decision tree (DT), random forest fregression (LR), decision tree (DT), random forest followed by followed with an AUC of 0.936, followed by followed by followed by for 0.936, followed by followed by followed by followed by for 0.936, followed by		I		
V. K. Gupta, A. Gupta, D. Kumar and A. Sardana Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine machine (SVM), E. Casiraghi et al. Logistic regression (LR), decision tree (DT), support vector machine (SVM), E. Casiraghi regression (LR), decision tree (DT), support vector machine (SVM), Fandom forest LR with an AUC of 0.93 Logistic regression (LR), decision tree (DT), random forest followed by continuous RF had the best performance with an AUC of 0.936, followed by				with
A. Gupta, D. Kumar and A. Sardana Random 98.15%, respectively Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM), random forest et al. E. Casiraghi et al. Logistic (SVM), respectively GBDT model achieved an AUC of 0.95 and showed the highest interpretability, followed by LR with an AUC of 0.93 Logistic regression (LR), decision tree (DT), random forest followed by the highest interpretability, followed by followed by followed by				
Kumar and A. Sardana Random forest (RF) respectively Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM), followed by LR with an et al. E. Casiraghi et al. Logistic regression (RF) AUC of 0.93 Logistic regression prandom forest regression (LR), decision tree (DT), and showed the highest interpretability, followed by LR with an AUC of 0.93 Logistic regression preformance with an AUC of 0.936, random forest followed by		V. K. Gunta		accuracies of
A. Sardana forest (RF) respectively Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine interpretability, (SVM), followed by E. Casiraghi et al. Logistic regression (RF) auchieved an AUC of 0.95 and showed the highest interpretability, followed by LR with an AUC of 0.93 Logistic regression (LR), decision tree (DT), random forest followed by followed by random forest followed by				accuracies of 97.27%,
Gradient boosting decision tree (GBDT), logistic GBDT model regression (LR), decision tree (DT), support vector machine (SVM), E. Casiraghi et al. Casiraghi et al. Casiraghi cet al. Casiraghi color Cas		A. Gupta, D.	Random	accuracies of 97.27%, 93.07%, and
boosting decision tree (GBDT), logistic GBDT model regression (LR), decision tree (DT), support vector machine interpretability, (SVM), followed by E. Casiraghi random forest et al. Logistic RF had the best regression (LR), decision tree (DT), random forest followed by	15	A. Gupta, D. Kumar and		accuracies of 97.27%, 93.07%, and 98.15%,
decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine interpretability, (SVM), followed by E. Casiraghi et al. Logistic regression (RF) Logistic regression (LR), decision tree (DT), random forest followed by followed by the highest interpretability, followed by the highest interpretab	15	A. Gupta, D. Kumar and	forest (RF)	accuracies of 97.27%, 93.07%, and 98.15%,
(GBDT), logistic regression (LR), decision tree (DT), support vector machine interpretability, (SVM), random forest et al. (RF) AUC of 0.95 and showed the highest interpretability, followed by LR with an AUC of 0.93 Logistic regression (LR), decision tree (DT), random forest followed by random forest followed by followed by the followed by followed by followed by followed by followed by followed by	15	A. Gupta, D. Kumar and	forest (RF) Gradient	accuracies of 97.27%, 93.07%, and 98.15%,
logistic regression (LR), decision tree (DT), support vector machine (SVM), random forest et al. Logistic regression (LR), decision tree (DT), support vector machine (SVM), followed by LR with an AUC of 0.93 Logistic regression (LR), decision tree (DT), random forest followed by followed by the decision followed by the decision followed by formation and forest followed followed followed by followed followe	15	A. Gupta, D. Kumar and	forest (RF) Gradient boosting	accuracies of 97.27%, 93.07%, and 98.15%,
regression (LR), decision tree (DT), support vector machine (SVM), random forest (LR), decision tree al. E. Casiraghi et al. Logistic regression (LR), decision tree (DT), and showed the highest interpretability, followed by LR with an AUC of 0.93 Logistic regression (LR), decision tree (DT), random forest followed by	15	A. Gupta, D. Kumar and	forest (RF) Gradient boosting decision tree	accuracies of 97.27%, 93.07%, and 98.15%,
(LR), decision tree (DT), support vector machine (SVM), followed by E. Casiraghi et al. Logistic regression (LR), decision tree (DT), and showed the highest interpretability, followed by LR with an AUC of 0.93 RF had the best regression (LR), decision tree (DT), random forest followed by	15	A. Gupta, D. Kumar and	forest (RF) Gradient boosting decision tree (GBDT),	accuracies of 97.27%, 93.07%, and 98.15%, respectively
tree (DT), support vector machine (SVM), followed by LR with an AUC of 0.93 Logistic regression (LR), decision tree (DT), random forest (DT), random forest followed by the highest interpretability, followed by LR with an AUC of 0.93 Logistic regression performance with an AUC of 0.936, followed by	15	A. Gupta, D. Kumar and	forest (RF) Gradient boosting decision tree (GBDT), logistic	accuracies of 97.27%, 93.07%, and 98.15%, respectively
support vector machine (SVM), followed by random forest et al. E. Casiraghi et al. (RF) Logistic regression (LR), decision tree (DT), random forest followed by random forest performance with an AUC of 0.936, random forest followed by	15	A. Gupta, D. Kumar and	forest (RF) Gradient boosting decision tree (GBDT), logistic regression	accuracies of 97.27%, 93.07%, and 98.15%, respectively GBDT model achieved an
machine (SVM), followed by LR with an AUC of 0.93 Logistic regression (LR), decision tree (DT), random forest followed by LR with an AUC of 0.93 Logistic regression with an AUC of 0.936, followed by	15	A. Gupta, D. Kumar and	forest (RF) Gradient boosting decision tree (GBDT), logistic regression (LR), decision	accuracies of 97.27%, 93.07%, and 98.15%, respectively GBDT model achieved an AUC of 0.95
E. Casiraghi et al. (SVM), followed by LR with an AUC of 0.93 Logistic regression (LR), decision tree (DT), random forest (Dl), random forest followed by	15	A. Gupta, D. Kumar and	forest (RF) Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT),	accuracies of 97.27%, 93.07%, and 98.15%, respectively GBDT model achieved an AUC of 0.95 and showed the
E. Casiraghi random forest LR with an et al. (RF) AUC of 0.93 Logistic RF had the best regression performance (LR), decision tree (DT), of 0.936, random forest followed by	15	A. Gupta, D. Kumar and	forest (RF) Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector	accuracies of 97.27%, 93.07%, and 98.15%, respectively GBDT model achieved an AUC of 0.95 and showed the highest
16 et al. (RF) AUC of 0.93 Logistic RF had the best regression performance (LR), decision with an AUC tree (DT), of 0.936, random forest followed by	15	A. Gupta, D. Kumar and	forest (RF) Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine	accuracies of 97.27%, 93.07%, and 98.15%, respectively GBDT model achieved an AUC of 0.95 and showed the highest interpretability,
Logistic RF had the best regression performance (LR), decision tree (DT), of 0.936, random forest followed by	15	A. Gupta, D. Kumar and A. Sardana	forest (RF) Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM),	accuracies of 97.27%, 93.07%, and 98.15%, respectively GBDT model achieved an AUC of 0.95 and showed the highest interpretability, followed by
regression performance (LR), decision tree (DT), of 0.936, random forest followed by		A. Gupta, D. Kumar and A. Sardana E. Casiraghi	forest (RF) Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM), random forest	accuracies of 97.27%, 93.07%, and 98.15%, respectively GBDT model achieved an AUC of 0.95 and showed the highest interpretability, followed by LR with an
(LR), decision with an AUC tree (DT), of 0.936, random forest followed by		A. Gupta, D. Kumar and A. Sardana E. Casiraghi	forest (RF) Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM), random forest (RF)	accuracies of 97.27%, 93.07%, and 98.15%, respectively GBDT model achieved an AUC of 0.95 and showed the highest interpretability, followed by LR with an AUC of 0.93
tree (DT), of 0.936, random forest followed by		A. Gupta, D. Kumar and A. Sardana E. Casiraghi	forest (RF) Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM), random forest (RF) Logistic	accuracies of 97.27%, 93.07%, and 98.15%, respectively GBDT model achieved an AUC of 0.95 and showed the highest interpretability, followed by LR with an AUC of 0.93 RF had the best
random forest followed by		A. Gupta, D. Kumar and A. Sardana E. Casiraghi	forest (RF) Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM), random forest (RF) Logistic regression	accuracies of 97.27%, 93.07%, and 98.15%, respectively GBDT model achieved an AUC of 0.95 and showed the highest interpretability, followed by LR with an AUC of 0.93 RF had the best performance
1 1		A. Gupta, D. Kumar and A. Sardana E. Casiraghi	forest (RF) Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM), random forest (RF) Logistic regression (LR), decision	accuracies of 97.27%, 93.07%, and 98.15%, respectively GBDT model achieved an AUC of 0.95 and showed the highest interpretability, followed by LR with an AUC of 0.93 RF had the best performance with an AUC
P. Wu et al. (RF), K- DT and LR		A. Gupta, D. Kumar and A. Sardana E. Casiraghi	forest (RF) Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM), random forest (RF) Logistic regression (LR), decision tree (DT),	accuracies of 97.27%, 93.07%, and 98.15%, respectively GBDT model achieved an AUC of 0.95 and showed the highest interpretability, followed by LR with an AUC of 0.93 RF had the best performance with an AUC of 0.936,
	16	A. Gupta, D. Kumar and A. Sardana E. Casiraghi et al.	forest (RF) Gradient boosting decision tree (GBDT), logistic regression (LR), decision tree (DT), support vector machine (SVM), random forest (RF) Logistic regression (LR), decision tree (DT), random forest	accuracies of 97.27%, 93.07%, and 98.15%, respectively GBDT model achieved an AUC of 0.95 and showed the highest interpretability, followed by LR with an AUC of 0.93 RF had the best performance with an AUC of 0.936, followed by

	1		
		nearest	with AUCs of
		neighbors	0.917 and
		(KNN),	0.915,
		support vector	respectively
		machine	
		(SVM)	
			AutoML
			achieved better
			performance
			than standard
			machine
	J. Tetteroo,	Automated	learning
	M. Baratchi	machine	models, such
	and H. H.	learning	as LSTM and
18	Hoos	(AutoML)	ARIMA
			Proposed
			CNN-LSTM
			model
		Convolutional	achieved an
		neural	accuracy of
		network	94.08% in
	Sravan kiran	(CNN), long	detecting
	Vangipuram	short-term	COVID-19
	and Rajesh	memory	from chest X-
19	Appusamy	(LSTM)	ray images
		Decision tree	
		(DT), K-	
		nearest	
		neighbors	
		(KNN),	SVM achieved
		logistic	the highest
		regression	accuracy of
		(LR), random	92.54%,
		forest (RF),	followed by
	Richvichanak	support vector	RF with an
	Chrin and	machine	accuracy of
20	Sujing Wang	(SVM)	91.53%

Table.2. Literature Review

10.7. Challenges and Limitations of Approaches

Despite the promising results obtained from various ML models in predicting and detecting COVID-19, there are several challenges and limitations that need to be addressed:

10.7.1. Data Quality and Availability. The performance of ML models heavily depends on the quality and quantity of the available data. Insufficient data or data with a high level of noise may lead to inaccurate predictions or model overfitting. Moreover, collecting high-quality, reliable, and up-to-date data on COVID-19 cases, deaths, recoveries, and other relevant factors remains a significant challenge.

10.7.2. Model Generalizability. While the ML models show promising results in specific scenarios, their generalizability to other settings remains uncertain. Factors such as variations in demographics, healthcare systems, and local COVID-19 policies may affect the model's ability to perform well in different contexts. Therefore, it is essential to evaluate and refine the models to ensure their applicability and effectiveness across various settings.

10.7.3. Model Integration. Integrating ML models into existing healthcare systems and workflows can be challenging. Various practical, technical, and regulatory barriers may hinder the seamless implementation and use of ML models for COVID-19 prediction and detection. Overcoming these barriers is essential to fully leverage the potential of ML models in combating the pandemic.

10.7.4. Ethical and Privacy Considerations. The use of ML models in healthcare applications, including COVID19 prediction and detection, raises ethical and privacy concerns. Ensuring the responsible and secure use of sensitive data, while maintaining individuals' privacy, is a critical challenge that must be addressed to promote trust and acceptance of these technologies.

In conclusion, while the current applications of ML models in predicting and detecting COVID-19 show promising results, addressing the challenges and limitations mentioned above is crucial for further improving the models' performance and maximizing their potential in combating the pandemic.

11. Conclusion

In conclusion, this review has analyzed the recent advancements in machine learning models for predicting and detecting COVID-19. Various ML models, including XGBoost, LSTM, Random Forest, SVM, CNN, and AutoML, have shown promising results in different applications related to the pandemic. Despite the success of these models, several challenges and limitations remain, such as data quality and availability, model generalizability, and the need for interdisciplinary collaboration.

The analysis has highlighted the importance of using diverse and reliable data sources and adapting models to various settings to ensure their applicability and robustness. It is crucial to continue researching and refining these models to further enhance their predictive capabilities, which can aid in improving public health response and decision-making during the ongoing pandemic and potential future health crises.

Moreover, fostering interdisciplinary collaboration among researchers in the fields of data science, epidemiology, and public health can lead to the development of innovative and effective solutions for addressing global health challenges. By building on the advancements and lessons learned from the COVID-19 pandemic, the research community can work together to create a more prepared and resilient world in the face of future health emergencies.

References

[1] Bhandari S, Tak A, Gupta J, et al. Evolving trajectories of COVID-19 curves in India: prediction using autoregressive

- integrated moving average modeling [Preprint] Posted 2020 Jul 7. Research Square. c.
- [2] E. Casiraghi et al., "Explainable Machine Learning for Early Assessment of COVID-19 Risk Prediction in Emergency Departments," in IEEE Access, vol. 8, pp. 196299-196325, 2020, doi: 10.1109/ACCESS.2020.3034032
- [3] Ferdib-Al-Islam, Rayhan Robbani, and Md. Wali Ullah. 2022. COV-HM: Prediction of COVID-19 Patient's Hospitalization Period for Hospital Management Using SMOTE and Machine Learning Techniques. In Proceedings of the 2nd International Conference on Computing Advancements (ICCA '22). Association for Computing Machinery, New York, NY, USA, 25–33. https://doi-org.cyrano.ucmo.edu/10.1145/3542954.3542959
- [4] F. Rustam et al., "COVID-19 Future Forecasting Using Supervised Machine Learning Models," in IEEE Access, vol. 8, pp. 101489-101499, 2020, doi: 10.1109/ACCESS.2020.2997311 [5] H. Turabieh and W. Ben Abdessalem Karaa, "Predicting the Existence of COVID-19 using Machine Learning Based on Laboratory Findings," 2021 International Conference of Women in Data Science at Taif University (WiDSTaif), Taif, Saudi Arabia, 2021, pp. 1-7, doi: 10.1109/WiDSTaif52235.2021.9430233
- [6] Joanna Albargi and Salma Elhag. 2022. Developing an Automatic COVID-19 Diagnostic Care System Using Machine Learning. In The 5th International Conference on Future Networks & Distributed Systems (ICFNDS 2021). Association for Computing Machinery, New York, NY, USA, 155–161.

org.cyrano.ucmo.edu/10.1145/3508072.3508097

- [7] J. Tetteroo, M. Baratchi and H. H. Hoos, "Automated Machine Learning for COVID-19 Forecasting," in IEEE Access, vol. 10, pp. 94718-94737, 2022, doi: 10.1109/ACCESS.2022.3202220
- [8] L. Wang, H. Shen, K. Enfield and K. Rheuban, "COVID-19 Infection Detection Using Machine Learning," 2021 IEEE International Conference on Big Data (Big Data), Orlando, FL, USA, 2021, pp. 4780-4789, doi: 10.1109/BigData52589.2021.9671700.
- [9] L. W. Mary and S. A. A. Raj, "Machine Learning Algorithms for Predicting SARS-CoV-2 (COVID-19) A Comparative Analysis," 2021 2nd International Conference on Smart Electronics and Communication (ICOSEC), Trichy, India, 2021, pp. 1607-1611, doi: 10.1109/ICOSEC51865.2021.9591801.
- [10] M. Rohini, K. R. Naveena, G. Jothipriya, S. Kameshwaran and M. Jagadeeswari, "A Comparative Approach To Predict Corona Virus Using Machine Learning," 2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS), Coimbatore, India, 2021, pp. 331-337, doi: 10.1109/ICAIS50930.2021.9395827.
- [11] M. F. Jojoa Acosta and B. Garcia-Zapirain, "Machine Learning Algorithms for Forecasting COVID 19 Confirmed Cases in America," 2020 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT), Louisville, KY, USA, 2020, pp. 1-6, doi: 10.1109/ISSPIT51521.2020.9408742.
- [12] Mohamed M. Dessouky, Sahar F. Sabbeh, and Boushra Alshehri. 2022. A Survey on Deep Learning and Machine Learning for COVID-19 Detection. In The 5th International Conference on Future Networks & Distributed Systems (ICFNDS 2021). Association for Computing Machinery, New York, NY, USA, 128–137. https://doiorg.cyrano.ucmo.edu/10.1145/3508072.3508094
- [13] P. Podder and M. R. H. Mondal, "Machine Learning to Predict COVID-19 and ICU Requirement," 2020 11th International Conference on Electrical and Computer Engineering (ICECE), Dhaka, Bangladesh, 2020, pp. 483-486, doi: 10.1109/ICECE51571.2020.9393123.

- [14] P. Wu et al., "An Effective Machine Learning Approach for Identifying Non-Severe and Severe Coronavirus Disease 2019 Patients in a Rural Chinese Population: The Wenzhou Retrospective Study," in IEEE Access, vol. 9, pp. 45486-45503, 2021, doi: 10.1109/ACCESS.2021.3067311
- [15] Richvichanak Chrin and Sujing Wang. 2022. Analysis and Prediction of COVID-19 Data using Machine Learning Models. In 2021 10th International Conference on Computing and Pattern Recognition (ICCPR 2021). Association for Computing Machinery, New York, NY, USA, 296–301. https://doiorg.cyrano.ucmo.edu/10.1145/3497623.3497671
- [16] S. A. -F. Sayed, A. M. Elkorany and S. Sayed Mohammad, "Applying Different Machine Learning Techniques for Prediction of COVID-19 Severity," in IEEE Access, vol. 9, pp. 135697-135707, 2021, doi: 10.1109/ACCESS.2021.3116067
- [17] Sravan kiran Vangipuram and Rajesh Appusamy. 2021. MACHINE LEARNING FRAMEWORK FOR COVID-19 DIAGNOSIS. In International Conference on Data Science, Elearning and Information Systems 2021 (DATA'21). Association for Computing Machinery, New York, NY, USA, 18–25. https://doi-org.cyrano.ucmo.edu/10.1145/3460620.3460624
- [18] Stefanos Zervoudakis, Emmanouil Marakakis, Haridimos Kondylakis, and Stefanos Goumas. 2021. Prediction of COVID-19 Infection Based on Symptoms and Social Life Using Machine Learning Techniques. In The 14th PErvasive Technologies Related to Assistive Environments Conference (PETRA 2021). Association for Computing Machinery, New York, NY, USA, 277–283.

org.cyrano.ucmo.edu/10.1145/3453892.3462696

- [19] V. K. Gupta, A. Gupta, D. Kumar and A. Sardana, "Prediction of COVID-19 confirmed, death, and cured cases in India using random forest model," in Big Data Mining and Analytics, vol. 4, no. 2, pp. 116-123, June 2021, doi: 10.26599/BDMA.2020.9020016
- [20] Yiming Fei. 2021. Analysis the use of machine learning algorithm-based methods in predicting COVID-19 infection. In Proceedings of the 2nd International Symposium on Artificial Intelligence for Medicine Sciences (ISAIMS '21). Association for Computing Machinery, New York, NY, USA, 88–94. https://doiorg.cyrano.ucmo.edu/10.1145/3500931.3500948
- [21] Zhanyang Sun, Rui Ding, and Xinyu Zhou. 2022. Machine Learning Applications in Forecasting of COVID-19 Based on Patients' Individual Symptoms. In Proceedings of the 3rd International Conference on Intelligent Science and Technology (ICIST '21). Association for Computing Machinery, New York, NY, USA, 39–44. https://doi-org.cyrano.ucmo.edu/10.1145/3507959.3507966