

Systematic Review

Covid-19 Outbreak Prediction: A Systematic Review of Mechanistic, Statistical, and Artificial Intelligence–Based Model

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Abstract

With the emergence of the COVID-19 pandemic, reliable methods for predicting future disease trends must be developed to improve planning and public health interventions at national and global scales. An accurate and robust method of epidemic forecasting is a necessary foundation for evidence-based public health response and pandemic preparedness efforts. The emergence of the novel coronavirus outbreak sparked an unprecedented rapid development of various kinds of predictive frameworks, including mechanistic models, classical statistics-based approaches, machine learning methods, as well as hybrid or ensemble strategies, each offering unique strengths and weaknesses in different epidemiological situations. This study conducts a comprehensive and integrated evaluation of the mentioned predictive models, with a focus on their underlying assumptions, forecasting performance, and practical significance in real-life scenarios. Although important for generating future scenarios, mechanistic compartmental models such as SIR and SEIR and their variations are increasingly inaccurate when transmission coefficients change due to mutations, differences among populations, and sudden shifts in human behaviour. Despite providing a good short-term prediction, statistical models struggle with the lack of stationarity in data and potential surveillance biases. Hybrid and ensemble approaches proved to be the most robust methods in times of high epidemiological uncertainty, reliably minimising biases associated with specific models and improving overall robustness. It was found that accuracy in forecasting can only be ensured when data quality, model complexity, forecast period, and structural changes in the epidemics' evolution process are taken into account. The present review combines all these findings to point out some key limitations in all existing models and highlight possible areas for further research based on advanced data pipelines, interpretable AI and multi-level prediction environments.

1. Introduction

The emergence of coronavirus disease (COVID-19) caused by the virus SARS-CoV-2 has been one of the most daunting public health problems in the world recently. With its rapid spread, high transmission potential, and unpredictable epidemiology, it became important that this pandemic was predicted with utmost accuracy. Prediction is of vital importance in making plans to combat the pandemic effectively. However, owing to the difficult nature of this virus, prediction has been quite a daunting task. According to Ioannidis, “many early COVID-19 predictions have been spectacularly wrong” [1].

The approaches employed for predicting the onset of a coronavirus outbreak are epidemiological modelling, statistical modelling, and AI-based modelling. Epidemiological modelling approaches include SIR and SEIR, which place individuals into compartments, and model their progress through stages of infection [2]. These models are interpretable and help understand the process of disease transmission.

Statistical approaches such as ARIMA and exponential smoothing use previous data and do not model any biological processes while predicting the number of cases in the future [3]. They are useful for short-range forecasting when data is reliable.

The use of machine learning (ML) and deep learning (DL) approaches, including support vector regression (SVR), random forests (RF), and LSTM, exploits heterogeneous data (including mobility indices, climate variables, demographics) to reveal nonlinear associations in the disease's spatial-temporal diffusion [4]. Additionally, hybrid or ensemble approaches can be applied to benefit from the advantages of multiple methods while minimizing biases in prediction results [5].

The process of developing an outbreak prediction model requires following an algorithmic approach consisting of four stages: data collection, modelling, validation, and uncertainty quantification.

The data include confirmed cases, recoveries, deaths, population density, mobility indices, social media posts, and web search frequencies. Modelling consists of estimating parameters in epidemiological models (like transmission rates, recovery rates) or in ML/DL models (feature selection, hyper parameters' tuning). Cross-validation, rolling window evaluation, and out-of-sample evaluation are ways to validate a model.

Uncertainty quantification is an important stage that adds realism to forecasts by providing confidence intervals or probability distributions. As Yang et al. note in their paper (2023), uncertainty should be included when predicting the long lead times of the COVID-19 pandemic due to changes in virus strains [6].

However, despite significant developments, none is always better than the others under all circumstances. This is because predictions are influenced by variables such as data accuracy, geographic location, methods of intervention, and modelling timescales. Most researchers point out that hybrid approaches might have greater predictive success due to their combination of epidemic theory and AI-based predictions [7].

2. Prediction Techniques for Covid-19 Outbreaks

Several different modelling approaches have been devised for forecasting the transmission trends of COVID-19. Compartmental epidemiological models like the Susceptible-Infective-Recovered model (SIR) and the Susceptible-Exposed-Infective-Recovered model (SEIR) serve as the foundation of any mechanistic model, wherein individuals in a population are divided into states of diseases and their transitions are modeled with respect to time. The dynamics of an epidemic can be described using mathematical equations based on epidemiology [8].

Statistical forecasting models that utilize time series data, such as ARIMA (Autoregressive Integrated Moving Average) models, do not include biological processes and use past data to predict future trends. These models are ideal for near-future predictions because they are based on very recent trends [9].

Due to developments in algorithms and the availability of huge amounts of data, ML and DL techniques, in particular LSTM networks, have been extensively used for predicting future trends in COVID-19. The above models can make use of nonlinearity and various types of predictors, including population movements, weather factors, etc., and often result in superior predictive accuracy than conventional statistical models [5]. In order to benefit from both mechanisms, there have been efforts toward hybridising the models. For instance, using mechanistic epidemic modelling techniques, such as SEIRD, together with the ARIMA correction approach can enhance the forecast performance by improving the residuals due to the structural error of the compartmental models [10]. An example of another hybrid approach that is commonly used is the ARIMA-LSTM approach, where the ARIMA accounts for linearity in the time series and the LSTM part models non-linearities [11].

Other possible hybrid approaches involve nesting, where there is the incorporation of the compartmental approaches, such as SIRV models, together with other models [12]. Overall, these models provide an adaptable toolbox for predicting pandemics and aiding decision-making processes. These models not only increase their precision and robustness in different regimes of data but also contribute to making decisions regarding public health in terms of analysing various scenarios and projecting them in the short term.

2.1. Epidemiological Methods

Models based on epidemiology have been crucial in understanding the transmission pattern and epidemic development in the case of COVID-19, by giving mechanistic insights into phenomena that statistical and machine learning models cannot provide. Amongst those models, compartmental models serve as the theoretical foundation of modelling of diseases and epidemics. Classic models, such as the Susceptible-Infectious-Recovered (SIR) describe the transmission process of a disease in terms of rates of transition between compartments in the population. It is from such models that newer models were devised for SARS-CoV-2 [13].

As COVID-19 presents an incubation period and substantial pre-symptomatic transmission, the use of Susceptible-Exposed-Infectious-Recovered (SEIR) models became prevalent over simpler models due to their superior description of the transmission dynamics of the virus [8].

During the early stages of the pandemic, simulations based on SEIR modelling had a pivotal influence on decision-making in healthcare. In particular, one such influential simulation used an age-specific SEIR model with compartments for hospitalisation and deaths to examine non-pharmaceutical interventions (NPIs) [14].

In the early days of the pandemic, simulations based on SEIR models helped make significant contributions towards public health policy making. In a groundbreaking study that employed an SEIR model with age-structure along with hospitalisation and death compartments, the efficacy of NPIs was determined [14]. Through their analyses, it was found out that there would be an overwhelming impact on healthcare systems without any interventions, while social distancing and shutting schools were among the measures that helped lower R_e significantly [15].

With time, more complex modelling efforts came into focus, providing insights into long-term trends and heterogeneities of the disease. These provided evidence to show that the possibility of recurrent outbreaks of the disease was quite high without the development of immunity or interventions for quite some time [16].

Additional modelling efforts focused on the spatial structure of epidemics, taking into account mobility networks of people in the process. It was shown that mobility networks sped up the rate of infection spread initially, whereas region-specific policies helped produce different peak times in different areas of interest [5].

While there are many advantages, however, epidemiological models also have certain shortcomings. Firstly, key values like β , σ^{-1} , and γ^{-1} differ depending on the population being examined, the specific strain of the virus in question, and any policies adopted by the government, thus adding an element of uncertainty when making predictions about future trends. Secondly, the assumption that mixing is homogeneous in the population may not be realistic. Despite all these factors, epidemiological models are irreplaceable due to their simplicity, explanatory power, and ability to assess the impact of hypothetical interventions.

2.2. Statistical Methods

Statistical modelling methods have been extensively used for trend analysis, prediction generation, and uncertainty quantification in the case of the transmission dynamics of COVID-19. While the epidemiological approach utilises a set of predetermined mechanistic assumptions, statistical models identify temporal patterns based on data. As such, these approaches prove useful in short-term prediction, particularly during the early stages of the outbreak due to the lack of precise knowledge about biological factors.

ARIMA is one of the most frequently applied statistical techniques for the early prediction of the spread of COVID-19. The method uses the autocorrelations present in the time series dataset to predict the future values of confirmed cases, hospitalisations, and mortality rates. Specifically, as Ceylan found out, the models ARIMA (0,2,1) and ARIMA (2,1,2) proved to be highly accurate in short-term predictions of the disease prevalence in Italy, Spain, and France [17].

Other than ARIMA, various exponential smoothing methods have been widely utilised to model the high variability noted in the incidence rate of COVID-19. These models give more weight to recent values while reducing the weight assigned to older ones, thus making it possible to adapt to changes quickly. According to Perone, exponential smoothing and Holt-Winters models proved to be highly accurate when making 7- and 14-day predictions in a few European nations, surpassing some mechanistic models in scenarios with noise and missing data [18].

Statistical models based on regression also played an important role in increasing the predictive value of forecasting. Regression methods such as multiple linear regression, Poisson regression, and negative binomial regression were used regularly to establish the relationship between the growth in the number of COVID-19 cases and explanatory variables like the number of tests conducted, changes in mobility, meteorological conditions, and government interventions. Liu et al. used GLM models for analysis of data about the initial stages of the pandemic in Wuhan and concluded that decreasing population mobility significantly slowed the spread of the disease in February 2020 [19].

Another statistical tool that is worth noting is that of the time-varying reproduction number (R_t). This tool played an important role in epidemiological tracking, allowing one to estimate changes in the reproduction rate before an increase in cases. Estimating R_t can be done using Bayesian approaches such as EpiEstim [9].

However, some limitations exist within these models. The models' reliance on historical trends means that the assumption of continuity is made; hence, they tend to be unreliable when there are sudden changes in structures, like new variants or fast behavioural shifts. Also, they cannot explain biological pathways or infection processes. However, due to their minimal demand for data, efficiency, and accurate predictive abilities in the short run, these models form an important component of forecast models used in the projection of the COVID-19 pandemic [20].

2.3. Machine Learning and Deep Learning Models

ML and DL techniques have emerged as critical components in predicting the behaviour of the spread of COVID-19, owing to their capability to analyse complex nonlinear interactions, incorporate multiple sources of information, and outperform conventional statistics-based and compartment-based models in terms of short- and mid-range forecasts. These methods leverage various data sources, including mobility indicators, medical data, social media, environmental factors, and historical case numbers to generate flexible and accurate forecasts [21].

In terms of ML techniques, SVMs, RFs, DTs, and gradient boosting, like XGBoost, are frequently used for disease outbreak forecasting. For example, Ardabili et al. found that RF and XGBoost performed better than ARIMA for daily infections forecasting in several countries, as indicated by RMSE values less than 2.5% [22]. Similarly, Singh et al. found that regression analysis based on SVM was successful in predicting the infection trend for the next 5 days and 10 days in India compared to traditional exponential and polynomial models [23]. The application of ML techniques is especially useful when dealing with noisy and incomplete data, which is common in the initial phase of pandemics.

DL techniques improve on this by identifying patterns in time sequences. RNNs, especially those based on LSTM and GRU types of neural networks, have found wide use since they can model sequential dependencies over extended periods. Chimmula and Zhang used an LSTM network for predicting the outbreak of COVID-19 cases in Canada. They successfully predicted the date of peak cases and then accurately predicted when the number of cases would start declining; their model was better performing than both ARIMA and Holt-Winters models [24]. In addition, CNN and combined CNN-LSTM models have been applied for identifying spatial dependencies in geographical data, generating predictions at regional levels [25].

Current advances in deep learning (DL) include attention models and transformer networks, facilitating long-range predictions by incorporating multiple data sources such as mobility patterns, demographics, policy indexes, and environmental variables. The resulting models create a more realistic depiction of the real-life drivers of spread dynamics and can easily adapt to unexpected changes due to new variants or policies. Ensembles of LSTM, XGBoost, and mechanistic epidemiological assumptions have proved to be better at maintaining forecast robustness. However, despite their superior prediction capabilities, ML and DL algorithms suffer from numerous drawbacks. They require big high-quality data sets, limiting their usefulness in early outbreak periods or areas where there is low testing. Their lack of transparency due to the “black box” principle reduces their interpretability and hence affects policy decisions. Overfitting and sensitivity to distributional changes in the data are recurring issues. However, by combining these algorithms with mechanistic epidemiology, one creates hybrid forecasting models that are interpretable while retaining superior predictive accuracy.

2.4. Hybrid and Ensemble Model

Hybrid modelling as well as ensemble modelling techniques have been proven to be some of the most accurate and reliable ways of predicting outbreaks of the COVID-19 virus. These types of models leverage the strengths of conventional disease and statistical models, which include interpretability, together with ML/DL abilities that incorporate nonlinear learning to reduce biases, increase generalisation, and build resilience in the event of noisy or fast-changing epidemic data [26]. Hybrid frameworks exhibited high levels of adaptability in response to new waves and variant strains of the COVID-19 virus.

One of the early and most used hybrid modelling strategies involves the integration of linear time-series analysis with artificial neural networks using the ARIMA–ANN strategy. Ribeiro et al. showed that the ARIMA–ANN model is capable of producing much more accurate multi-step predictions of the case numbers of the COVID-19 outbreak in Brazil, outperforming the traditional ARIMA and ANN methods by 21% according to the RMSE criterion [27]. The idea behind the hybrid strategy is that the ARIMA process captures the deterministic features while the ANN handles the non-linear components, making the hybrid model well-suited to highly dynamic epidemics.

Zeroual et al. tested the effectiveness of a model ensemble that included LSTM, CNN, and Bi-LSTM models in predicting the number of cases globally for COVID-19, where they achieved considerable success compared to using individual models for prediction, particularly in cases of sudden spikes attributed to super-spreaders or testing variations [28]. Various techniques such as ensembling, weighting, and stacking were employed to counteract overfitting.

The development of hybrid systems that incorporate epidemiological models and machine learning layers presents a breakthrough. The hybrid model delivered more accurate forecasts of outbreak scenarios in provinces of China, as it incorporated real-time mobility, demographic, and policy information, thus addressing the shortcomings of both fully mechanistic and fully data-driven models [29].

While hybrid and ensemble models deliver more accurate predictions than other methodologies, they are highly complex, and the tuning process is laborious. Moreover, when multiple deep learning networks are used in such models, the predictions become less transparent. Nevertheless, due to their higher precision, ability to adapt to rapid shifts in data, and capability to handle diverse types of datasets, hybrid and ensemble approaches remain essential components of modern epidemic prediction.

3. Comparative Performance of Different Models

The prediction of the path of progression of the disease has entailed the employment of various mathematical and computational approaches, which are efficient at predicting over specific intervals of time, types of data, and policy considerations. Research comparing various models based on epidemiology, statistics, machine learning (ML), deep learning (DL), and hybrids shows that there is no best approach when applied across different scenarios. The success of one model is thus contingent upon the prediction interval, available data, epidemic structure, and need for interpretation.

3.1. Short-Term Forecasting Performance

Short-term prediction (covering a timeframe of up to 14 days) is mostly driven by changes that took place recently in terms of disease transmission dynamics, testing strategies, reporting delays, and population movement. At this time scale, ML and DL models have been found to perform significantly better than conventional statistics-based and epidemiological models, mainly because of their capacity to quickly adapt to changes in the input data.

For instance, tree-based models such as Random Forest, Gradient Boosting, and XGBoost have exhibited a considerable reduction in forecasting accuracy metrics such as RMSE and MAPE in comparison to autoregressive models. This gain in performance has been observed especially for ML models when high frequency of temporal features and recent case trajectories are used as an input [21].

Short-term forecast performance is further enhanced by modelling temporal dependencies found in time series through deep learning methods. It has been shown that RNN models, particularly LSTM and GRU, are suitable for conducting multistep predictions since they model long-term dependencies as well as complex nonlinearities that linear models cannot effectively represent. The usage of LSTM-based models has been successful in improving peak and trend reversal forecasts of cases of COVID-19 in the short term [15].

Further evaluation of machine learning and deep learning models using rolling origin and sliding window techniques on both nationwide and regional data also highlights the importance of continually training models with fresh data in order to respond to sharp deviations in behaviour in reporting practices, interventions, or outbreaks [9].

Although ML and DL models have proven highly effective in short-term prediction, there are drawbacks associated with these models. For example, they depend on large and well-organised data and also lack interpretability compared to mechanistic models. However, ML and DL models still constitute the most prominent modelling techniques used in short-term predictions that require quick response times and accuracy.

3.2. Long-Term Forecasting and Scenario Projections

Long-range forecasts, ranging from several weeks to months, require modelling techniques capable of capturing the underlying disease transmission dynamics and other related phenomena, including immunity and vaccination, as well as public health intervention effects. In this regard, epidemiological models, specifically SEIR-type models, have more advantages compared to black-box machine learning methods. Being built upon the representation of fundamental biological and epidemiological processes, epidemiological models become highly advantageous for scenario analysis due to their transparency and capacity to simulate a wide range of possible situations, such as lockdown policies, vaccination, and appearance of immune escape variants [8].

In comparative evaluations of predictive performance on long horizons, it was revealed that machine learning models demonstrate deteriorating forecast quality beyond 14–21 days, especially in cases when there is some behavioural shift or public health intervention. The main cause behind this limitation consists in the fact that these approaches are not able to capture long-term trends beyond recent historical dynamics. On the contrary, compartmental models (especially those with age structure) are more consistent for longer periods due to their explicit representation of susceptible depletion and potential re-infections.

3.3. Stability Across Variant Waves and Structural Breaks

The quality of prediction usually suffers during times of structural change, including the discovery of new strains of SARS-CoV-2 (such as Alpha, Delta, and Omicron) or a sudden imposition of NPIs. In these scenarios, a combination or ensemble model outperforms traditional statistics, epidemiological, and machine learning techniques. Hybrid models that couple SEIR with machine learning or artificial neural network calibration can modify mechanistic parameters, such as transmission rate (β), incubation period, and intervention impacts, thereby facilitating accurate predictions [29].

Ensemble methods of forecasting also offer an extra degree of stability through the aggregation of predictions from different types of mechanistic and statistical models. Studies have found that the predictions generated from such ensemble systems often outperform the predictions generated using most other models, especially when there is a lot of uncertainty in the environment, as has been proven using studies on COVID-19 prediction at national and global forecast centres [30].

3.4. Interpretability and Policymaker Usability

The concept of interpretability can be considered an important measure in assessing the practicality of forecasting models for decision-making purposes in public health. Statistical modelling and compartmental epidemiological models, especially SEIR-type models, are currently the most interpretable types of forecasting models. Such models estimate epidemiologically significant measures, including the effective reproductive number (R_t), epidemic growth rate, fatality rate of infections, and the effect of NPIs. Interpretable results allow making reasonable decisions on locking down the city, hospital capacity planning, prioritising vaccination, etc.

At the same time, despite the advantages that machine learning models and especially deep learning models have in short-term predictions, their inner workings are highly unpredictable. Consequently, interpretability cannot be a defining characteristic of such models. Hybrid modelling, on the other hand, is capable of combining interpretable epidemiological models with more advanced models based on real data [8]. Nevertheless, even hybrid models usually offer less certainty than either pure mechanistic models or purely statistical models. For that reason, when considering applications of models for policy, ease of use and understanding of the model tend to take precedence over incremental increases in precision of the forecast.

The epidemiological modelling approaches are compared in Table 1.

Table 1: Comparative Overview of Epidemiological Modelling Approaches for COVID-19

Model Type	Core Structure	Key Features	Applications in COVID-19	Strengths	Limitations
SIR Model	Susceptible → Infectious → Recovered	Simple compartmental framework using transition rates	Early theoretical understanding of COVID-19 spread	Mechanistically interpretable; low data requirements	Does not account for incubation period or asymptomatic transmission
SEIR Model	Susceptible → Exposed → Infectious → Recovered	Incorporates latent (incubation) period	Widely used for national and regional COVID-19 forecasting	Better representation of disease progression	Assumes homogeneous mixing; sensitive to parameter estimation
Extended SEIR Models	SEIR + additional compartments (hospitalised, ICU, deceased)	Age-structured and severity-based modelling	Evaluation of non-pharmaceutical interventions (NPIs)	Useful for healthcare capacity planning	Increased complexity and parameter uncertainty
SEIRS Model	SEIR with loss of immunity	Includes waning immunity and reinfection	Long-term and post-pandemic scenario analysis	Captures recurring outbreak dynamics	Requires long-term immunity data
Spatial / Metapopulation Models	Multiple interconnected SEIR systems	Incorporates geographic regions and mobility patterns	Assessment of travel restrictions and regional lockdowns	Models ^a inter-regional transmission realistically	High data demand; computationally intensive
Hybrid Epidemiological Models	SEIR combined with ML/statistical calibration	Mechanistic structure with data-driven tuning	Improved short-term and adaptive forecasting	Balances interpretability and accuracy	Integration complexity; model transparency challenges

The statistical models and their applications in COVID-19 prediction are summarized in Table 2.

Table 2: Summary of Statistical Models and Their Applications in COVID-19 Prediction

Model Type	Description	Strengths	Limitations	Real Examples
ARIMA (Autoregressive Integrated Moving Average)	Linear time-series model capturing autocorrelation and overall temporal trends.	Good for short-term forecasting; low data requirement; easy to interpret.	Performs poorly during sudden trend shifts (R_t e.g. new variants, policy changes); assumes linearity; no mechanistic insight.	Ceylan predicted COVID-19 cases in Italy, Spain, and France and reported high accuracy with ARIMA (0,2,1) and (2,1,2) [10].
SARIMA (Seasonal ARIMA)	Extension of ARIMA incorporating seasonality and periodic fluctuations.	Handles seasonal trends; better fits medium-term data with weekly cycles.	Requires stable seasonal patterns; pandemic waves are often irregular.	Perone applied SARIMA to European data, achieving strong weekly forecasts [11].
Exponential Smoothing (SES, Holt, Holt-Winters)	Smoothens noisy data; Holt-Winters adds seasonality.	Robust for short-term prediction; works well when data is incomplete or fluctuating.	Cannot model nonlinear or multi-wave patterns; limited long-term accuracy.	Perone showed Holt-Winters outperforming ARIMA in noisy European case curves [11].
Poisson Regression	Models count data where variance $\approx$ mean (λ). Useful for case numbers, deaths, tests.	Simple; interpretable; identifies significant predictors of transmission.	Not suitable when overdispersion occurs (variance $\gg$ mean).	Liu et al. used Poisson GLM to estimate Wuhan transmission early in 2020 [12].
Negative Binomial Regression	Addresses overdispersion in epidemic data.	More realistic for real-case counts; handles heterogeneity.	Still linear; limited nonlinear pattern learning.	Used in multiple clinical forecasting studies for death and hospitalization counts (e.g., Lancet Infect. Dis. 2020).
Generalized Linear Models (GLM)	Regression framework linking predictors (mobility, weather, policies) to case growth.	Highly interpretable; supports hypothesis testing; quantifies effect of NPIs.	Requires stable data relationships; sensitive to missing variables.	Liu et al. demonstrated GLM accurately modelling Wuhan's early outbreak dynamics [12].
Bayesian Time-Series Models (e.g., EpiEstim, Bayesian smoothing)	Estimates real-time effective reproduction number (R_t) using Bayesian inference.	Excellent for real-time monitoring; quantifies uncertainty; early detection of surges.	Not ideal for long-term forecasting; dependent on incidence data quality.	Widely used globally by public health agencies for real-time R_t tracking.
State-Space & Kalman Filters	Combines observed data with hidden state estimation for smooth predictions	Handles noisy and incomplete datasets; adaptive “online” learning.	Requires careful tuning; unstable in rapidly changing outbreaks.	Used in mobility- integrated forecasting dashboards (2020-2022).

The comparative performance, strengths, and limitations of COVID-19 forecasting models are summarized in Table 3.

Table 3: Model Performance, Strengths, and Limitations Across COVID-19 Forecasting Horizons

Forecasting Dimension	Best-Performing Model Family	Empirical Evidence (RMSE/MAPE/Qualitative)	Key Strengths	Key Limitations
Short-Term (1-14 Days)	ML/DL (RF, XGBoost, LSTM, GRU)	Lower error than ARIMA; RMSE $\downarrow$ 10-30% in comparative studies [9, 17, 19]	High accuracy; captures nonlinear dynamics	Requires large datasets; low interpretability
Medium-Term (2-6 Weeks)	ML/DL + Hybrid Models	Stable accuracy when retrained; hybrids reduce drift [20]	Adaptive; robust to noise	Still sensitive to structural changes
Long-Term (Months)	SEIR / Compartmental Models	More stable projections; coherent scenario analysis [21, 22]	Mechanistic realism; interpretable	Lower precision for short-term
Variant Waves / Structural Breaks	Hybrid + Ensemble Models	Outperform single models during surges and policy shifts [20, 23]	High robustness; mitigates model bias	Computationally intensive
Interpretability for Policymakers	Statistical + SEIR	Provides R_t , β , intervention effects [18, 21]	Simple communication; transparent	Lower raw predictive accuracy
Data Requirements	Statistical (low), SEIR (moderate), ML/DL (high), Hybrid (very high)	-	Matches model complexity to data availability	Limits ML/DL in low-data settings

4. Limitations

Although there have been great strides made in the area of modelling COVID-19 spread, there are still several constraints that exist irrespective of the type of model. Although the epidemiological model is understandable based on its mechanics, it assumes certain static parameters related to the rate of infection, mixing, and immunity period, assumptions that may be unrealistic during abrupt behavioural shifts, sudden policy changes, or due to the emergence of new immune-evading strains [8].

On the other hand, the use of data in statistics, machine learning (ML), and deep learning (DL) models makes them vulnerable to data quality and availability concerns. The performance of such models may be poor under low testing situations, at early stages of the outbreak, or when there is a shift in data patterns, such as new variants causing subsequent waves. ML and DL models also operate as black boxes and are less interpretable, rendering them ineffective in guiding policy decisions in light of the need for clear explanations [9].

5. Conclusions

The area of COVID-19 forecast development has become quite multifaceted, involving epidemiology, statistics, artificial intelligence, and other techniques. The current review has shown that there is no universal superiority of any category of models throughout the whole course of a pandemic. Epidemiological models, especially SEIR variants, will always be necessary for making long-term predictions since they include biological processes that are related to the dynamics of transmission, latent periods, and various interventions. Nonetheless, the effectiveness of such models depends significantly on the stability of parameters that worsen under conditions of rapidly changing policies, behavioural patterns, or mutations.

Statistical models and machine learning techniques have proven to provide greater accuracy in making short-term forecasts since they have a better capability of analysing the patterns, seasonality, and noise present in recent data. They also tend to experience limitations in the form of overfitting, difficulty in interpretation, and sensitivity to reliable data streams, especially in the context of real-time monitoring of pandemics. Deep learning models are highly accurate but require extensive training on high-quality data.

The hybrid and ensemble modelling paradigms proved to be the most robust modelling classes when the virus experienced very unstable behaviour phases. The reason for this was the effectiveness of hybrid models, which, through combining theoretical concepts with actual learning experiences, increased their potential to cope with any changes in structures, whereas ensemble modelling ensured lesser model biases and proved superior to most models in international evaluations.

To sum up, it is evident from the COVID-19 pandemic that future epidemic prediction frameworks need to focus particularly on the aspects of adaptability, robustness, and transparency in addressing uncertainties. To conclude, the ongoing pandemic has demonstrated that the next generation of epidemic prediction frameworks would have to include all elements of a modelling ecosystem, including data management, validation, and reporting mechanisms.

Abbreviations

COVID-19	Coronavirus Disease 2019
SARS-CoV-2	Severe Acute Respiratory Syndrome Coronavirus 2
SIR	Susceptible–Infectious–Recovered
SEIR	Susceptible–Exposed–Infectious–Recovered
R_0	Basic Reproduction Number
R_t	Effective Reproduction Number
AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
LSTM	Long Short-Term Memory
ARIMA	AutoRegressive Integrated Moving Average
SEIRD	Susceptible–Exposed–Infectious–Recovered–Deceased
MCMC	Markov Chain Monte Carlo
PDE	Partial Differential Equation
ABM	Agent-Based Model
NPI	Non-Pharmaceutical Intervention
WHO	World Health Organisation
CDC	Centres for Disease Control and Prevention
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error

Recommendation

According to the findings of this systematic review, there are several recommendations that can be formulated to improve the accuracy of predictive models of the COVID-19 pandemic. It is necessary to focus on developing hybrid models, which incorporate mechanisms, statistics, and artificial intelligence, to get better results. The synergy between epidemiology and artificial intelligence may lead to the higher accuracy of predictions in terms of a fast-moving pandemic.

There is a necessity to utilise larger databases with higher-quality information, which is provided in real-time from all over the world, in order to maximise prediction accuracy and avoid any bias in the findings. Also, researchers should focus on data standardisation to receive consistent results regardless of the type of the model applied.

The potential significance of AI models based on artificial intelligence and deep learning can be emphasised in order to predict pandemic trends and detect new outbreaks, as well as allocate healthcare resources. However, AI models need to be more transparent to provide clear insight into their structure.

Finally, it should be kept in mind that the vaccination rates, population movement, interventions, environment, and virus mutations will also have to be taken into consideration.

It is highly advised that collaboration be encouraged between epidemiologists, statisticians, computer scientists, and other health professionals for the purpose of developing interdisciplinary models of prediction that will assist in creating proper pandemic preparedness plans. Digital surveillance systems can also be used by governments and health organizations to predict and handle infectious disease outbreaks.

Regular evaluation and validation of prediction models are necessary in order for them to be applicable in future infectious disease outbreaks.

Article Information

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