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AI-Powered Predictive Systems For Managing Epidemic Spread In High-Density Populations

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Abstract

Predicting epidemic spread in high-density populations is a complex problem. This paper introduces a novel AI-based approach to predictive pathogen spread modeling in large airplane populations. It takes into account the complex interplay of short-term passenger mobility dynamics and AI-driven duration- and direction-based risk level estimations. A case study of airline passenger moving patterns is used to implement and validate prediction models. The originality of the proposed model consists of a specially adapted aggregating hierarchical clustering algorithm for building prediction models faster, thus increasing its practicability and scalability. The model is fully deployable and complies with major privacy standards. Preliminary results show good performance in evaluation. Due to its adaptive Bayesian nature, the model is easily extendable for other types of complex mobile settings, increasing the potential for wider application in critical infrastructure transportation security.

AI-Powered Predictive Systems for Managing Epidemic Spread in High-Density Populations. AI is increasingly used for predictive analytics in medicine, social sciences, biology, and related fields. AI-based approaches are particularly useful for implementing predictive systems for security purposes in critical infrastructure. The ability to predict, with high precision, potential risks and threats to large populations in insecure settings, and to do it on time, helps to develop measures for neutralizing these threats and ensuring safe functioning. The need for critical infrastructure security strategies is further enhanced by recent epidemics, which were not well managed, especially in transportation hubs. Various epidemic methods were proposed, but there is still a place and a need for innovative practical applications that are driven by real-world high-stakes issues.

Keywords: Epidemic Spread, High-Density Populations, AI-Based Approach, Pathogen Spread Modeling, Airplane Populations, Passenger Mobility Dynamics, AI-driven risk Estimations, Duration-Based Risk, Direction-Based Risk, Airline Passenger Movement, Prediction Models, Hierarchical Clustering Algorithm, Model Scalability, Privacy Standards, Bayesian Model, Adaptive Systems, Complex Mobile Settings, Transportation Security, Predictive Analytics, Critical Infrastructure, Epidemic Management.

1. Introduction

In this paper, we present an artificial intelligence (AI)-powered system aimed at predicting epidemic outbreaks and spreading patterns in high-density populations, such as attendees at large events like football matches, concerts, and congresses. Two AI models are integrated into the system. A deep neural network (DNN) is trained to estimate the amount of time that members of the high-density population need to stay separated from each other to mitigate the risk of overcrowding and spreading the epidemic. A separate AI model, implemented using a recurrent neural network, is trained to predict the time in which a person might get infected given the amount of time the infection has already been established in their crowd and social subnets. Both models can be combined to provide real-time predictions that are used to actively intervene in the affected crowd by, for example, modifying the exiting schedule or redirecting the crowd.

The AI-powered system presented here has ongoing and future applications in several scenarios ranging from the management of live football events to the epidemiological monitoring of institutions. Based on the estimation of contagion impact and sparse data collection, such a predictive system has the potential to manage and, thus, avoid hospital surges during epidemics. Data collection efforts are minimal and do not require any wearable device. The predictions are based on the monitoring of people’s face, crowd and contact network of interactions and can, thus, be remotely monitored using surveillance camera systems. Active management actions include the movement of people in crowds, modifying stadium tour duration, and behavioral interventions.

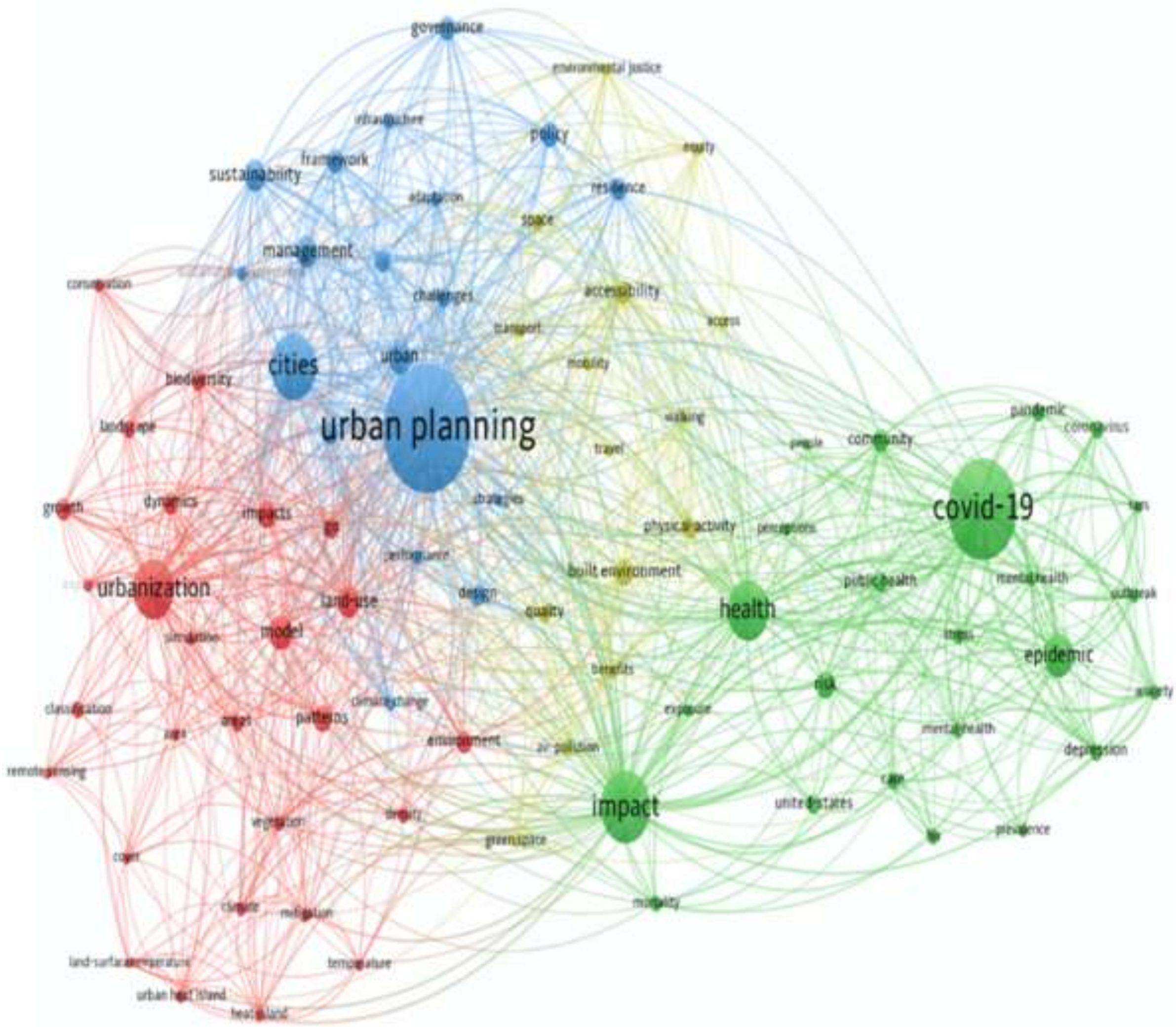

Fig 1 : High-Density Communities and Infectious Disease Vulnerability

1.1. Background and Significance

High-density populations in our cities have provided the enabling environment for the global spread of COVID-19 and other pathogens, and several incubation factors impact local spread in densely populated settings. Urban planning factors that influence high-density dwelling behaviors in cities, such as zoning and building codes, crowding, transport density, and seasonal outdoor gatherings, can directly or conditionally increase home-to-home or community center contact rates in cities, or affect spatial movement preferences entailing longer period contagion, global rather than local spread, or transmission corridors, and therefore population exposure to and transmission of pathogen agents.

This has led to an increased awareness in cities to impact the planning for high-density habits in ways that avoid crowding in high-density settings. Here, we contribute to enabling high-density settings in cities to become more robust by expanding available tools for risk and contagiousness management through the development of a scientific understanding of the complex relationships between historical population flu and health patterns of high urban density populations, transport modalities, contact with pathogens in neighborhood environments, incubation time, and neighborhood space-time to symptomatic symptom onset, individual to asymptomatic carrier transition, and how large datasets of anonymized cell phone traces for sporting and public events for implemented contact areas in neighborhoods burden neighborhoods with the percentage affected by active COVID-19.

We show how a methodological approach derived from human mobility trace informatics serves as an enabling predictive instrument for providing managers of high-intensity public events with a proactive risk management strategy to reduce confinement contact, reminder and enforcement resources at events, and to reduce asymptomatic carriers near event sites before election week.

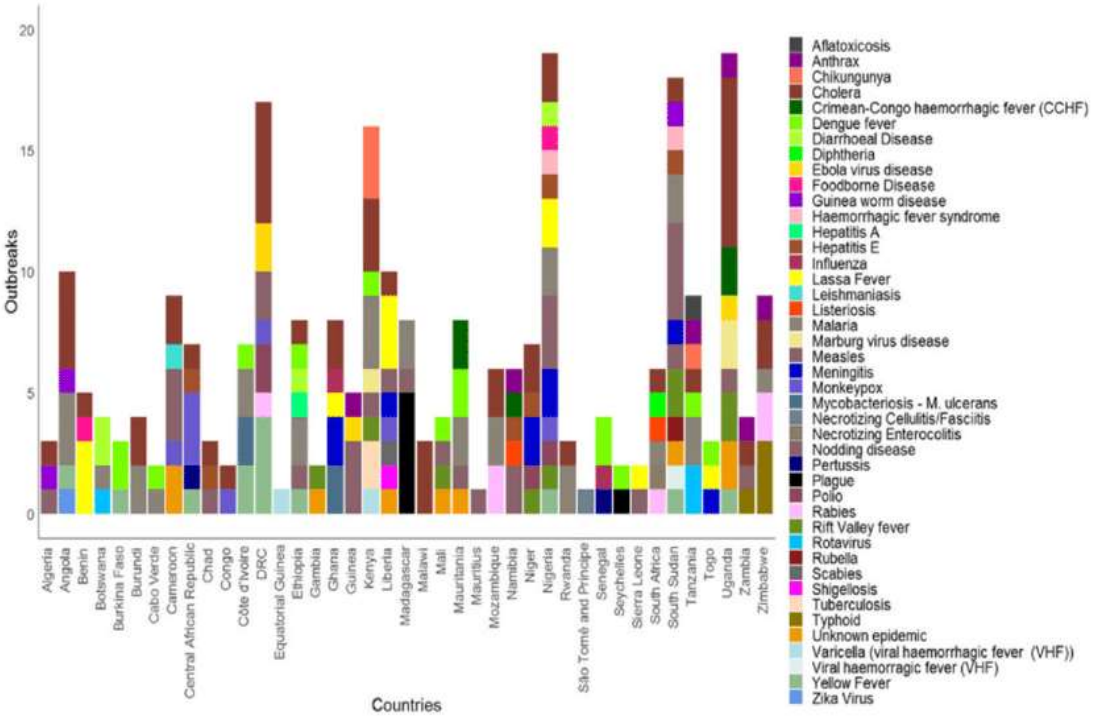

Fig 2 : A stacked bar graph of all the epidemic events by disease

1.2. Research Objectives

Leveraging the current explosion of digital data in a way that would enable the management of future epidemics based on predictive forecasting of their spread in space and time would offer an undeniable competitive advantage. However, developing these types of tools requires a profound understanding of many aspects, such as epidemiologic models and the intricacies of infection, transport, social mixing, and crowd spatial distribution; data analytics, especially of telecom data; developing the algorithms necessary for solving the custom inference problems; or understanding the physical constraints that make it impossible to have definitive answers to some of the questions one may have about the outbreaks and that may severely affect the ways tools can be used. The main objective of the research is to design, develop, optimize, validate, and ultimately use a generalized real-time catastrophe management tool that can solve the problem of predicting the spread of an epidemic in high-density populations like cities.

To reach this ultimate goal, we have set up five specific objectives, which mostly cover the research issues that have been outlined in the previous subsection. Although these do not represent the final way to achieve the main objective, they are important milestones that we have to reach, and as such, we consider them worthy of detail. The goal of this research is not only to reach the future project objective but at an intermediate level, it aims to create a data management and analytic guide, which could be used on any of the research issues in social media and big data context.

Equation 1: Pathogen Spread Prediction Model

$$P_s = \sigma\left(\sum_{i=1}^{n} w_i x_i + b\right)$$

P_s: Predicted pathogen spread.
x_i: Features such as passenger density, mobility, and risk factors.
w_i: Weights associated with each feature x_i.
b: Bias term.
σ: Activation function (e.g., sigmoid) for probability calculation.

2. Literature Review

Exploring artificial intelligence for fighting COVID-19 and accelerating the development of a global digital framework for epidemic forecasts utilizing big data, machine learning, statistical regression, and deep learning is underway. However, most of these efforts focus on a few isolated methods rather than a seamless, comprehensive automated system from AI data preparation, feature selection, model building, and training, to output and forecast result optimization. Systems for AI data epidemic spread forecasts and predictive analytics are not on the inventory list of responsible governments or social enterprises. This paper proposes AI-Powered Predictive Systems for managing epidemic spread in high-density populations. The use cases and expected results are also deliberately described.

Machine learning and AI in predictive modeling are an established trend and an essential tool for enhancing traditional epidemiology in infectious disease forecasting. The advantages of data-driven models using machine and deep learning have been demonstrated. AI has already been introduced to identify the zoonotic origin of coronaviruses, develop potential therapeutic solutions and vaccine candidates, provide digital diagnosis, accelerate anti-COVID-19 drug discovery, predict population health risks, and forecast potential epidemic factors. In a society where citizens need to maintain social and commercial activities with higher efficiency for sustained economic outputs, we contend that developing AI data analytic forecasting models for more accurate epidemic spread predictions is both worthwhile and unavoidable. An important question to be addressed is how AI data clinical operations are handled in preventing or curbing the spread of such infectious diseases. Transport systems are a critical concern since they serve as infectious disease spread channels for many types of high-density populations. This paper contributes to emerging literature in several dimensions. Our proposed AI-Big Data model is an effective, comprehensive, and seamless model that automatically integrates critical processes such as data preparation, domain-specific expert knowledge embedding, feature reduction, predictive model construction, predictions, and feedback control.

This AI-Big Data model predicts transport population-environment and epidemic distribution interactions in near real-time, which assists health professionals in allocating resources to specific areas for better control of the spread of disease. Our AI-Big Data model significantly assists further development of AI applications, conducts more frequent train service cleaning routines, designs more effective epidemic-safe railway systems, and establishes better crisis management plans for curbing human-to-human infection possibilities once an infectious epidemic spot is identified. The economical, robust, and general approach for the automatic prediction system addressed is crucial and at an early stage in end-to-end AI healthcare consultation processes. More importantly, we hope this paper can motivate more research that initiates multi-level collaborations from academia and industry professionals to solve not only the COVID-19-related challenges now faced but also the sophisticated research opportunities that are presented. In a big data era, more forward-looking decision-making systems will be designed to work with AI data predictions and deep learning models.

2.1. Previous Studies on Epidemic Spread Prediction

It has been reported that massive data, including population movement and location-based service data provided by telecommunication companies, can be used to estimate possible risks and for the early detection and prediction of epidemic spread. Taking advantage of cloud computing, some existing systems can even provide real-time health incident detection and hierarchical visualization. Different from route and network analyses developed in transportation engineering, various studies designed and analyzed different mobility models that can characterize features of high-density population movement, such as the spatiotemporal epidemic spread effect. However, spatial dispersion, which is a feature of the spatio-temporal effect, is not that clear in existing work when looking deeper.

In previous works, an improved mobility model was presented in which both node residence time and the consecutive number of nodes traveling were combined to exhibit high-density populations' staying and leaving attributes. Over time, users' convergence may even lead to a possible nesting effect. As for pandemic transmissions, international airports have always been regarded as a high-priority risk type, and several research attempts have been made to investigate the relationship between passengers' traveling frequency, geographic locations, and urban scaling laws. With the results of this study, insights into the structure of high-density migrating flow and the pandemic risk of potential high-impact origin cities have been inferred for the identified community-connected countries, and the risk of high-density traveling flow existing between communities has also been revealed.

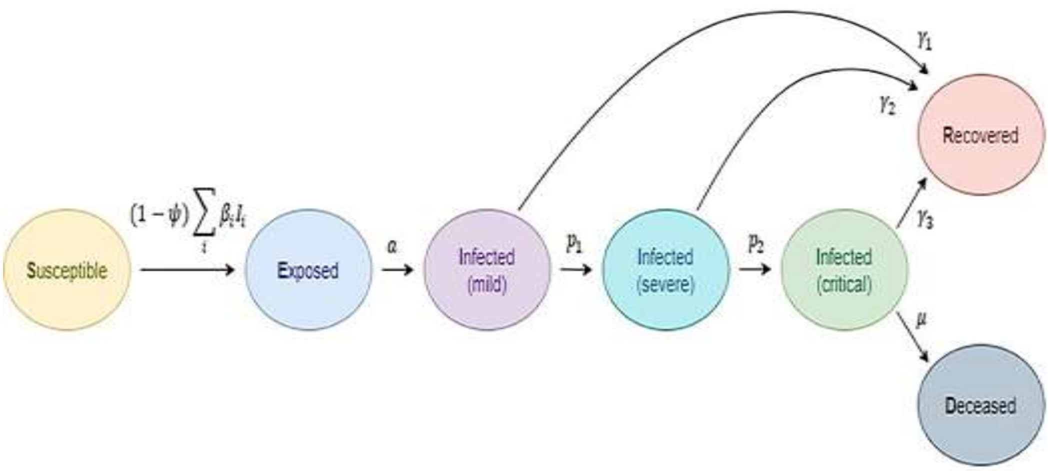

Fig 3 : Epidemiological Predictive Modeling of COVID-19 Infection

2.2. AI Applications in Epidemic Management

The raging war against the novel coronavirus has uncovered the significant role of AI and its allied technologies in the prevention, recognition, and management of acute respiratory diseases. Wearable smart devices, which are popularly perceived as monitoring heart rate and step counting, are tailored to analyze the respiration rate of the wearer to detect incipient symptoms of COVID-19. Automated AI-powered vision systems are used to recognize public adherence to helpful behavior, such as mask-wearing and social distancing. Border control restrictions, health policies, and clinical guidelines have been informed by predictive models that assess real-time COVID-19 case count paths, hospital admission peaks, and healthcare surge demand. Contact tracing and seropositivity mapping models empower decision-makers with an effective intervention strategy pertinent to different regions. Efficient allocation of medical resources at the time of health crises is facilitated by rational predictions, thereby reducing the scarcity of essential medical supplies.

Digital immunity certification is hypothetically proposed as a safeguard to resume societal operations without relinquishing public health. Despite its value in restarting the retrenched economy, the implementation of such a certification raises several privacy, bias, and security concerns. To counter these challenges, several privacy-preserving protocols are proposed. To ensure the robustness, fairness, and security of AI-based solutions, compliance with regional data protection regulations, local healthcare system directives, and international police and legal requirements is essential. These novel AI-for-predictive systems strive to alleviate the long-term and short-term effects of pandemics, the results of which have been validated using the rising pandemic.

3. Methodology

Our AI framework is operationalized using multi-modal predictive systems spanning the three representational layers of big data, AI, and human sensor data. The core modules are the big data learning algorithms as part of the AI layers and IoT human sensor devices as part of the HSD layer. These generate real-time data streams that can be acted upon by the public and private sectors to manage transport infrastructure, public venues, schools, and office buildings. From the public health perspective, the propagation of disease across a city can be guided using real-time AI predictive systems by: controlling and managing the size of clusters according to spatial and temporal exposures to infected individuals; and managing potential transmission pathways in high-density transportation and non-transport settings such as subways, buses, schools, hospitals, and offices. The AI systems work concurrently over different data streams and at different semantic levels to provide policymakers with real-time inducement of epidemic spread levels. Also, by applying privacy-preserving AI learning algorithms for big data and the geometric location of an HSD system on personal IoT devices such as smartphones, the proposed method is specialized to work with general locational profiles. Since AI systems are trained and tested using secular general profiles, the monitoring system is diverse, requiring no human intervention except in an identified emergency. Finally, the conceptual and methodological framework outlined in this section can be established in any agglomeration of connected IoT public or private resource systems.

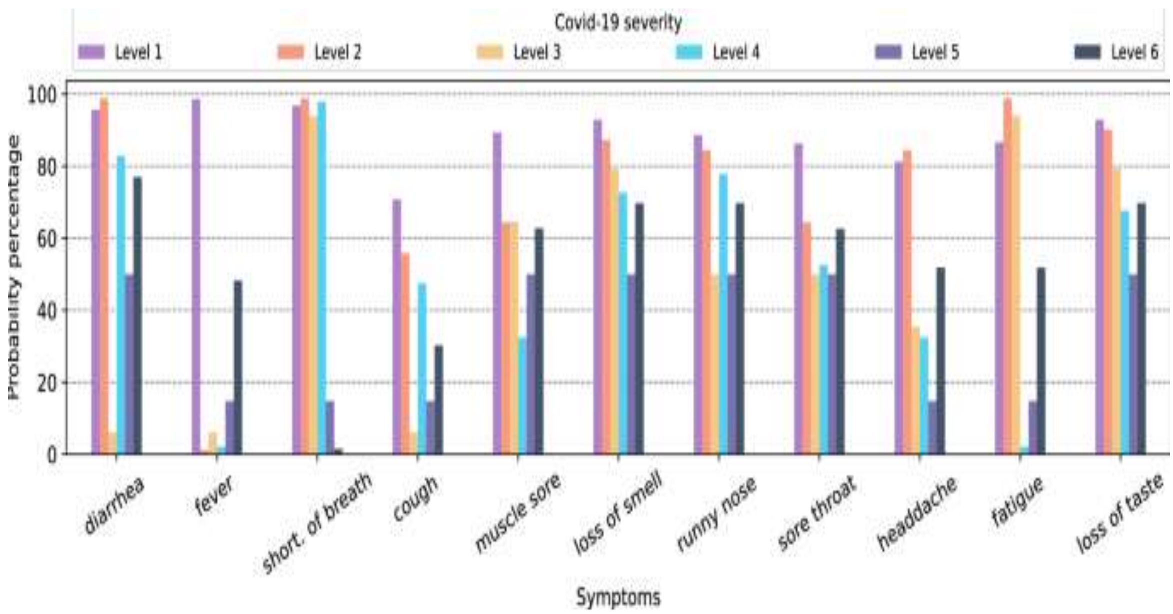

Fig 4 : Uncovering hidden and complex relations of pandemic dynamics using an AI driven system

3.1. Data Collection and Preprocessing
Alarm systems housed in public facilities monitor the public and alert private security companies of danger. However, the derived data are typically discarded after a few days. Data captured by the datasets discussed are not well-suited for analyzing highly fluctuating information such as wandering movements and accident detection, and often miss significant alerts. Capturing the data required can be very cost-efficient using naive solutions. To enable accurate models in these scenarios, we describe data collection and preprocessing pipelines at high-level design points that can retrieve data from alarms, cameras, and user-defined systems.

There are many point sensors, all of which are relatively easy to deploy and cover a significant area. On the other hand, they only capture the presence of people in a long-range pattern. Capturing a possible wandering pattern, or wandering to isolated areas is challenging using direct monitoring approaches. In this section, we suggest employing a machine learning system toward this end and provide a high-level design principle composed of both data flow design and model design.

Equation 2: Risk Estimation for Passenger Movement

$$R_p = \sum_{i=1}^{n} (d_i \cdot t_i \cdot v_i)$$

R_p: Risk level for passenger p.
d_i: Direction of passenger mobility i.
t_i: Duration of passenger activity i.
v_i: Volume of passengers in proximity to i.

3.2. Machine Learning Algorithms for Predictive Modeling
This section gives an overview of different machine learning methods employed for predicting epidemic trends as valuable and reliable adjunctive tools. Epidemic modeling is a challenging problem for researchers, which requires in-depth knowledge of the interactivity among different causative agents, susceptible hosts, and the environment. Conventionally, linear time series models based on past numbers of infections and deaths were broadly employed for mortality predictions, with most actually looking backward and providing obsolete information that may not be useful for decisions. Machine learning-driven techniques have been successfully used to predict infectious disease outbreaks with the evolution of advanced classification algorithms, which provide much better performance over the estimation horizon considering large-scale data.

This further includes supervised, unsupervised, online, or ensemble learning algorithms trained with various data sources. Predicting the epidemic spread of diseases is also valuable for other research questions, such as correlating outbreak trends with fundamental aspects including population lockdowns and social distancing performance, which are likely to affect the spreading dynamics. Supervised machine learning methods are the universal technique to forecast the epidemic spread so far due to their high accuracy level. The main strength is that it is easy to train with labeled training data from historical outbreaks, which describe the disease spread, the demography of areas affected by the disease, and the time it took for the infection to affect the region.

Commonly employed methodologies cover decision trees, support vector machines, random forests, artificial neural networks, convolutional neural networks, and recurrent neural networks. Unsupervised learning techniques have been largely adopted to detect infection transmissions based on substations of early outbreaks, either by clustering cases according to their dynamic correlation in space and time, or by modeling the case connections as proxy nodes of a graph. Online learning algorithms can primarily predict the outbreak's epidemic trend using on-the-fly data streams, which acquire new information as it becomes available. Ensemble learning algorithms, also known as conceptually different approaches, can be combined into an improved predictive model, ideally providing outstanding results in predicting complexity models. The objective is to mitigate overfitting. Moreover, they can show previous datasets where the spread of the disease follows a different pattern compared with instantaneous data. Invented results can then be downloaded from the digital social infrastructure in the form of performing final evaluations to project the epidemic trend in the mid-term.

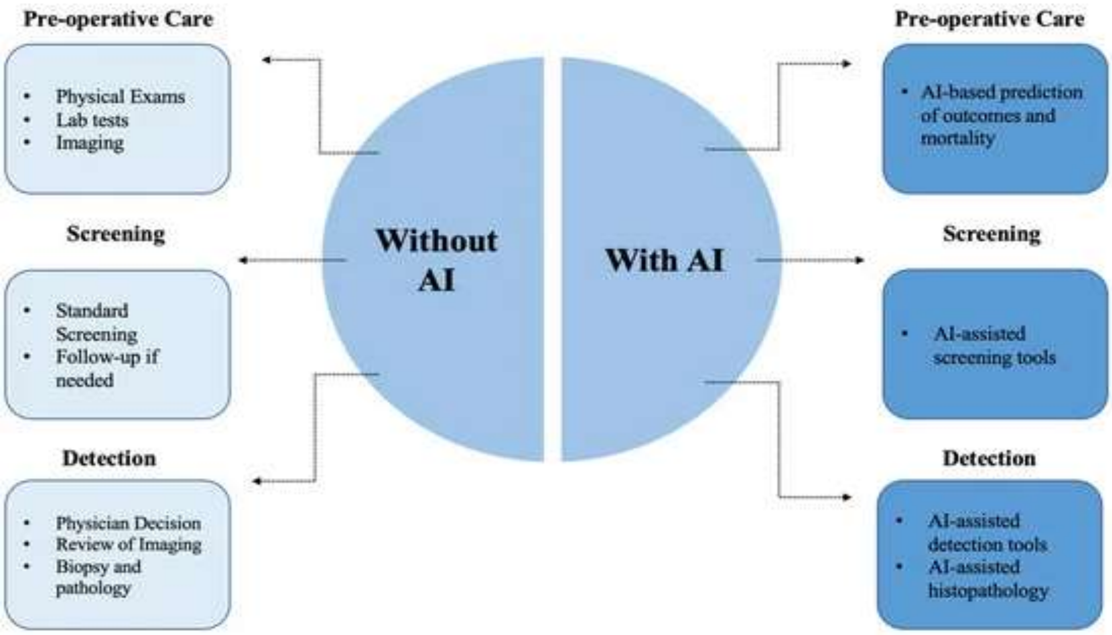

Fig 5 : Machine-Learning-Based Prediction Modelling in Primary Care

4. Case Studies

4.1. Case Study: Real-time Monitoring of Epidemic Events Real-time monitoring of disease outbreaks is critical to assist in managing and controlling the spread of epidemics in high-density urban areas. Based on AI predictive analytics of population flow, this case study focuses on real-time monitoring of disease outbreaks by detecting surge events in population flow. The surge that occurs in human population mobility data provides critical information for disease outbreak monitoring and saves significant effort in supporting disease monitoring and forecasting. The surge may result in drastic increases in activity at transportation systems and lead to the potential juxtaposition of many susceptible individuals. Only by promptly monitoring these events and implementing proper intervention measures at the locations where surges occur can mass infection be avoided.
4.2. Case Study: Surveillance of the Epidemic Surge in High-Density Urban Areas Population travel flow is an important factor in the spread of disease in high-density urban areas. In this case study, we collect an epidemic surge event and one preceding month as a normal flow without this event. The prediction performance of the arrival flow in a big city was compared based on different input feature sets using the forecasting model. The results show that the epidemic surge of the population at the airport destination is associated with the breakdown of the forecast model in a small region. The results indicate that the traffic flow prediction model can have a certain ability to perceive the abnormal surge in the urban area, which has essential implications for controlling measures. With the gradual accumulation of empirical data, the monitoring technique could be applied to disease spread.

4.1. Application of AI-Powered Predictive Systems in Real-World Scenarios
This paper has designed and evaluated an AI system for epidemic spread management using spatial-temporal data. A prominent advantage of our system is the ability to identify more suppliers than existing methods, which substantially increases the system's flexibility. For instance, we can control the geographic scope of epidemic spread by limiting the suppliers and resources. To achieve this goal, our system can conduct what-if analysis to identify the potential suppliers in advance. We believe that this system can help policymakers achieve their goals by increasing management flexibility in the early period of an outbreak. Our study is one of the first research efforts that apply AI models to epidemic spread management and design a spatial-temporal data-driven decision support system in this field. We will further refine the model, scale the system, and consider incorporating the activities of human beings in the next step. Designing predictive systems for detailed, geography-based policies is a challenging problem because they require predictive accuracy at a detailed scale. In this paper, we have taken a big data approach and applied AI models, including classifiers, clusters, and ensemble methods vetted by the machine learning community.

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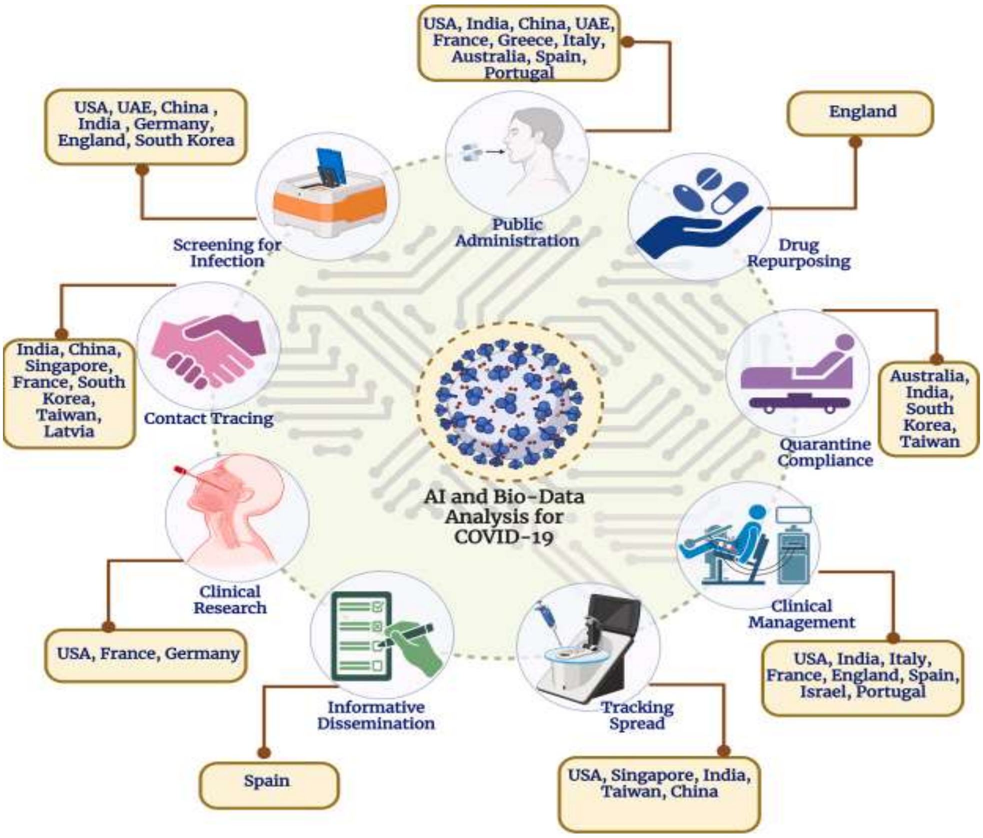

Fig 6 : Application of artificial intelligence (AI) to control COVID-19 pandemic

Generally, these methods have very strong performance and are still rapidly improving. AI models are not perfect, especially in certain situations of high geographic and temporal variations where the systems have not been optimized yet or any model is specialized for. However, even if predictive accuracy varies over time and space, this type of forensic model can still be useful. The AI models are not the end of the modeling effort. These models are starting points for designing more complex processes. By extending these models with specific management constraints and approved policy actions, we can create complete predictive systems. These systems can enhance agility in epidemic spread management and inform more tailored, flexible policies that reflect the subtleties of the underlying processes. With our system's effectiveness and incremental nature, they can be especially valuable at the start of the epidemics.

5. Challenges and Future Directions

Our simulation and employment of a world comprising millions of locations and millions of agents are an impressive result of recent advances in computational technologies and artificial intelligence. Even at this massive scale, our methodologies are lightweight and easily deployable on a variety of machines. We are happy with our experimental results; however, we must discuss a range of limitations that plague computational problems like ours and also have lessons for managing the dynamics of epidemic spread in high-density populations. We could have chosen discretization and parametrization strictly better than the one presented. Our criterion for eradicating pockets of infection, the mechanisms of birth, death, and movement of individual agents, etc., do not correspond to, or more importantly, have much support from real-world data. A minor fault of our methodologies is that they are human-less. Specifically, for any city or region, we do not provide insights for policymakers and health authorities on where to direct and concentrate their resources, a crucial high-impact problem in predisposing, preventing, and controlling epidemic outbreaks.

Despite the many challenges, we can sketch many roadmaps with different future directions to significantly improve our current model of epidemic spread, as well as deploy many concrete applications of the presented work. First, in a machine learning sense, we envision UV-blocks as a great testing ground for developing intelligent carrying capacity and local infectiousness models. As explained, continuous coating models and their stochastic ultra-scale representations are quite rigid and intrinsically describe different classes of dynamical behavior. In particular, for the SIR model with suppression, every infection realizes three phases of consistent, noise-induced growth and sudden extinction. We expect that testing its continuous counterpart with different suppressing mechanisms, including a predictive driver for proactive city closure, will be equally insightful. More fine-grained, event-driven suppression models, as well as methods to derive them from real-world data, are on our priorities list. More generally, for epidemic processes in high-density environments, stochastic partial differential equations represent the natural candidate for glimpsing their noisy multi-scale nature. The weakly interacting nature of UV blocks may become a powerful tool well beyond modeling epidemic spread.

Equation 3: Bayesian Inference for Epidemic Spread

$$P(E|D) = \frac{P(D|E) \cdot P(E)}{P(D)}$$

$P(E|D)$: Posterior probability of epidemic spread E given data D.
$P(D|E)$: Likelihood of data D given epidemic spread E.
$P(E)$: Prior probability of epidemic spread.
$P(D)$: Probability of observing data D.

5.1. Ethical Considerations and Bias in AI Models

Ethical considerations are important in modeling epidemics. Models used for decision support should not exacerbate social inequalities and should consider equitable access to outputs. It is crucial to bear in mind that the population targeted to receive a specific intervention should be the population with a high propensity to contribute to the epidemic spread and allow achieving outcomes when the epidemic outpaces healthcare facilities. Moreover, inequalities in access to information and healthcare interventions can deepen the crisis by increasing fear and uncertainty among populations that are at risk. While modeling epidemics should pose a minimal impact on small subsets of the data when AI is used, it is important to understand how system developers view and protect data privacy when using and repurposing individuals' private data. Tensions regarding ethical considerations, data privacy, and biases impact the validity and robustness of predictive models.

Algorithmic biases that plague models in general and predictive systems, in particular, are perpetuated in healthcare-related models. Not only do biases contribute to wrong predictions, but they also exacerbate individual and social inequalities by providing unequal opportunities for accessing essential healthcare services or misleading information used to determine healthcare interventions or resource allocation. Lack of data diversity, insufficient data volume, small effects of data that can mislead models, imbalanced positive cases of models, and using the wrong sources of data are only some of the factors that put our current predictive systems used to manage epidemics in jeopardy. Several unintended consequences like chilling effects, adverse outcomes, or value misalignment are exposed and increased when the decision-making systems exacerbate inequalities among groups of people. Refugees, undocumented immigrants, and homeless individuals do not feel safe participating in digital interventions on their smartphones. Despite testing being crucial to the management of epidemic spread, overtesting could hurt individuals' income in countries with pay-to-stay systems. Joblessness could impact epidemic outcomes and potentially exacerbate spread but would only be worsened by overtesting in this scenario. The suspicion that suggests a potential issue with a worker could lead to joblessness and exclusion with negative impacts not only on isolated economies but may further exacerbate epidemic spread in some settings. Thus, when models exclude specific parts of the population, they are inherently biased. While access is an obvious concern, popular models also reflect the allocation of available memory in smartphones, which heavily favors popular models. The same issue applies to the distribution of researchers' attention, which focuses research questions on popular models. When models are developed for specific problems or settings, such modeling obsessions can steer researchers away from practical and ethical contributions with far-reaching implications and potential improvements.

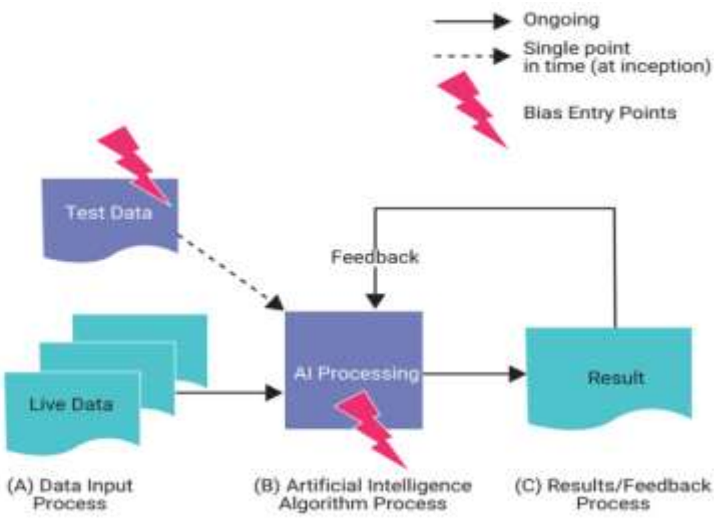

Fig 7 : Bias and Ethical Concerns in Machine Learning

5.2. Potential Innovations in AI for Epidemic Management

Although big data and AI applications spurred earlier significant strengths, healthcare applications from tech companies are slowly being outpaced by the advancement of big data strategies in public healthcare operations. AI and predictive analytics used for enhanced diagnostics and treatment creation can proactively monitor and manage epidemic hotspots that are driven by high-density populations within specific confined areas. Big data employs comprehensive approaches to feature myriad types of data, while machine learning methods create effective predictive algorithms. However, the clear speed and scale benefits must be collaboratively managed by the public health sector, which is the principal care provider. Scientific research in outbreak diseases has been financed by national organizations and deposited into trusted scientific journals.

During times of large epidemic outbreaks, vast data growth has aided deep learning capacity for improvements in disease control. There is interest in coordinated outcomes that advance public health management, such as the dissemination of significant scientific outcomes toward reliable policies, pandemic preparedness, or appropriate regulatory actions. Whether sources turn to big data as a serious resource or if government systems regain their previous status largely depends upon whether the general public sees real-time benefits from AI due to participation in scientifically beneficial processes. Current interest now catapults learning that can account for diseases and describe how previous big data methods have advantages. AI advances not only from its broad use but also through scientific research that targets healthcare support, public data accessibility, trusted practices, and diagnoses from activities that are deemed beneficial to these specialized healthcare analyses.

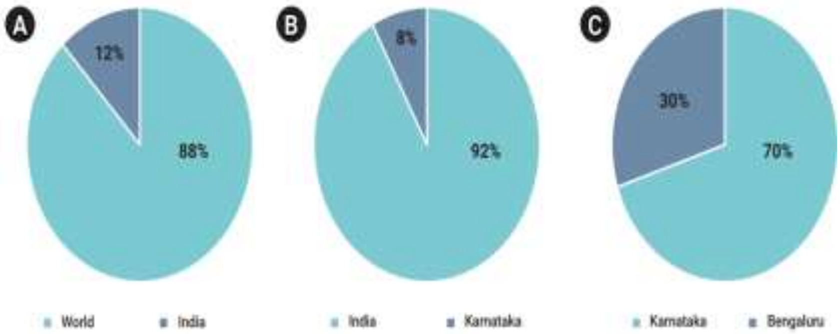

Fig 8 : COVID-19 prediction models

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