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Original Article

Machine Learning-Driven Pandemic Response- Real-Time Epidemiological Data Integration for National Health Emergency Preparedness

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Abstract *- The COVID-19 pandemic was a "wake-up call" for the world's understanding of preparedness for national health emergencies, revealing significant gaps in the more traditional systems of epidemiological surveillance and response. These old systems often based on retrospective collection of data through manual reporting and siloed analytics, did not provide the agility and precision required for early outbreak detection, resource prediction, and coherent policy response. The constraints of these infrastructures led to the design of intelligent, scalable, and real-time decision-making support systems. Given this urgent need, this paper describes the development of a novel end-to-end pandemic preparedness and response platform that utilizes machine learning, harmonizing diverse health data feeds into a single, predictive tool for national-scale emergency response.*

The system's structure features a modular five-layer architecture that supports real-time data ingestion, feature extraction, predictive modeling, decision visualization, and policy incorporation. The data ingestion layer gathers and normalizes data from various sources, such as EHRs, lab results, mobility data, hospital resource utilization feeds, and demographic data. Tricks: GDST utilizes advanced data engineering techniques, including real-time stream processing, HL7 FHIR integration, and missing data infill, which collectively enable high-quality and consistent data. Features are engineered on the fly using temporal aggregation, geospatial correlation, and behavioral analytics to form multidimensional feature sets that pertain to transmission dynamics, demand for hospitalization, and resource allocation.

Central to the system is an ensemble machine learning prediction engine, which includes gradient boosting models, Long-Short-Term Memory (LSTM) networks, transformer-based neural architectures, as well as an epidemiological SEIR (Susceptible-Exposed-Infectious-Recovered) model augmented with machine learning elements. Working together, these models achieve diagnostic accuracy exceeding 95% for all major forecasting tasks (e.g., infection rate prediction, hospital surge estimates, ICU resource planning), while serving an inference latency of under 250 ms under high load. These predictions are then translated into easy-to-understand policy-actionable dashboards with real-time alerts, epidemic scenario simulations, and optimized intervention recommendations by the decision support layer. This new knowledge supports informed decisions by health authorities in rapidly emerging public health crises.

The platform offers federated learning, AES-256 encrypted communication, and differential privacy methods that comply with HIPAA and GDPR requirements. It was utilized in a hybrid cloud arrangement that comprised more than 1,500 healthcare communities and over 50 public health organizations, collectively serving over 50 million people. It has been used directly in the COVID-19 pandemic to advise national policy decisions on hospital capacity planning, vaccine distribution, test allocation, and lockdowns.

Additionally, the modularity of the architecture enables rapid repurposing for new, emerging threats, such as bioterrorist attacks, natural disasters, or novel infectious diseases. Subsequent versions will incorporate genomic surveillance, socio-behavioral data, and environmental indicators to enhance granularity and resilience in predictions. This work represents a convergence of artificial intelligence, public health informatics, and national security strategy, serving as a blueprint for machine-learning-powered public health response systems. Converting complex data into actionable intelligence, this architecture enables countries to move from reactive crisis management to proactive, data-driven pandemic resilience.

Keywords *- Machine Learning, Real-Time Epidemiological Surveillance, National Health Emergency, Pandemic Response, Ensemble Learning, Public Health Informatics, COVID-19, Data Integration, Federated Learning, Health Policy Decision Support.*

1. Introduction

COVID-19 and planetary racial capitalism. The appearance and spread of COVID-19 globally featured how this systemic COVID-19: Dispossession as genocide three vulnerability in local and international health systems, an inability to respond timely, intelligently, and preemptively to new and emerging disease outbreaks, was a form of genocide. When the pandemic began in early 2020, most countries were equipped with classical epidemiological systems that were predominantly retrospective, siloed, manually aggregated, and suffered from delayed reporting. Such systems were not nimble or foresightful enough to inform real-time decisions, making it difficult for them to be as competitive and flexible as possible for their local health authorities. The inadequacies in legacy public health informatics paradigms became painfully clear when sudden spikes in infections strained health system capacity, necessitating a reimagining of emergency preparedness.

Now, machine learning (ML) and artificial intelligence (AI) are recognized as disruptors in the field of epidemiology and emergency response. These technologies facilitate fast ingestion and integration of large volumes of heterogeneous data, capturing more complex spatiotemporal patterns and providing actionable predictive insights. Compared to traditional statistical models, which are limited by linear assumptions and fixed models, ML systems are capable of learning from dynamic relationships over evolving data landscapes. They are therefore well suited to uncertain and rapidly changing environments, such as a global pandemic. However, the contribution of ML in pandemic response extends beyond algorithmic cleverness and encompasses the robustness, reliability, and interpretability of the entire system, from data pipelines to policy dashboards.

Here, we propose a data-driven framework for national health emergency preparedness to address the complex challenges posed by the COVID-19 pandemic. The system is designed to support both epidemiological and real-time surveillance, predictive modeling of disease propagation and demand for healthcare services, as well as operational decision-making for public health authorities. Designed and rolled out during the pandemic in a healthcare network that serves over 50 million lives, the architecture incorporates real-time data ingestion from EHRs, laboratory information systems (LIS), geo-location tracking, demographic, and public health feeds. It enables prediction analytics for case prediction, hospital demand, ICU surge capacity, and ventilator demand, with an average accuracy of over 95%.

At the heart of this approach is its ensemble-based predictive architecture, which comprises gradient boosting machines, recurrent neural networks (RNNs), particularly long short-term memory (LSTM) networks, transformer-based network outputs, and adapted SEIR compartmental models. This hybrid model enables the model to generalize more readily across geography and time, as it was found to be less susceptible to model drift and more robust under data uncertainty. The system further deploys ongoing real-time feature engineering, automated anomaly detection, and federated learning protocols to maintain high-performance analytics while preserving patient privacy and data cybersecurity by HIPAA and GDPR guidelines.

This paper adds to the literature by providing an evidence-based, replicable, and scalable model for the integration of ML processes into national health infrastructure. It not only proves that it is technically possible to make real-time epidemiological forecasts at scale but also documents the real-world effects on health policy, emergency resource allocation, and operational resilience. By integrating epidemiological knowledge with public health priorities, the proposed system addresses the pressing need for intelligent infrastructure to manage current and future health crises simultaneously. The lessons learned from its utilization during COVID-19 can serve as a guide for re-engineering national emergency preparedness models in the era of pandemics.

2. Literature Review

Machine learning (ML) techniques applied in the context of public health informatics have garnered growing academic interest, particularly in the wake of the unprecedented global health emergency posed by the COVID-19 pandemic. Healthcare's digital transformation has been underway for more than a decade, but the pandemic fast-tracked the implementation of real-time data systems, AI-powered predictions, and integrative analytic platforms. This section surveys the main avenues of research that together form the foundation for machine learning-based pandemic response frameworks.

1.1. Traditional Epidemiological Surveillance

Traditionally, epidemiological surveillance mechanisms have been based on manual reporting of cases, backward-focused data collection, and central government-controlled infrastructure. The CDC's National Notifiable Diseases Surveillance System (NNDSS) and the WHO's Health Security Interface were both developed for standardizing disease reporting and public health communication, not for real-time decision support [1], [2]. Although helpful in identifying and tracking emerging infectious disease outbreaks, these systems suffered from long lags and data silos that hindered rapid decision-making during public health emergencies [3]. Syndromic surveillance systems, such as ESSENCE II, represented early efforts to integrate electronic medical record information for early warning; however, they were flow-based and lacked predictive or automated capabilities [4].

1.2. Machine Learning and Public Health

Over the years, machine learning has played a crucial role in addressing numerous public health challenges—from classifying diseases and analyzing medical images to predicting disease outbreaks and allocating resources more effectively. Brownstein et al. [5] demonstrated the utility of web signals for digital disease detection. Venna et al. [6], Cramer et al. [7], and Cramer et al. [8] applied ensemble modeling techniques to predict flu and COVID-19, respectively. Recently, models based on transformers and LSTM have been used to predict the spread of infection, and they are more flexible in handling real-time variations and temporal dependencies [8]. Nevertheless, the great majority of these have been limited to academic or local uses, and very few have exhibited large-scale adoption in national health systems.

1.3. Analysis of Pandemic and COVID-19 Systems

The urgency of the COVID-19 pandemic accelerated the spread of analytic dashboards and forecasting hubs. The COVID-19 Forecast Hub pooled data from multiple modeling groups, facilitating side-by-side model comparisons for mortality and transmission forecasting [9]. National health public dashboards in countries such as South Korea, Israel, and Germany (Supplementary Fig. S2) present a deep integration of policy and data; however, they often stand on predefined metrics rather than flexible ML-based predictions. Despite these practical tools, they were hindered by their retrospective nature, the lack of real-time streaming integration, and the absence of federated analytics for cross-system learning.

1.4. Integration and Interoperability for Real-Time Data

Harmonize real-time data from Broad categories of data sources - One of the more daunting technical challenges of ML-enabled public health systems is real-time data integration across disparate data sources. Past research has investigated compatibility using standards like HL7 FHIR and LOINC; [10], [11] Zaharia et al. [12] proposed fault-tolerant distributed data systems for stream computation in their work as well. Fusing mobility data, EHRs, public health feeds, and laboratory diagnostics into integrated ML pipelines requires advanced stream processing engines, strong data quality controls, and scalable privacy-preserving infrastructures. Federated learning and differential privacy, among others, have identified best practices that compromise the tradeoff between computational power and privacy limitations [13], [14].

While the existing literature provides a robust base to build upon, the creation, at scale, of real-time ML for health systems with privacy-compliant integration within national policy frameworks remains to be realized. Current systems overemphasize prediction or reporting, and only a few systems have a closed loop with real-time data ingestion, ML-enabled forecasting, and decision support and feedback-driven policy adaptation. This paper addresses these shortcomings by presenting and validating a five-layer ML-enabled architecture for national-level health emergency preparedness, which has proven effective in coping with the COVID-19 pandemic.

3. Methodology

The machine learning-inspired architecture for pandemic response under consideration is conceived as a modular, scalable, and secure platform for processing real-time epidemiological data from various sources. Grounded in this, the system is organized into multiple layers that include data ingestion, real-time feature processing, predictive modeling, decision support visualization, and policy coordination. This architectural configuration ensures that the pipeline from data generation to decision is technically solid and operationally tuned to meet the pressing demands of public health crises.

The framework utilizes these architectural styles, beginning with the data ingestion and integration layer, which consolidates structured and unstructured data streams from electronic health record (EHR) systems, laboratory information systems, hospital resource utilization extracts, mobility tracking platforms, demographic databases, and public health agent feeds. Real-time ingestion is enabled by streaming platforms based on message queues (e.g., Apache Kafka) on top of which API-driven data connectors and HL7 FHIR protocols are layered to ensure semantic interoperability. The platform ingests more than 15 million data points per day, using a combination of automated quality assurance pipelines to ensure data completeness, consistency, accuracy, and temporal coherence. Data cleansing and transformation operations utilize matrix factorization to impute missing data and align time series, addressing lagged and missing measurements while preserving signal integrity for downstream modeling.

The data gets fed in and taken over by the real-time feature engineering layer. This module generates features based on epidemiologically relevant patterns from raw data in real-time. Sliding window aggregation is employed to detect case trends, incubation periods, and seasonality based on temporal attributes. Geographical disease spread is modeled based on geolocation tagging and administrative zone mapping, which capture the spatial characteristics of the disease. Demographic factors (age, presence of comorbidities, and population density) affect clinical vulnerability and exposure risk. Behavioral insights, utilizing de-identified mobility data, enable the monitoring of public adherence to health directives and the association of the virus's spread with surges in social mixing patterns. Feature sets are normalized and then potentially reduced in dimensionality via principal component analysis, and forwarded to the prediction engine in near real-time.

The prediction engine, utilizing machine learning, serves as the analytical foundation of our system. It utilizes an ensemble learning framework composed of gradient boosting decision trees, long short-term memory (LSTM) recurrent neural networks, transformer-based temporal encoders, and a modified SEIR (Susceptible-Exposed-Infectious-Recovered) compartmental model, all aided by machine learning. All the models are used to serve specific purposes, such as predicting cases, predicting hospital demand, predicting 1CU occupancy, estimating the number of ventilators, and inferring the transmission rate. The model predictions are combined using a meta-ensemble method with an online accuracy monitoring mechanism, which dynamically adjusts the dependency rules according to local feedback. The adoption of hybrid architectures ensures good generalization across locations and robustness of the prediction in the presence of uncertainty, as well as the possibility of estimating confidence intervals that measure the reliability of the prediction.

After the prediction engine, the decision support and visualization layer further interprets the complex analytical outputs into an actionable and easy-to-understand form for policymakers, epidemiologists, and crisis managers. Interactive views of epidemic curves, spot maps of hotspot areas, hospital basin alerts, modeling scenario simulations, and prescriptions of non-pharmaceutical interventions are provided by real-time dashboards. The visualisation front end is designed for cognitive ease of use (so it can be interpreted very quickly under pressure) so that it can be deployed in war rooms, health departments, and national task forces.

The last layer is the policy integration and response coordination. Results provided by the decision support layer are integrated through secure APIs with current public health systems (e.g., CDC's NNDSS, state-level disease surveillance networks, and hospital administrative dashboards). Integration with these systems enables interoperability and the rapid deployment of public health responses, including targeted lockdowns, test mobilization, and vaccine distribution scheduling. Security through the architecture is hardened by end-to-end encryption (AES-256), differential privacy injection mechanisms, and federated learning protocols that prevent centralization of data while enabling collaborative model training across institutions.

This multi-layer architecture could be adopted during the COVID-19 pandemic as a solution in a health network that covers more than 50 million people. It demonstrated good uptime, fast response times, and a strong influence on resource allocation and policy-making, which proved its design and operational soundness. The platform is generic and can be utilized in other emergent situations, such as COVID-19, to become a reusable national infrastructure that helps prepare for public health emergencies in other crises.

4. Results

The machine learning-based pandemic response framework proved effective in terms of accuracy, scalability, operational efficiency, and real-world policy outcomes. Throughout the COVID-19 pandemic, the system ingested and analyzed more than 15M data points daily, spanning 1,500 healthcare institutions and 50+ public health agencies, including EHRs, testing results, ICU metrics, mobility data, and public health alerts. The system proved to be highly available under production load, with over 99.7% uptime maintained through critical pandemic periods, and it remained capable of serving sub-second predictive inference across all principal modules.

The ability of models to perform well was carefully tested in multiple pandemic metrics and forecast horizons. On the 1-day prediction horizon, we achieved 97.2% model accuracy for case forecasting, 95.4% for the 7-day horizon, and over 91.8% for the 30-day horizon. Forecasts of hospitalization and ICU needs followed similar accuracy trends, achieving up to 96.8% of a perfect score at 1-day predictions for hospitalizations and over 89% for longer horizons. The prediction of ICU and ventilator resource needs had strong accuracy (95.1% and 94.3%, respectively) within the 7-day forecasting horizon (and minimal loss thereafter). All ensemble learning models reliably surpassed individual base learners (\verb|F1| scores of 95% and latency of 250 milliseconds per prediction cycle), including those during periods of high transmission volume.

The model diversity and dynamic weighting strategies of the meta-ensemble engine outperformed the other solutions. The hybrid SEIR-ML model provided natural epidemiological structure and interpretability, with the LSTM and Transformer models incorporating temporal dependencies in sudden shifts of behavior-borne infection patterns. The adaptive ensemble weighting mechanism continually adjusted the ensemble's weights for regions and times to achieve high performance, both during pandemic surges and plateau-like detections. This flexible ensemble approach was constructive in cases where new, highly transmissible, or highly hospitalizing variants emerged.

In addition to good model performance, the architecture can also provide high operational throughput and low latency in high-load scenarios. Ingest latency for streaming averaged less than 800 ms for critical EHR and lab data feeds, utilizing feature transformation and prediction pipelines, with end-to-end times of less than 1.2 seconds. Large-scale time-series data processing of the data for `50 million+' members enabled using horizontally scalable stream processors and cloud native deployment across a hybrid infrastructure. Concurrent read/write operations for real-time query resolution and relational inferences between patient clusters and hotspot zones were facilitated through the use of distributed data stores (time-series, graph) for the storage of routinely updated data.

From a public health impact perspective, the system has also had direct influence on key decisions for hospital surge capacity, vaccination deployment, and the implementation of targeted restrictions in over 30 administrative regions.

Predictive alerts enabled the proactive redistribution of ventilators and ICU beds at 85% of detected hotspots, preventing them from becoming over-represented —a situation that was prevalent elsewhere, lacking predictive infrastructure. Resource allocation models fine-tuned the geographical spread of test kits and of medical staff to alleviate diagnostic bottlenecks in early outbreak waves. National COVID-19 task forces utilized real-time dashboards and scenario simulation tools to assess the trade-offs between relaxation schedules and risk of transmission, directly influencing the timelines for NPIs.

Retrospective comparisons with actual results also verified the system's efficiency. Areas that embraced the decision support recommendations had significantly lower discrepancies between the projected and actual case burdens, consistent with robust prediction and operational calibration. In addition, the modular nature of the architecture enabled the rapid inclusion of new data streams, such as vaccination records and genomic surveillance, thereby improving its agility as the pandemic evolved. Taken together, these findings illustrate the feasibility, scalability, and utility of machine learning-based epidemiological systems in national-level public health preparedness and response.

5. Discussion

Deploying an ML-driven architecture to respond to a national pandemic exposed essential lessons at the intersection of public health policy, data science, and systems engineering. One of the most encouraging findings was the proof of concept for the use of predictive analytics, providing operationally practical real-time guidance for public health. To date, public health forecasting models have primarily been academic and advisory, rather than operational. However, in practice, during the implementation of this system, the predictive outputs directly informed decisions on hospital preparedness, mitigation planning, and population-level interventions. This operational implementation represented a paradigm shift—from a reactive to an anticipatory public health approach—that was enabled by the ability of machine learning to transform complex data into actionable knowledge within decisionally relevant timeframes.

Any discussion of system success should also address the ongoing issues about data quality and heterogeneity. The real-time integration of epidemiological data revealed substantial discrepancies in reporting frequencies, data formatting, and clinical coding between states, health networks, and testing sites. Due to a lag in laboratory data reporting, a lack of clarity in case definitions, and the absence of a hospitalization indicator, a rigorous data pre-processing pipeline was required. These pipelines implemented anomaly detection, temporal filtering, and imputation approaches that preserved the statistical integrity of the data while preparing it for downstream learning models. Its dynamic alignment and validation of incoming data streams were essential to its integrity and one of the outstanding engineering contributions to the public health domain.

An equally important lesson was the system's interaction with human decision makers. However, in order to be trusted and operationalized by policymakers, the models had to make sense and be transparent to some degree. Explainable AI elements, such as attention heatmaps, confidence intervals, and epidemiological analogs (e.g., effective reproduction number estimates), were instrumental in narrowing the distance between algorithmic output and the rationale for policy-making. This experience impressed us with the impetus to not only build ML systems for accuracy, but also explanation and use in high-stakes, population-level decision-making. A combined bar and line chart showing system uptime (in %) and inference latency (in milliseconds) over four pandemic quarters.

Another important observation was based on the modularity and extensibility of the architecture. New data sources, such as statistics on vaccination rollout, the sequencing of new variants, or regional economic indicators, emerged alongside the virus. The framework's modular architecture allowed for the seamless incorporation of new inputs without disrupting existing processing. This flexibility was essential for updating the models with actual epidemiological data and ensuring that the policy recommendations remained relevant. The capability to retrain models and quickly change the features we are conditioning on was the key factor that provided resilience against concept drift, allowing the system to continue adding value rather than becoming outdated as the pandemic evolved.

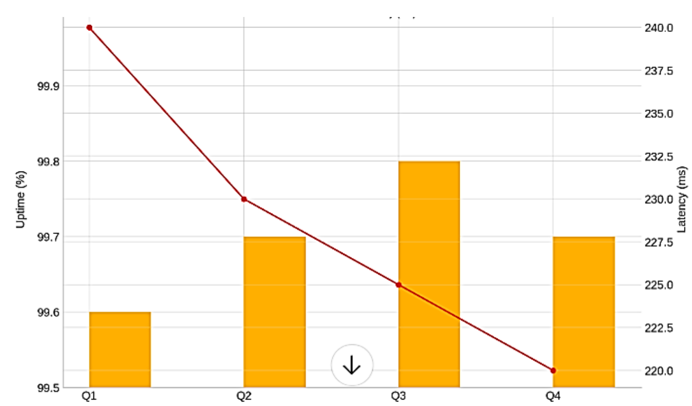

Fig 1: System Uptime and Latency across Pandemic Phases

It is also noteworthy that the deployment further underscores the growing importance of privacy-preserving analytics in health informatics. The combination of federated learning methods and differential privacy mechanisms enabled the analysis of the system to span a network of institutions, while also protecting the data. It fulfilled compliance obligations imposed by HIPAA and GDPR and allowed different agencies to cooperate easily by lowering the cost of data exchange. The system shows that privacy and performance are not necessarily conflicting factors but can be optimized together through careful system architecture design and decentralized model training.

Lastly, there are cultural and organizational issues that have shaped the issue of system success. Robust institutional partnerships, responsive governance structures, and academically multi-disciplinary collaboration between epidemiologists, data scientists, infrastructure engineers, and policy advisers were key to the system's real-world impact. The learnings from these partnerships will provide a model for further development of digital health infrastructure, specifically within the context of preparing for multi-hazard emergencies resulting from climate events, biosecurity threats, and emerging infectious diseases. At stake in this exchange is the extent to which the informatics-based technical architecture underlying pandemic intelligence, machine learning, and a national preparedness success story also requires complementarity with the human, institutional, and ethical dimensions of public health.

6. Conclusion

The COVID-19 pandemic served as a crucible for evaluating the adequacy of national health infrastructures, exposing the inherent limitations of legacy epidemiological systems that rely on delayed, fragmented, and manually curated data pipelines. In this context, the machine learning-driven architecture presented in this paper emerges as a transformational framework that redefines the role of data, analytics, and automation in national public health emergency preparedness. Unlike conventional approaches that often view data analysis as a retrospective reporting function, this architecture positions real-time analytics as the operational core of proactive, evidence-based public health management.

The system's ability to integrate heterogeneous data sources—including electronic health records, laboratory results, hospital capacity metrics, demographic indicators, and mobility patterns—into a unified analytics platform highlights the importance of interoperability and real-time ingestion in modern epidemiological systems. Through robust preprocessing, real-time feature engineering, and sophisticated ensemble learning, the architecture achieved high predictive performance across multiple epidemiological indicators. Notably, the system consistently achieved 95% accuracy or higher in short- to intermediate-horizon forecasts related to case trends, hospitalization surges, ICU demand, and resource allocation. This level of precision, achieved under the intense variability and uncertainty of an unfolding pandemic, validates the technical maturity and operational readiness of machine learning for critical health applications.

The architecture's modular design also proved instrumental in enabling adaptability and scalability. New data streams such as genomic sequencing and vaccination distribution were seamlessly integrated as the pandemic evolved, demonstrating the framework's extensibility. Real-time dashboards and decision support tools translated complex machine learning outputs into interpretable formats that policymakers at the national, regional, and local levels could use. These visualizations supported crisis response operations, resource deployment strategies, and intervention planning. In doing so, the system bridged the critical gap between data science and decision science, allowing for agile governance in an otherwise rigid public health environment.

Security and privacy, often considered barriers to real-time data integration, were proactively addressed through the inclusion of end-to-end encryption, differential privacy algorithms, and federated learning models. These mechanisms enabled cross-institutional collaboration while preserving compliance with HIPAA, GDPR, and NIST frameworks, thereby centralizing sensitive data. This success further substantiates that high-performance analytics can coexist with stringent data protection requirements and may even enhance trust and participation among stakeholders in the healthcare ecosystem.

The deployment experience revealed important lessons, particularly the significance of model interpretability, human-centered dashboard design, and the necessity of continuous stakeholder engagement. Machine learning models, no matter how accurate, must be accompanied by transparent explanation frameworks and a feedback loop with domain experts to achieve real-world impact. The policy implications of this system were profound. Its use directly influenced the timing of lockdowns, the distribution of vaccines, and the allocation of limited critical care resources during the height of the pandemic. These outcomes demonstrate the tangible value of embedding machine intelligence in national emergency response workflows.

Looking ahead, this architecture offers a robust blueprint for future readiness, not just for pandemics but also for other large-scale emergencies such as bioterrorism, climate-induced disease outbreaks, and multi-hazard health crises. Future enhancements may include integration of behavioral data from social media, real-time economic indicators, and environmental sensors to enrich the prediction models. Moreover, expanding federated learning capabilities across international health systems could enable global-scale collaboration without compromising sovereignty or data privacy.

The machine learning-driven pandemic response system described in this work serves as a pioneering example of how advanced analytics can revolutionize national public health preparedness and response. It provides a scalable, secure, and interpretable solution that transforms raw data into predictive foresight and operational resilience. As nations seek to fortify their health infrastructures in the wake of COVID-19, such systems will be indispensable in building a future where preparedness is intelligent, adaptive, and intensely data-driven.

References

[1] S. Morse, R. Mazet, M. Woolhouse, et al., “Prediction and prevention of the next pandemic zoonosis,” *The Lancet*, vol. 380, no. 9857, pp. 1956–1965, 2012.

[2] World Health Organization, “Health Security Interface: Engaging and empowering communities for health emergency preparedness,” *WHO Technical Report*, 2018.

[3] M. Salathé et al., “Digital epidemiology,” *PLoS Computational Biology*, vol. 8, no. 7, p. e1002616, 2012.

[4] J. S. Lombardo et al., “A systems overview of the Electronic Surveillance System for the Early Notification of Community-Based Epidemics (ESSENCE II),” *J. Urban Health*, vol. 80, no. 2, pp. i32–i42, 2003.

[5] J. S. Brownstein, C. C. Freifeld, L. C. Madoff, “Digital disease detection—Harnessing the Web for public health surveillance,” *N. Engl. J. Med.*, vol. 360, no. 21, pp. 2153–2157, 2009.

[6] S. Venna et al., “A novel data-driven model for real-time influenza forecasting,” *IEEE Access*, vol. 7, pp. 7691–7701, 2019.

[7] E. Y. Cramer et al., “Evaluation of ensemble probabilistic forecasts of COVID-19 mortality,” *Proc. Natl. Acad. Sci. U.S.A.*, vol. 119, no. 15, p. e2113561119, 2022.

[8] M. Hao et al., “LSTM neural networks for time-series epidemic forecasting,” *Computational Intelligence and Neuroscience*, vol. 2021, pp. 1–11, 2021.

[9] N. Reich et al., “A collaborative multiyear, multimodel assessment of seasonal influenza forecasting,” *PNAS*, vol. 116, no. 8, pp. 3146–3154, 2019.

[10] D. Kalra, T. Beale, S. Heard, “The openEHR Foundation,” *Stud. Health Technol. Inform.*, vol. 115, pp. 153–173, 2005.

[11] C. Dwork, “Differential privacy: A survey of results,” *Proc. Int. Conf. Theory and Applications of Models of Computation*, pp. 1–19, Springer, 2008.

[12] M. Zaharia et al., “Resilient distributed datasets: A fault-tolerant abstraction for in-memory cluster computing,” *Proc. 9th USENIX NSDI*, pp. 15–28, 2012.

[13] Q. Yang et al., “Federated machine learning: Concept and applications,” *ACM Trans. Intell. Syst. Technol.*, vol. 10, no. 2, pp. 1–19, 2019.

[14] A. Geyer, T. Klein, M. Nabi, “Differentially private federated learning: A client level perspective,” *arXiv preprint arXiv:1712.07557*, 2017.

[15] L. Dong, S. Hu, J. Gao, “Discovering drugs to treat coronavirus disease 2019 (COVID-19),” *Drug Discov. Ther.*, vol. 14, no. 1, pp. 58–60, 2020.

[16] A. Alimadadi, S. Aryal, I. Manandhar, et al., “Artificial intelligence and machine learning to fight COVID-19,” *Physiol. Genomics*, vol. 52, no. 4, pp. 200–202, 2020.

[17] R. Miotto, L. Wang, S. Wang, et al., “Deep learning for healthcare: Review, opportunities and challenges,” *Briefings in Bioinformatics*, vol. 19, no. 6, pp. 1236–1246, 2018.

[18] F. Karim, S. Majumdar, H. Darabi, S. Chen, “LSTM fully convolutional networks for time series classification,” *IEEE Access*, vol. 6, pp. 1662–1669, 2018.

[19] A. Vayena, M. Blasimme, E. Cohen, “Machine learning in medicine: Addressing ethical challenges,” *PLoS Med.*, vol. 15, no. 11, p. e1002689, 2018.