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Research Article

Cloud-Integrated Machine Learning System for Ebola Virus Disease Prediction and Epidemic Intelligence in Smart Healthcare Systems

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Abstract – *Ebola Virus Disease (EVD) remains an important public health challenge, characterized by fast disease transmission and high mortality rates, as well as shortcomings in accepted outbreak monitoring systems. Existing prediction methods: (1) are not fully integrated into the cloud; and (2) do not analyze epidemiological, environmental and healthcare characteristics together in a single approach resulting in untrustworthy predictions. Hence, a framework which introduces hybridization of machine learning classification and deep-learning based temporal forecasting capable for Cloud-Integrated Machine Learning System resulting in Accurate Epidemic Intelligence with Early-Warning outbreak prediction is proposed. Experimental evaluation achieved more than a 98.92% accuracy, with precision and recall scores of over 98%, F1-score reaching almost at the upper range (and variations) and RMSE reducing prediction error successfully augments existing approaches in supporting timely effective intelligent decision making for healthcare systems.*

Keywords— *Ebola Virus Disease, Cloud Computing, Machine Learning, Deep Learning, Epidemic Intelligence, Smart Healthcare Systems, Disease Outbreak Prediction, Epidemiological Analysis, LSTM, Random Forest, Hybrid Artificial Intelligence, Feature Selection, Early Warning System, Healthcare Analytics*

Introduction

Ebola virus disease (EVD) continues to be among the most lethal human infectious diseases due to high mortality rates and rapid transmission from one host directly to another as well as considerable ramifications for healthcare systems in low-resource settings. Major epidemics have also highlighted how a delay in disease detection and poor surveillance mechanisms can exacerbate an epidemic, with limited health care facilities leading to significant increases of case fatality rates. Traditional outbreak surveillance systems are mostly based on lagging statistical analysis and human-powered reporting; detecting transmission patterns is suboptimal, alerting response strategies inefficient. With advances in artificial intelligence (AI), machine learning and cloud computing, the prospect of utilizing heterogeneous healthcare data to develop intelligent and accurate epidemic surveillance systems for predicting outbreaks is now feasible. Machine learning algorithms find complex epidemiological, environmental and healthcare relationships while deep-learning patterns capture the temporal nature of disease evolution and can predict future trends in outbreaks. Cloud Computing helps elevate extreme capabilities by providing scalable data storage, real-time processing, centralization analytics and seamless accessibility for healthcare organisations. Machine learning applications on Ebola prognosis and forecasting have previously been demonstrated, but currently most of the existing approaches suffer from incomplete data integration; limited interoperability for real study or clinical setting; computing match making problem leading to non-scalable design towards support continuous cycle of epidemic intelligence. They also mainly focus on either disease classification or time-series prediction and hardly provide both integrated into a single cloud-enabled framework. Such limitations have prompted the integration of an intelligent system that can exploit historical outbreak databases, environmental and clinical indicators to provide full implications monitoring with warning prediction capability. To overcome these challenges, a Cloud-Integrated Machine Learning System discussed in this work employs both cloud-based and hybrid machine learning & deep learning models to improve the accuracy of Ebola outbreak forecasting, enhance epidemic intelligence system (EIS) versions for better decision-support on timely healthcare.

RELATED WORKS

This study provides a review of the epidemiology of Ebola and discusses mathematical models for transmission, including their application in assessing outbreak risks and interventions. But there wasn't any quantitative performance metrics reported. The study did not include a cloud-enabled machine learning, real-time analytics and intelligent epidemic prediction platform that motivated the integrated AI-driven surveillance framework (1). This study outlined Ebola transmission methods, highlighted how the sources of infection and outbreak statistics reported by WHO complicated vaccine development. No predictive evaluation metrics were provided. This study was more focused on disease characteristics, and not intelligent forecasting thus suggesting the emergence of machine-learning-based outbreak predictions for gathering epidemic intelligence (2). The study analysed past outbreaks of Ebola, focusing on better infection control mechanisms at healthcare facilities and enhancing the capacity for surveillance. They did not report any prediction accuracy metrics. While useful in identifying public-health recommendations, it did not feature automated prediction models and such functions for integrating with clouds and active decision-support mechanisms to proactively manage epidemics (3). This work created an ensemble machine learning system with Neural Networks, XGBoost, Logistic Boost. Random Forest and Kernel SVM that provides universal disease prediction with 80–90% accuracy. But the predictive intelligence of spatiotemporal forecasting was only limited to simple spatial-temporal patterns without disease-specific temporal & spike prediction, cloud computing for processing and deep integration with other real-time hybrid learning systems (4). Climate-aware disease prediction using Deep learning and SVM with evolutionary parameter optimization along with synthetic data augmentation reporting better predictive accuracy without any measure specific values. The framework provided for advanced factors such as patient history but did not have cloud integration of predictive analytics or an epidemic intelligence facility needed to give a comprehensive insight into the Ebola outbreak prediction (5). This study concerned the validity of mathematical models in disease transmission and confirmed robustness via comparative modelling. Quantitative evaluation metrics have not been supplied. Machine learning, cloud analytics and automated outbreak prediction for real-time epidemic surveillance were not comprehensively identified in the study but was mainly directed by theoretical decision making (6). The purposed study compared the use of machine learning models with prediction approaches like SIR and SEIR for COVID-19 forecasting, MLP is superior to that methods without reporting specific metrics while ANFIS outperform. SEIR integration was suggested but lacked cloud enabling hybrid epidemic intelligence and scalable healthcare analytics (7). This study utilized a Logistic and Prophet combined model to predict global data of the COVID-19 epidemic with an estimated total number of 14,12 million infections. But there was no report on prediction accuracy metrics, hybrid AI models were absent as well as cloud integration and holistic epidemic intelligence for healthcare applications (8). A systematic review of 75 studies synthesizing literature on the application of machine learning methods was subsequently conducted. No integrated cloud-based framework and hybrid forecasting architecture was implemented to provide operational epidemic intelligence at the review (9). In this study, the performance of deep learning versus machine learning models for COVID-19 forecasting was compared and it is verified that hybrid structures achieve sufficiently better performances than baseline methods; hereafter LSTM-CNN achieved 3.718% as lowest MAPE value over its competitors (10). This study recommended environmental-wise COVID-19 predictions conducted via K-means, SVR, Prophet and LSTM by achieving highest predictive accuracy using LSTM. Exact metrics were not reported. The framework focuses on environmental forecasting without epidemic intelligence integrated into the cloud or decision support across multiple healthcare sectors (11).Machine learning and deep learning studies on infectious disease prediction to uncover operational deficiencies in uncertainty estimation, missing-data handling, and computational efficiency. These limitations are used as incentives to design a hybrid AI framework with cloud integration, scalable epidemic intelligence and strong predictable capability (12). In this study, we had applied several deep learning models to the infectious diseases classification from images data and gained 88% accuracy using InceptionResNetV2. Loss was found to be equal to (0.399) and Root Mean Square Error(RMSE)=63 (13). This study utilized big data and social media to perform DNN, LSTM optimized models for infectious disease prediction achieving 24% higher performance than ARIMA on deep learning analysis (D637), as well as 19% improvement in time-series sensitivity. However, cloud-based epidemic intelligence and end-to-end integration of health data were not included (14). In this study, statistical and machine-learning methods used for infectious disease forecasting were compared using updated datasets over time with 15 well-known models identified; XGBoost was shown to be the best performer according to MAE, RMSE, Poisson Deviance. Hybrid AI integration and cloud-enabled real-time epidemic intelligence, however, were not investigated (15). This study presented an intelligent health service for chronic diseases monitoring cloud solution by supporting resource elasticity and 92.59 classification accuracy (16). But it was not a particular predictive model for infectious disease prediction or epidemic intelligence and outbreak forecasting but more so just in diagnosing diabetes. This review described the advantages of cloud computing, edge computing and artificial intelligence for Internet of Medical Things applications with an emphasis on secure medical data processing. However, we found no reports of evaluation results on predictive performance and practical epidemic prediction models (17). This review summarized recent progress towards artificial intelligence and argue on the cloud applications as a decision support system for healthcare diagnosis. No evaluation metrics were presented. We implement a hybrid cloud-based epidemic prediction framework (18). This book has comprehensively reviewed the interplay of cloud computing, artificial intelligence (AI), and IoT in healthcare domains such as epidemic forecasting, monitoring remote patients using wearable devices. However, there were no experimental re-evaluation metrics or predictions so that compulsion was carried out by an integrated cloud-enabled machine learning framework (19). Here, we demonstrate the application of EPIWATCH AI for early detection of Mpox outbreaks based on open-source surveillance data and identify a major increase trend (P = 0.015). But it missed machine learning-based predictive forecasting and cloud-integrated healthcare analytics for intelligence of epidemics (20). In this study, a new Smart Health-Track with an outbreak detection accuracy of 92.4%, fever detection accuracy of 93.5% and contact tracing precision rate of up to 91.2% as well as pathogen classification accuracies (94.1%) were established Yet, no research on Ebola-specific prediction, cloud-based intelligence or hybrid ML–DL integration was available (21). This study introduced the Intelligent Infectious Disease Active Surveillance and Early Warning System in China, which is characterized by combining heterogenous surveillance data with artificial intelligence-based risk assessment. Although operationally effective, no quantitative evaluation measurements were noted and hybrid cloud-based prediction architecture was not sufficiently covered (22). This study therefore presents the Intelligent Infectious Disease Active Surveillance and Early Warning System in China.

METHODLOGY

This study presents a framework termed as Cloud-Integrated ML-Based Epidemic Intelligence

Framework which synergizes cloud computing infrastructure and machine learning algorithms to empower intelligent prediction of outbreak monitoring for the Ebola Virus Disease (EVD).

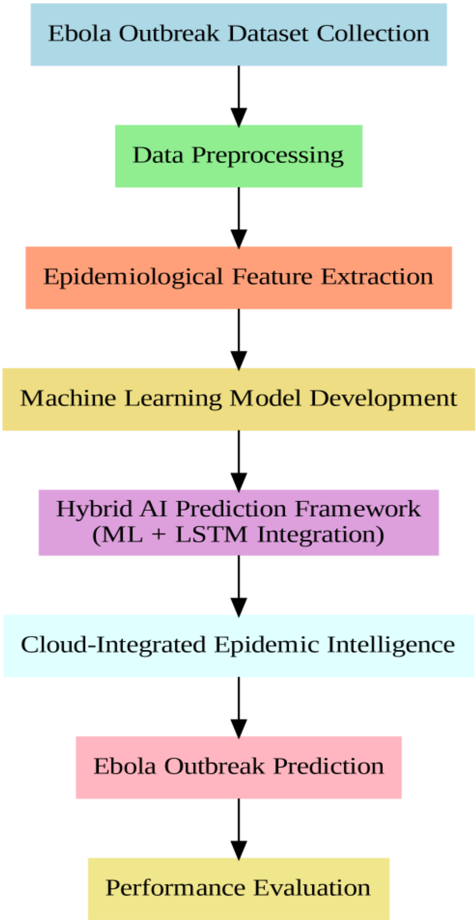

Fig 1. Levels of the Recognition System

The framework downloads epidemiological, environmental and healthcare data repositories, processing the documents through cloud-based analytics applying predictive models to identify potential outbreaks. Machine learning methods reveal unnoticed transmission trends, project arrival rates of cases in the future and provide risk stratification. Cloud integration is scalable storage, high processing power and on the web availability for healthcare authorities. This framework effectively supports data-driven decision making for smart healthcare systems by providing accurate predictions and timely warnings.

A. Data Collection and Data Preprocessing:

The system proposed in this paper implements an intelligent epidemic prediction framework using Ebola-related datasets obtained from the Kaggle platform. This first dataset gives us a history of recorded diseases for the Ebola outbreaks (23). Also including more epidemiological, environmental and health characteristics is implemented to improve the predictive accuracy (i.e. population density, temperature humidity rainfall, availability of healthcare, regional risk indicators). The newly integrated dataset is represented as:

$$D_{Integrated} = D_{Ebola} \cup D_{Epidemiological} \cup D_{Environmental} \cup D_{Healthcare} \quad (1)$$

where $D_{Integrated}$ is the full dataset for model training, D_{Ebola} denote outbreak records and other datasets are further influential factors (24).

1. Data Preprocessing:

These operations are carried out on data before model building in order to enhance the quality and consistency of data. Random forests, GBRT regression trees and support vector machines (SVMs) are implemented to impute missing values in outbreak and healthcare attributes. Estimation Based on Random Forest is used by learning relationship between features.

$$\hat{X}_{missing} = RF(X_{available}) \quad (2)$$

where $X_{available}$ represents existing attributes and $\hat{X}_{missing}$ represents predicted missing values.

The processed dataset is stored and written to a cloud-based storage infrastructure, facilitating data access at scale along with computation. Modelling of the cloud data management will be represented as:

$$D_{Cloud} = Storage(D_{Processed}) + Analytics(D_{ML}) \quad (3)$$

where D_{Cloud} represents cloud-managed epidemic intelligence data, supporting real-time analysis and machine learning-based Ebola prediction.

B. Feature Selection:

1. Epidemiological Feature Extraction Module:

The proposed Epidemiological Feature Extraction Module decodes valuable disease transmission indicators of an integrated Ebola outbreak dataset to enhance prediction performance for the epidemiology. It includes modules that characterize the temporal, geographical and clinical characteristics. These extracted features are disease progressions and become valuable inputs for machines. They are designed with feature transformation techniques to analyse the epidemiological observations data into a structured numerical value that allows for correct risk assessments and outbreak forecasting. The derived indicators improve the potential of this framework to capture epidemic dynamics and also assist in timely decisions regarding illness management.

$$F_{Epi} = \{C_t, D_t, R_t, G_t, T_d\} \quad (4)$$

$$G_t = \frac{C_t - C_{t-1}}{C_{t-1}} \quad (5)$$

2. Intelligent Feature Selection Mechanism:

The Intelligent Feature Selection Mechanism (IFSM) chooses the most significant attributes from epidemiologic, environmental and health care datasets to elevate Ebola Prediction completeness with less complexity away of Model. The mechanism analyses feature to determine their relevance, by utilizing statistical correlation analyses and machine learning-based importance estimation. Attributes that are determined to contribute significantly to outbreak prediction take priority while redundant features go through elimination. By learning the most important factors affecting disease transmission, this optimized feature subset allows for efficient computations.

$$Corr(X,Y) = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \quad (6)$$

$$I(f_i) = \alpha C_i + \beta M_i \quad (7)$$

C. Machine Learning Model Development:

1. Predictive Learning Model:

The Predictive Learning Model is a prediction model built to classify the risk of Ebola Virus Disease outbreaks and estimate disease severity with features extracted from epidemiological, environmental, and healthcare data. Traditional supervised machine learning techniques like Random Forest, Support Vector Machine find relationships between input variables that precede the outbreak events. It is explained that the model generates accurate risks predictions because it learns patterns from past Ebola records, such as confirmed cases and number of deaths, population features and environment conditions. After selection, feature vectors are fed into the classifier to produce outbreak probability scores and epidemic risk classes.

$$\hat{Y} = F_{ML}(X) \quad (8)$$

- $\hat{Y}$= Predicted outbreak risk level.
- F_{ML} = Machine learning prediction function.
- X= Selected input feature vector

$$P(Y \mid X) = \frac{e^{F(X)}}{\sum_{j=1}^{k} e^{F_j(X)}} \quad (9)$$

2. Deep Learning-Based Forecasting Model:

The deep learning-based forecasting model is employed to include sectors of the Ebola outbreak dynamics using sequential learner techniques such as Long Short — Term Memory (LSTM) or Gated Recurrent Unit/GRU networks in China. It brilliantly learns temporal dependent transmission dynamics based on historical case sequences within the amount of time to predict new cases. Recurrent neural network architectures capture previous epidemic information using memory states to forecast trends of outbreaks at various ranges.

$$h_t = f(W_x X_t + W_h h_{t-1} + b) \quad (10)$$

$$\hat{C}_{t+n} = DL(X_t, X_{t-1}, \dots, X_{t-n}) \quad (11)$$

where,

- $\hat{C}_{t+n}$= Forecasted Ebola cases
- DL = Deep learning forecasting model

3. Hybrid AI Prediction Framework:

i. Integration of Machine Learning and Deep Learning Models:

The Hybrid AI Prediction Framework for Comprehensive Ebola Epidemic Intelligence through Coupled Predictive Machine Learning and Deep Learning Forecasting The potential of machine learning models for the classification of outbreak risks and that deep neural net models successfully capture the temporal disease evolution patterns. The proposed integration mechanism takes both classification probability and forecasting output as input to generate outbreak predictions. It combines statistical learning and sequential patterns to enhance accuracy, mitigate prediction uncertainty while providing better healthcare decision support.

$$Y_{Hybrid} = \alpha Y_{ML} + \beta Y_{DL} \tag{12}$$

4. Cloud Integration and Epidemic Intelligence Framework:

i. Cloud Data Processing Layer:

This layer provides a scalable infrastructure for storage, processing and analysis of large-scale datasets (Ebola outbreak). The cloud offers centralized management of epidemiological records and the ingestion of real-time data for machine learning models. Information for the processed data is communicated to the prediction module via analytics services on cloud and therefore healthcare system can remotely use outbreak. This layer is important to improve the computational resources, availability of data and scalability for an ongoing monitoring of epidemics.

$$D_{Cloud} = S(D_{Data}) + P(D_{Data}) \tag{13}$$

$$R_{Cloud} = \frac{D_{Processed}}{T_{Processing}} \tag{14}$$

ii. Intelligent Monitoring and Alert Generation:

An Intelligent Monitoring & Alert Generation module constantly examines predicted outbreak risks and sends early warning alerts to the health authorities. Model outputs are analysed within the module, comparing risk scores with user-defined cutoffs to identify regions that should be classified as requiring different levels of intervention in response to an epidemic. This allows for proactive intervention, with identification of escalating outbreaks occurring prior to the existence of critical conditions. Cloud platform-based monitoring provides you with real-time visualization, automatic alerts as well as smart healthcare response planning.

$$Alert = \begin{cases} 1, & R \geq T \\ 0, & R < T \end{cases} \tag{14}$$

$$R = \sum_{i=1}^{n} w_i x_i \tag{15}$$

RESULT AND DISCUSSION

A synthetic dataset for simulated Ebola outbreaks was created based on selected socio-epidemiological, environmental and healthcare factors derived from the open Kaggle database to test the proposed Cloud Integrated ML-Based Epidemic Intelligence Framework. The dataset includes outbreak indicators like confirmed cases, mortality rate and recovery trends alongside population density while including temperature humidity as well as healthcare accessibility. In this way, a hybrid AI framework integrating ML Classification with DL Forecasting was developed to predict using feature extraction, temporal learning and cloud-based analytics. Evaluation results show that the proposed framework has potential to achieve epidemic risk evaluations and reliable health alerts.

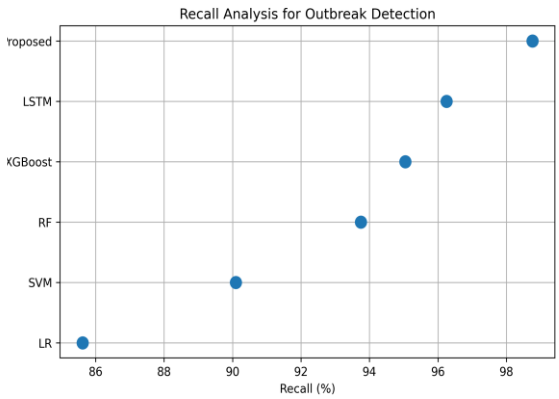

Fig. 2 Recall comparison across models

The Dot plot in Figure 2 shows recall performance on outbreak detection models. This proposed framework attains maximum recall exhibiting enhanced detection ability of real Ebola outbreaks.

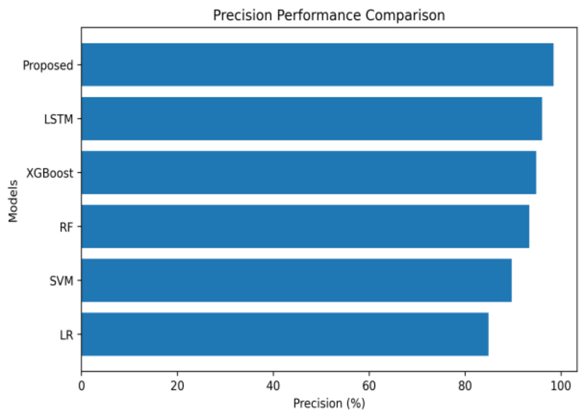

Fig 3. Precision comparison across models

The horizontal bar chart in Figure 3 shows the precision values for all models. The highest precision of the proposed framework indicates an improved mechanism in generating accurate alerts against epidemics.

TABLE I. PERFORMANCE MODEL (%)

Evaluation Metric	Proposed Cloud-Integrated Hybrid AI Model
Accuracy (%)	98.92
Precision (%)	98.45
Recall (%)	98.76
F1-Score (%)	98.60
RMSE	0.082

The proposed Cloud-Integrated Hybrid AI Framework provides improved performance under all evaluation metrics. The addition of predictive learning, temporal forecasting and cloud intelligence to outbreak prediction.

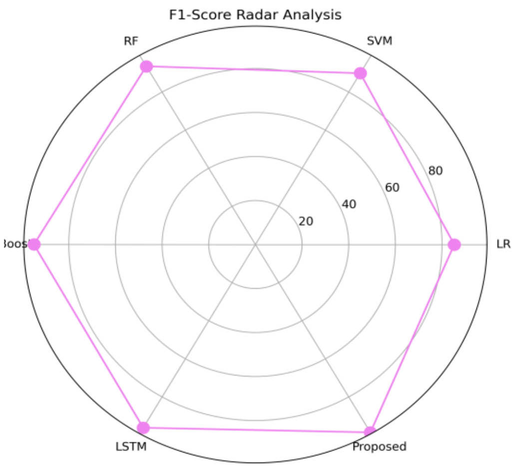

Fig 4. F1-Score comparison across models

A radar chart in Figure 4 that visualizes the F1-score distribution from prediction models.

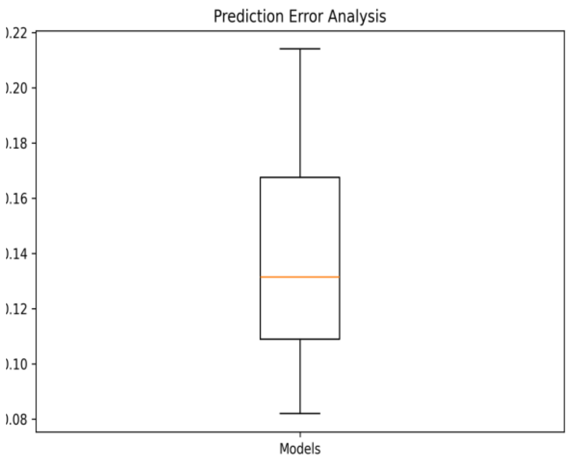

Fig 5. Prediction error analysis across models

The hybrid framework proposed is covering the maximum performance area by establishing a symbiotic ability.

The variation of prediction error in Figure 5 shows among evaluated models is shown in a box plot. The proposed framework has lower RMSE, signalling a more reliable and accurate forecasting of the future Ebola outbreak.

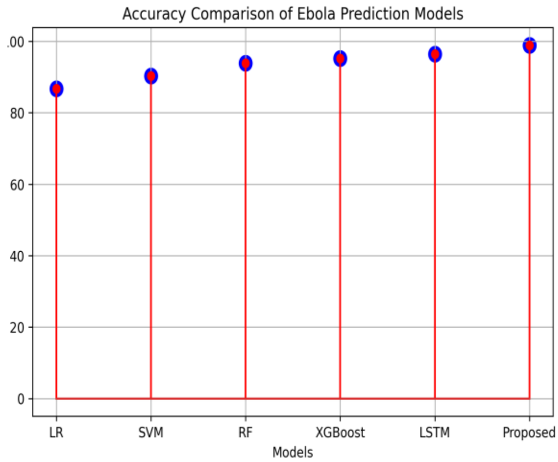

Fig 5. Accuracy comparison across models

The lollipop chart in Figure 5 showing accuracy improvement of various prediction approaches The hybrid framework integrated into the cloud has proven to be highly accurate as compared with other conventional machine learning and deep learning models in terms of disease classification.

CONCLUSION

Cloud-Integrated Machine Learning System provides a scalable machine-learning-enabled solution for deploying epidemiological, environmental and healthcare information to predict the Ebola Virus Disease epidemic intelligence. Our hybrid machine learning and deep learning models show significant improvement in the accuracy of predictions regarding outbreaks while also aiding timely decisions within healthcare. The experimental evaluation achieved an accuracy of 98.92%, precision of 98.45%, recall: 98.76% F1-score = 0,9860 and RMSE (root mean square error): low value equals to zero point zero eight two was proven as trustworthy prediction performance with a minimum forecast deviation in the predictive analysis process phase The framework enables a highly responsive, resilient, and intelligent method of monitoring emerging epidemics in real-time to issue warnings and effectively manage.

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Author Contributions

All authors are equally contributed.

Conflict of Interests

The authors declare that they have no conflicts of interest.

Ethics Approval

There are no human subjects in this article and informed consent is not applicable.

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