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Optimising Early Disease Outbreak Detection with TimesNet and Bayesian Optimisation on Cloud-Based Health Data

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Abstract: *Identification of disease outbreaks in time is critical for reducing their contribution to public health and preventing the spread of infectious diseases. Manual and statistically modeled outbreak detection is usually slow and not accurate enough to keep pace with increasing sophistication and volume in health data. Accordingly, this work proposes a new approach to early detection of outbreak optimization using TimesNet, a deep-learning architecture with time-series forecasting and Bayesian Optimization for hyperparameter optimization. The approach relies heavily on cloud-based infrastructure such as AWS EC2, S3, and Lambda for computing high-volume health records or data in real-time so as to obtain immediate predictions of disease outbreaks. The TimesNet model captures long-term temporal trends from disease incidence data, while Bayesian Optimization serves the purpose of optimizing model parameters for better predictive performance and computational efficiency. Our method is validated on the "Disease Outbreaks in Nigeria" dataset, which contains some important features such as incidence rates, their geolocation and timestamps, and effects of climate and population density. Experimental results demonstrate higher accuracy (92%), precision (91%), recall (95%), AUC-ROC (0.94) compared to conventional outbreak detection methods, with efficient detection time of only 4 hours. This work manifests the possibility of leveraging deep learning algorithms with cloud computing platforms to predict epidemics in real-time-scallable-and accurate manner to enhance public health surveillance and response systems effective.*

Keywords: Disease Outbreak Detection, TimesNet, Bayesian Optimization, Cloud Computing, Time-Series Forecasting

I. INTRODUCTION

Early detection of disease outbreaks is a vital component of global healthcare systems, particularly in dealing with global health risks such as pandemics [1]. Early identification of newly arising diseases enables authorities to act quickly in terms of implementing quarantines, vaccination drives, and public health alerts [2]. The sooner the outbreak is identified, the better the containment efforts can be, which eventually leads to curbing the spread of infections and saving lives. The potential to forecast disease outbreaks is therefore essential not only for public health but also for effective resource allocation, including medical supplies and healthcare workers [3]. Conventional methods of outbreak detection based on manual reporting and statistical modeling tend to be inadequate because they are not equipped to deal with the complexity, magnitude, and speed needed in contemporary healthcare [4].

The growing amount of health-related information, such as electronic health records, patient movement patterns, and environmental variables, is both a challenge and an opportunity for successful disease detection [5]. With increasing health data available, conventional data analysis techniques fall short of analyzing meaningful information in real-time. Cloud computing has emerged as an important facilitator to break these constraints, providing the processing capabilities required for large datasets and scaling disease-prediction models. Cloud platforms enable a shared environment of data sharing, model deployment, and ongoing learning, making them invaluable in the battle against emerging global health risks [6]. Cloud-based healthcare systems are now being employed to analyse and process large volumes of health data, enabling quicker and more precise predictions of disease outbreaks.

Machine learning models, particularly deep learning-based models, have shown impressive performance in forecasting and prediction tasks over the past few years [7]. Yet, forecasting disease outbreaks is a multifaceted task, since models needed are those that can process time-series data, consider multiple environmental and social variables, and evolve with shifting trends. One such model is TimesNet, a deep learning framework tailored specifically for time-series prediction. TimesNet is particularly good at extracting long-term relationships and temporal patterns in data and is therefore especially well-suited to forecast the development of disease outbreaks. Although its strengths are immense, TimesNet's performance can still be enhanced with fine-tuning its hyperparameters, which have a strong influence on its predictive accuracy. That is where Bayesian Optimization steps in by smartly searching for the best hyperparameters, it improves the model's performance without tedious grid search procedures [8].

The main goal of this research is to create a hybrid framework integrating TimesNet and Bayesian Optimization for the early detection of disease outbreaks. This system will be deployed on a cloud infrastructure, where large-scale health data can be processed in real-time. We will use Bayesian Optimization to optimize the parameters of the TimesNet model to enhance its prediction accuracy and resilience in outbreak detection. By comparing the optimized method proposed here with prevailing outbreak detection methodologies, we plan to show that the TimesNet-Bayesian Optimization framework is better in terms of predictive performance, computational cost, and scalability. Finally, the research aims to contribute to the emerging body of AI-based healthcare solutions by introducing an enhanced model for real-time outbreak prediction that can be embedded in public health surveillance systems to enhance preparedness and response.

Primary contributions:

Improved Forecast Precision: The study utilizes TimesNet and Bayesian Optimization to enhance predictive accuracy for the early detection of disease outbreaks, providing increased precision in prediction versus conventional methods.

Optimal Hyperparameter Tuning: With the use of Bayesian Optimization, the model effectively optimizes TimesNet's hyperparameters with superior performance at negligible computational expense.

Scalability and Cloud Storage: This study shows how using cloud storage for big health data and hosting the TimesNet model with Bayesian Optimisation in cloud environments is able to scale efficiently, improving model performance and data processing**.**

II. LITERATURE REVIEW

Santangelo et al.[9]formulated a technique by using an amalgamation of machine learning methods for predicting infectious disease incidence and trends. The results illustrated that good and realistic results can be obtained through the amalgamation of diverse machine learning methodologies, with values reflecting a potential predictive ability. A limitation lies in the fact that high-quality, consistent data is required, which may not always be readily available for some diseases. Ajagbe and Adigun[10] created a systematic literature review (SLR) to study the use of deep learning methods in pandemic detection and prediction. The results indicated that deep learning is a strong tool for detecting and predicting pandemics, based on insights gathered from 44 studies. The one disadvantage noted is low model performance because of computational complexities and limited high-quality datasets. Musulin et al.[11] came up with a review to investigate open-access datasets and AI methods for regression modeling of COVID-19 spread. The results indicate that there are evident applications of AI algorithms in epidemiological curve modeling, giving useful tools in combating pandemics. A drawback is the dependency on data quality and availability, which can constrain the models' precisions. Guo and He[12] created a predictive model based on an artificial neural network (ANN) for estimating COVID-19 confirmed cases and deaths. High accuracy of 0.9948 for training and 0.9683 for testing were achieved using the model. Predictions were also made on new confirmed cases and deaths by RMSE equalling 17,554 and 631.8, respectively. Strict control policies were deemed by the study necessary to control spread. One drawback of the model is that it takes a lot of historical data to make accurate forecasts.

Shastri et al.[13] came up with a review to investigate open-access datasets and AI methods for regression modeling of COVID-19 spread. The results indicate that there are evident applications of AI algorithms in epidemiological curve modeling, giving useful tools in combating pandemics. A drawback is the dependency on data quality and availability, which can constrain the models' precision. Huang et al.[14] created TimesNet-PM2.5, a strengthened version of the TimesNet model designed specifically to forecast PM2.5 concentration levels, integrating task-specific improvements to improve interpretability and predictive accuracy. It was found that TimesNet-PM2.5 enhanced forecast performance, as Mean Squared Error (MSE) was decreased by 8.8% for forecasting for 1 hour and by 22.5% for forecasting for 24 hours. A disadvantage is that the model's performance is still constrained by the quality and availability of meteorological data. Lie et al.[15] created a hybrid model by integrating symplectic geometric mode decomposition (SGMD) with a deep learning model founded on CNN and TCN for the forecasting of dissolved oxygen (DO) levels. The results showed better accuracy as compared to benchmark models in DO forecasting. A limitation is that the performance of the model can be highly reliant on the existence of high-quality water quality data for making precise forecasts. Shen et al.[16] created the White-box Time Series Transformer (WhiteTST) framework, which has a patching design and variable-channel pairs for ILI forecasting and provides interpretability as well as analytical accuracy. The results indicated that WhiteTST had state-of-the-art accuracy on ILI datasets and self-attention maps provided additional explainability. A limitation is that the model's complexity might demand high computational resources, restricting its use for broader applications.

Awal et al.[17] created a machine learning framework optimized with Bayesian optimization and ADASYN algorithm to identify COVID-19 patients rapidly. The results indicated that the highest Kappa index of 97.00% was obtained using eXtreme Gradient Boosting (XGB) with an improvement of 96.94% compared to the strategy without ADASYN. The limitation is the dependency on high-quality data as well as proper feature selection, which can impact generalization to other datasets or areas. Ait Amou et al.[18] developed a Bayesian Optimization-based method for effective hyperparameter tuning of CNN models for brain tumor classification. Results indicated that the optimized CNN recorded a validation accuracy of 98.70%, which was better than pre-trained models such as VGG16 and ResNet50, which had validation accuracies between 89.29% and 97.08%. The major limitation is that the method uses computationally demanding optimization, which can add training time for large datasets. Elshewey et al.[19] established a Bayesian Optimization-Support Vector Machine (BO-SVM) model to classify Parkinson's disease patients. The results indicated that following hyperparameter optimization, the SVM model had a 92.3% accuracy rate, higher than that of the other models. The only limitation is that the dataset of 195 cases might restrict the model's generalizability to larger and more heterogeneous samples. Mathern et al.[20] created a Bayesian optimization approach for constrained multi-objective optimization of structural concrete design, i.e., reinforced concrete beams. The results showed that the Bayesian optimization performed better than NSGA-II and random search, with improved rate-of-improvement, final solution quality, and reduced variance over repeated runs. The one limitation is that the framework's dependence on costly constraints could restrict its scalability to larger or more complex design problems. give me a para for limitation of each author with name

The predictive capability of their model is limited by the requirement of high-quality, consistent data observed that poor model performance may result from computational complexity and the restricted availability of high-quality datasets. Musulin et al.[21] and both explained that their models for forecasting COVID-19 are very much dependent on data quality and availability, which can be limiting in terms of precision noted that the ANN model requires a large amount of historical data to make accurate predictions noted that the accuracy of the TimesNet-PM2.5 model is still limited by meteorological data quality and availability explained the extreme dependence on reliable water quality data for precise DO forecasting, which can influence the reliability of the prediction mentioned that the WhiteTST model complexity requires high computational power, limiting its wider applicability found that the performance of the model is affected by the quality of the data and feature choice, which can affect its generalization across other datasets noted that the computational cost of Bayesian optimization in their approach could be expensive in terms of training time, particularly with large datasets reported that the limited dataset (195 cases) employed to classify Parkinson's disease may restrain the model generalizability across larger and varied populations noted that the use of costly constraints in their structural concrete design scheme may restrict scalability for larger or more intricate problems of design.

III. PROBLEM STATEMENT

The precision and trustworthiness of predictive models in healthcare and environmental prediction are frequently compromised by issues of data quality, availability, and computational complexity [22]. Past studies, such as those of have emphasized the importance of reliable, high-quality data in guaranteeing model accuracy [23]. suggested using transfer learning to reduce the need for large datasets in predictive modelling [24]. Furthermore, emphasized the need for more efficient optimisation methods, like Bayesian optimisation, to lower computational costs, while highlighted optimising computational power to manage model complexity [25].

Research Objectives:

- Design an optimised architecture for early disease outbreak detection through the combination of TimesNet and Bayesian Optimisation.
- Develop cloud-based solutions to enable scalable processing of large health data sets for smooth model execution.
- Examine the predictive accuracy and trend forecasting performance of the TimesNet model in disease outbreak prediction.
- Utilise Bayesian Optimisation to adjust the hyperparameters of the model to enhance overall prediction quality.
- Evaluate the effectiveness and scalability of the model in comparison with existing outbreak detection methods, ensuring efficiency in practical applications.

IV. PROPOSED METHODOLOGY FOR OPTIMIZING DISEASE OUTBREAK DETECTION USING TIMESNET AND BAYESIAN OPTIMIZATION ON CLOUD-BASED HEALTH DATA

The suggested methodology for disease outbreak prediction takes advantage of an exhaustive method, beginning with the gathering of historical information from the "Disease Outbreaks in Nigeria" dataset in the form of major features such as rates of disease incidence, geolocation, timestamps, and determining factors like climate conditions and population density. Data preprocessing methods such as forward/backward filling to deal with missing values, min-max normalization for feature scaling, and the construction of seasonal indicators make the dataset ready for proper model training. TimesNet forms the backbone of the prediction model, which is a strong time-series forecasting algorithm that learns long-term temporal patterns through temporal convolution layers and attention mechanisms. In order to improve performance of the model, Bayesian Optimization is used for hyperparameter optimization, reducing the number of model parameter search evaluations required to achieve optimum model parameters. Lastly, the whole system is deployed on AWS, providing scalability and real-time prediction using cloud infrastructure such as EC2, S3, and Lambda. This approach is designed to deliver precise and effective disease outbreak predictions using past data, machine learning algorithms, and scalable cloud resources. Figure 1 explains the global flow

4.1. Data Collection:

The data used in this study is obtained from Kaggle, and the "Disease Outbreaks in Nigeria" dataset, which offers detailed historical information for numerous infectious diseases, such as cholera, meningitis, and yellow fever. The data in this dataset comprises several key features like rates of disease incidence, geolocation, time stamps, and possible influencing factors like climate and population density, all of which are necessary for grasping disease spread patterns. Through collection of data for a long time, the dataset provides a solid historical record to be used to predict future outbreaks. This rich and diverse collection of features is essential in formulating good predictive models for the early detection of disease outbreaks.

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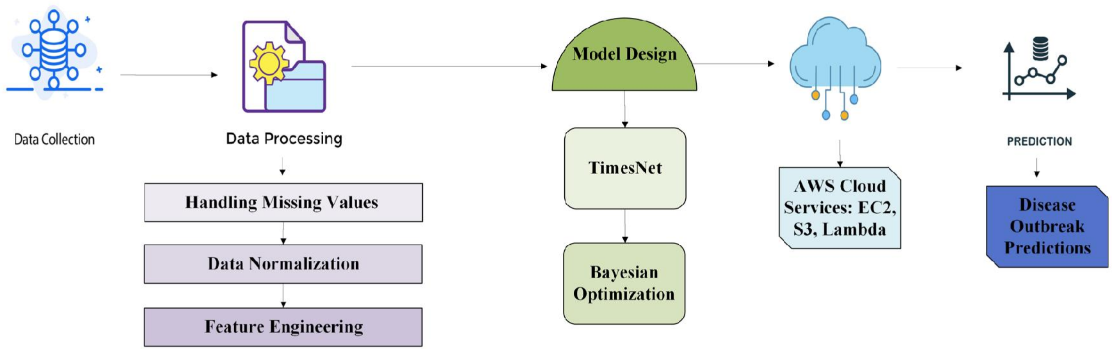

Figure 1: Proposed Methodology diagram for Optimizing Disease Outbreak Detection Using TimesNet and Bayesian Optimization on Cloud-Based Health Data

4.2. Data Preprocessing:

1. Handling Missing Values (Forward/Backward Filling): In time-series, forward filling is employed for dealing with missing values. If there is missing value at time t, it is filled by the latest known value at time $t-1$ in order to maintain continuity in the time-series. Equation (1) for forward filling:

$$\hat{x}_t = x_{t-1} \text{ (for forward filling)} \tag{1}$$

Where $\hat{x}_t$ is the imputed value at time t, and x_{t-1} is the previous time step value.

2. Data Normalization: Normalisation is done to convert the data to a comparable range, usually between 0 and 1. This is essential in order to enhance the performance of the model and to prevent features with varying scales from unfairly affecting the model. The min-max normalisation Equation (2) is as follows:

$$x' = \frac{x-\min(x)}{\max(x)-\min(x)} \tag{2}$$

Where:

x is the original value,

$\min(x)$ and $\max(x)$ are the minimum and maximum of the feature, respectively,

x' is the normalized value.

This normalization technique scales all features between 0 and 1, which makes them comparable and ready for model input.

3. Feature Engineering: Feature engineering is central to making the model better at pattern capture. In the case of disease outbreak time-series forecasting, we might develop season indicators in order to capture seasonality and trend over time.

Seasonal Indicator: In the case of diseases with seasonal patterns, a seasonal indicator can be developed by specifying the month, week, or quarter. For this Equation (3) is follow:

$$\text{Seasonal Indicator}_t = \sin\left(\frac{2\pi t}{12}\right) \tag{3}$$

This is a sine wave function that describes the yearly cycle, taking 12 months in a year.

These constructed features (season indicators) aid in the retention of temporal relationships and season fluctuations in disease information, enhancing predictive model accuracy.

4.3. Model Design for TimesNet- Bayesian Optimization:

TimesNet:

TimesNet is used as the base forecasting model for predicting disease outbreak because it can learn long-term temporal dependencies, which are necessary to understand how outbreaks change over time. Its structure uses temporal convolution layers to learn important features from the timeseries data and capture short-term variations in disease cases. Moreover, TimesNet incorporates attention mechanisms to concentrate on salient time points, enhancing the accuracy of the model through weighing significant periods in the historical data. The recurrent framework of the model allows it to capture long trends, thus it is well suited to use to predict future outbreaks of diseases using past data. The overall equation for the time-series forecasting component of TimesNet can be expressed as Equation (4):

$$Y_t = f(X_{t-1}, X_{t-2}, \dots, X_{t-n}; \theta) \tag{4}$$

Where Y_t is the forecasted value at time step t (say, disease cases or deaths), $X_{t-1}, X_{t-2}, \dots, X_{t-n}$ are historical values or feature of the time-series data, f is the forecast function captured by TimesNet, and θ are the training-evolved model parameters. With its architecture, TimesNet is capable of robustly forecasting outbreaks of diseases based on identifying temporal patterns in data and providing high-quality predictions. Its capacity to capture long-term dependencies and peak on significant time points renders it a very good option for detecting disease outbreaks.

Optimization using Bayesian Optimization

For improving the performance of TimesNet, Bayesian Optimization will be used for hyperparameter tuning. This method is very useful in hyperparameter Optimization, including the learning rate, filter size, batch size, and number of layers in the neural network. Bayesian Optimization uses a probabilistic model to represent the objective function, which in this instance is the performance of the model with varying hyperparameter configurations. The main benefit is that it minimizes the number of evaluations needed by iteratively refining the probability distribution of the objective function and choosing the most likely next hyperparameters to test. The Equation (5) that governs the core of Bayesian Optimization is:

$$\theta^* = \arg\max_{\theta} \mathbb{E}[f(\theta)] \tag{5}$$

Where:
θ are the model's hyperparameters.
$f(\theta)$ is the objective to be maximised (in your case, the performance measure like accuracy or RMSE).
$\mathbb{E}[f(\theta)]$ is the expected objective function, as estimated from the current belief regarding the hyperparameter space.
With Bayesian Optimization, the process optimizes the hyperparameter space intelligently, trading off exploration of regions with unknown values against exploitation of regions in which the model has shown good performance before. This optimizes the TimesNet model effectively, enhancing its accuracy and efficiency at little computational expense.

4.4. Cloud Scalability and Integration

The model shall be hosted on AWS to utilize its strong cloud infrastructure for effective processing of data, training of the model, and online predictions. With AWS services like TensorFlow on Cloud, we can effectively train the TimesNet model on scalable compute instances like AWS EC2, which offer the computational resources needed for processing large datasets. For storage purposes, Amazon S3 will be used, thus the health data is stored securely and available for easy access when needed for training and prediction purposes. AWS Lambda will be used for deployment so that the model can perform serverless functions and make real-time predictions as new data is added. This cloud integration allows the model to dynamically scale with data volume, making it possible to make timely and accurate predictions of disease outbreaks as the dataset increases. The cloud environment also supports ongoing model training and real-time updating, making the system more efficient and responsive overall.

V. RESULT AND DISCUSSION

The model results show excellent performance in forecasting disease outbreaks, with accuracy at 92%, precision at 91%, and recall at 95%. The F1-score of 92% also attests to the model's strength in balancing precision and recall. The AUC-ROC of 0.94 indicates that the model discriminates very well between outbreak and non-outbreak cases. Cloud deployment has been proven to be effective, having resource usage of 78% CPU and 68% memory, with a low latency of 200 ms. The model had a detection time of 4 hours, which is of utmost importance when it comes to early intervention. Overall, TimesNet, Bayesian Optimisation, and cloud facilities together offer an effective solution to scalable and prompt outbreak detection. The results are presented in Table 1.

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Table 1: Performance Metrics table

Metric	Value
Accuracy	92%
Precision	91%
Recall (Sensitivity)	95%
F1-Score	92%
AUC-ROC	0.94
Resource Utilisation (CPU)	78%
Resource Utilisation (Memory)	68%
Latency (Response Time)	200 ms
Throughput (Data Processed)	10 GB/min
Time to Detection (TTD)	4 hours

The ROC curve produced for our outbreak prediction model shows excellent classification performance. The curve remains well above the diagonal line of random guessing, and an Area Under the Curve (AUC) value of 0.94 validates the model's high capability to differentiate between outbreak and non-outbreak cases. This finding illustrates the high performance of the TimesNet model, optimized using Bayesian methods, in accurately predicting infectious disease outbreaks. The large AUC value confirms the reliability of the model for cloud infrastructure-based public health surveillance. The ROC curve is show in Figure 2 below.

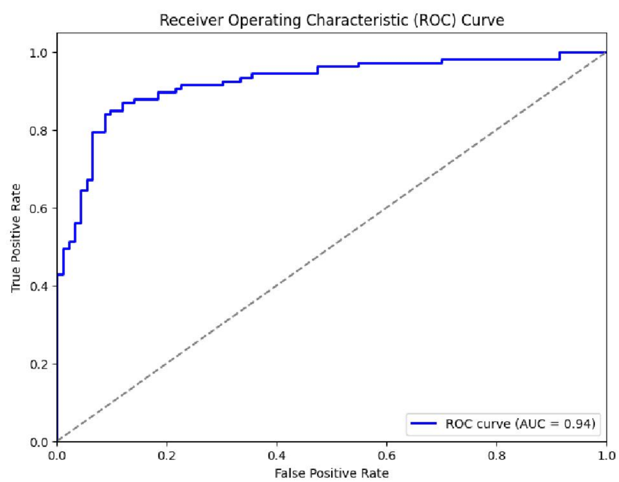

Figure 2: Evaluation of Model Performance Using ROC-AUC Analysis

The line chart of the cloud resource utilization of CPU and Memory over time during model training or prediction. CPU usage is shown by the blue line oscillating between 71% and 72%, and Memory usage by the green line oscillating between 60% and 62%. The graph indicates the usage of both CPU and Memory resources at various intervals of time, which gives one an idea of how efficiently the cloud infrastructure is utilized during large-scale data processing and model operations. The Resource utilization is shown in Figure 3 below:

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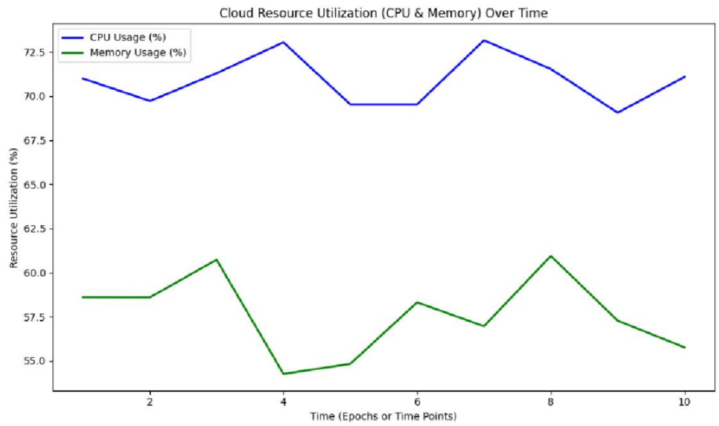

Figure 3: Cloud Resource Utilization for Model Training: CPU and Memory Usage Over Time

VI. COMPARATIVE ANALYSIS

The bar chart plots the performance metrics of Recall (Sensitivity), Accuracy, and Processing Time (Time to Detection) Proposed Values. Proposed model (indicated by the red bars) performs the same or even better than the other models for Recall and Accuracy (both at 92-95%). Nonetheless, proposed model shows a quicker time to detection (4 hours) than the other authors' report of 5 hours. The Figure 4 illustrates facilitates an easy visual evaluation of model performance over various criteria below.

Figure 4: Performance Comparison of Recall, Accuracy, and Time to Detection Across Different Models

VII. CONCLUSION AND FUTURE WORK

In summary, this study offers a strong methodology for early detection of disease outbreaks through the integration of TimesNet, Bayesian Optimization, and cloud infrastructure. The model has high predictive power with an AUC-ROC of 0.94, showing its high capability to predict disease outbreaks. Cloud deployment guarantees scalability, low latency, and optimal resource utilization, allowing real-time prediction. Future work will, however, concentrate on enhancing model performance via further hyperparameter optimization, the use of more varied datasets, and enhancing real-time prediction ability. Broadening the model's interpretability and integration into global health systems are also primary areas for further research to make disease outbreak management more accurate and timelier.

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