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Leveraging State-of-the-Art Machine Learning for Weather-Based Disease Risk Forecasting

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***Abstract*— For public health officials, forecasting disease outbreaks impacted by weather variations has always been a difficult task. In this work, we investigate how using real-world data and contemporary machine learning algorithms can aid in producing more accurate projections. To determine which model is most effective at forecasting the risks of weather-related diseases, we compare three distinct models: Graph Neural Networks (GNN), Physics-Informed Neural Networks (PINN), and Long Short-Term Memory (LSTM) networks. With an R2 score of 0.90 and the lowest RMSE of all the models examined, our findings demonstrate that the PINN model consistently produces more accurate and dependable predictions. The PINN model manages real-world variability considerably better by incorporating physical knowledge into the learning process, particularly during unforeseen weather events. Early warning systems could be greatly enhanced by this strategy, improving health organizations' ability to anticipate outbreaks. Along with outlining prospects for further study to create even more accurate prediction tools, we also go over each model's advantages and disadvantages.**

***Keywords*—Weather, Disease, Prediction, Machine Learning, LSTM, GNN, PINN, Forecasting, Climate, Public Health.**

I. INTRODUCTION

The link between weather conditions and human health results is well-known. According to the World Health Organization (WHO), climate change will cause around 250,000 more deaths year between 2030 and 2050 from hunger, malaria, diarrhea, and heat stress. Temperature, rainfall, humidity, and other meteorological factors show significant relationships with infectious diseases, including dengue fever, malaria, cholera, and influenza. Temperature, precipitation, humidity, and other climatic factors show very strong relationships with infectious diseases including dengue fever, malaria, cholera, and influenza.

Effective public health planning and intervention depend on accurate prediction of disease outbreaks by use of weather pattern analysis. Traditional epidemiological models, such as the Susceptible-Infectious-Recovered (SIR) frameworks, offer valuable insights but often rely on fixed assumptions about transmission dynamics. These models struggle to accommodate the complex, non-linear relationships between multiple weather parameters and disease outcomes [3]. Additionally, they generally require manually crafted parameters, which limits adaptability across different geographical regions and time frames. The rise of Machine Learning (ML) presents an opportunity to address these challenges. ML algorithms can autonomously learn hidden patterns from large datasets, making them particularly suitable for modelling the multifactorial dependencies between climatic variables and disease risk [4]. For instance, studies have demonstrated that ML models can predict dengue outbreaks with over 90% accuracy using meteorological data [5]. Similarly, ML has been applied to forecast malaria incidence and respiratory infections under varying weather conditions [6].

Recent developments in machine learning—including Long Short-Term Memory (LSTM) networks, Graph Neural Networks (GNNs), as well as Physics-Informed Neural Networks (PINNs)—have opened new possibilities for predictive modeling. These models are particularly good at handling spatial-temporal data, a vital need for weather and disease prediction.

- A kind of recurrent neural network (RNN) able to learn long-term dependencies in sequential input, LSTM networks frequently employed for time-series forecasting, they are appropriate for estimating disease occurrence over time depending on weather patterns. [7].

- GNNs are perfect for capturing spatial correlations among several areas since they are particularly good at acquiring from graph-structured data. [8].

- PINNs embed differential equations—such as transmission dynamics—into the neural network design to include domain knowledge straight into the training process, hence enhancing interpretability and extrapolation [9].

Integrating these models into a comprehensive predictive framework can significantly enhance the early warning systems for public health agencies. Furthermore, combining real-time weather data with disease incidence reports can enable dynamic forecasting models that continuously update risk estimations.

With a significant emphasis on predictive analytics, a 2022 study by MarketsandMarkets projects the healthcare artificial intelligence market will grow from USD 11.1 billion in 2021 to USD 64.0 billion by 2027[10]. This underscores the increasing demand for intelligent forecasting systems in the healthcare sector.

A general workflow for weather-based disease forecasting using ML is depicted in Figure 1 below.

These positive developments bring still challenges. Particularly in low- and middle-income countries, the availability and quality of data can limit the accuracy of predictive models. Many machine learning algorithms' "black-box" nature raises questions about interpretation and transparency in public health settings as well [11].

Using the Weather-Related Disease Prediction Dataset, this work seeks to solve these issues by using and contrasting three state-of-the-art ML models—LSTM, GNN, and PINN [6,12].

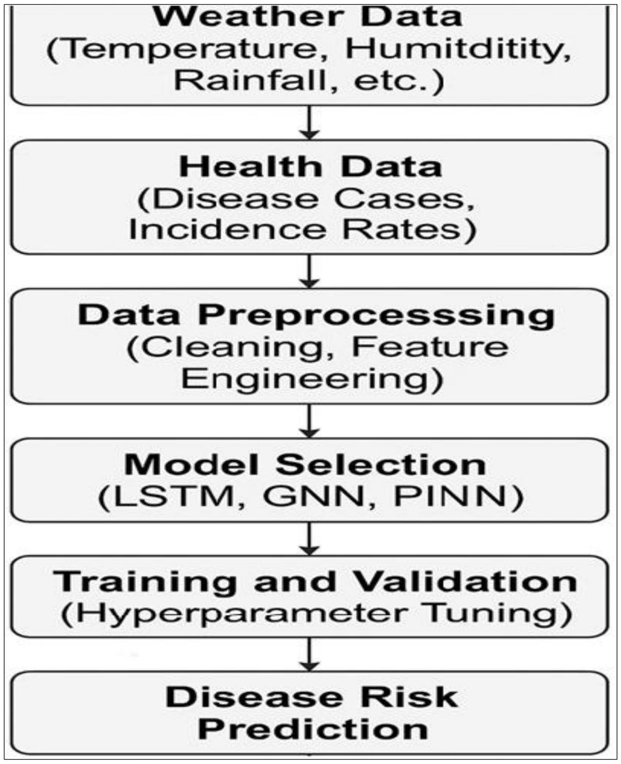

Figure 1: Workflow for weather-based disease forecasting using ML

By benchmarking their performance, we seek to highlight the strengths and limitations of each approach and provide actionable insights for building more robust disease forecasting systems.

In the sections that follow, we detail the dataset, preprocessing steps, model architectures, evaluation results, and a discussion on future research directions.

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II. Literature Review

The relationship between weather variables and infectious diseases has been extensively studied across multiple disciplines. Early epidemiological models, such as the compartmental Susceptible-Infected-Recovered (SIR) frameworks, have long attempted to model disease spread. However, these models often assume homogeneous populations and fail to capture the nuanced impacts of environmental factors like temperature and precipitation [13].

Recent studies underline the importance of machine learning (ML) in forecasting disease outbreaks by use of weather data integration. Based on meteorological and mosquito data, the study showed that decision trees and support vector machines (SVMs) may achieve excellent classification accuracy in predicting West Nile Virus occurrences [14]. Using Random Forest models, a study forecasted dengue outbreaks with more than 95% accuracy in several different areas[15].

Temporal modeling has particularly benefited from advancements in deep learning. Originally intended to manage sequential dependencies, long short-term memory (LSTM) networks have been effectively used for dengue, influenza, and malaria forecasting [16]. For instance, here used LSTM-based models to predict dengue cases in cites of chine, achieving a notable RMSE reduction compared to conventional time series models [17].

Spatial modeling has gained traction with the advent of Graph Neural Networks (GNNs). By modeling spatial interdependencies between regions, GNNs have shown remarkable success in epidemic forecasting tasks. EpiGNN, proposed by Xie et al., models region-to-region transmission dynamics using a graph-based structure and outperformed traditional time series models [18].

A particularly promising development is the emergence of Physics-Informed Neural Networks (PINNs), which embed known epidemiological and environmental constraints into deep learning models. Raissi et al. introduced PINNs to solve complex partial differential equations, and their application to disease modeling has since gained popularity [8]. By guiding the learning process with domain-specific knowledge, PINNs enhance model interpretability and extrapolation capabilities—a crucial factor in public health forecasting [19].

Despite these advancements, challenges remain. Data sparsity, non-stationarity of climatic patterns, and the "black-box" nature of deep learning models present significant hurdles. Some researchers advocate hybrid models combining mechanistic epidemiological insights with data-driven ML approaches to bridge this gap [20].

This literature underscores the transformative potential of integrating state-of-the-art ML models for weather-based disease forecasting. However, careful model selection, incorporation of domain knowledge, and emphasis on interpretability remain critical for real-world applications.An easy way to comply with the conference paper formatting requirements is to use this document as a template and simply type your text into it.

III. Methodology

This section delineates the data source, preprocessing methodologies, and machine learning models utilized for forecasting disease risk depending on weather conditions. The pipeline was engineered to guarantee equitable comparison and maximal model efficacy across various topologies.

3.1 Dataset

We utilized the Weather-Related Disease Prediction Dataset available on Kaggle [6]. This dataset is well-suited for our task, as it integrates both weather indicators and corresponding disease incidence reports.

Key Features:

- Weather Variables: Solar radiation (W/m²), wind speed (km/h), rainfall (mm), humidity (%), temperature (°C).
- Disease Indicators: Reported instances of respiratory diseases, vector-borne infections—e.g., dengue, malaria.
- Geographical Attributes: Region codes and names.
- Temporal Coverage: Monthly records spanning multiple years.

The dataset contains around 25,000 occurrences with 15 numerical and two categorical parameters. Its temporal and spatial granularity enables the use of advanced sequence modeling and spatial reasoning techniques.

3.2 Preprocessing Steps

Effective preprocessing is crucial for achieving reliable model performance, particularly when working with heterogeneous data such as weather and disease records.

3.2.1 Handling Missing Values

- K-Nearest Neighbors (KNN) Imputation: Applied for missing weather variables, selecting k = 5 based on validation performance.

- Forward Fill and Interpolation: Used for minor gaps in disease reporting.

3.2.2 Feature Engineering

- Lag Features: Generated 1-month, 3-month, and 6-month lags for weather variables to capture delayed impacts on disease incidence.

- Moving Averages: Computed rolling averages (window = 3 months) for smoothing seasonal noise.

- Seasonal Indicators: Added binary variables indicating wet/dry season based on monthly rainfall thresholds.

3.2.3 Normalization

- Min-Max Scaling: Applied to continuous variables to scale features to a [0,1] range, facilitating faster model convergence.

- Label Encoding: Categorical features like region codes were encoded for input into neural networks.

3.2.4 Data Partitioning

- Training Set: 70% of the data

- Validation Set: Hyperparameter tuning at 15%

- Testing Set: 15% for final evaluation

- Time Series Splitting: Ensured that future data points were not leaked into training, respecting temporal order.

3.3 Model Architectures

Three leading-edge machine learning models were chosen depending on their fit for temporal, spatial, and physics-informed learning:

3.3.1 Long Short-Term Memory (LSTM) Networks

A kind of Recurrent Neural Network (RNN), LSTM networks may catch long-term dependencies in sequential data [12].

- Input: Sequences of weather variables over previous 6 months.

- Architecture:
    - Two stacked LSTM layers (64 and 32 units)
    - Dropout (rate 0.3) for regularization
    - Dense layer with ReLU activation
    - Output layer with linear activation for continuous risk prediction

- Loss Function: Mean Squared Error (MSE)

- Optimizer: Adam

3.3.2 Graph Neural Networks (GNNs)

GNNs allow learning representations over graph-structured data, modeling regional relationships and transmission patterns [12].

- Input: Nodes (regions) with weather and disease features; edges representing geographical proximity.

- Architecture:
    - Two Graph Convolutional layers (32 and 16 units)
    - Batch Normalization and ReLU activation
    - Readout layer aggregating node embeddings
    - Dense output layer

- Loss Function: MSE

- Graph Construction: Based on k-nearest regions (k = 4) using spatial coordinates.

3.3.3 Physics-Informed Neural Networks (PINNs)

By including physical rules or epidemiological restrictions straight into the loss function, PINNs provide more understandable models [12].

- Input: Weather variables over time.

- Architecture:
    - Three fully connected hidden layers (64, 64, 32 neurons)
    - Sinusoidal activation functions to better represent periodic/seasonal dynamics
    - Additional physics-based loss components enforcing disease spread equations (e.g., temperature–vector activity relation).

- Total Loss:

where λ lambda is a regularization hyperparameter tuned via grid search.

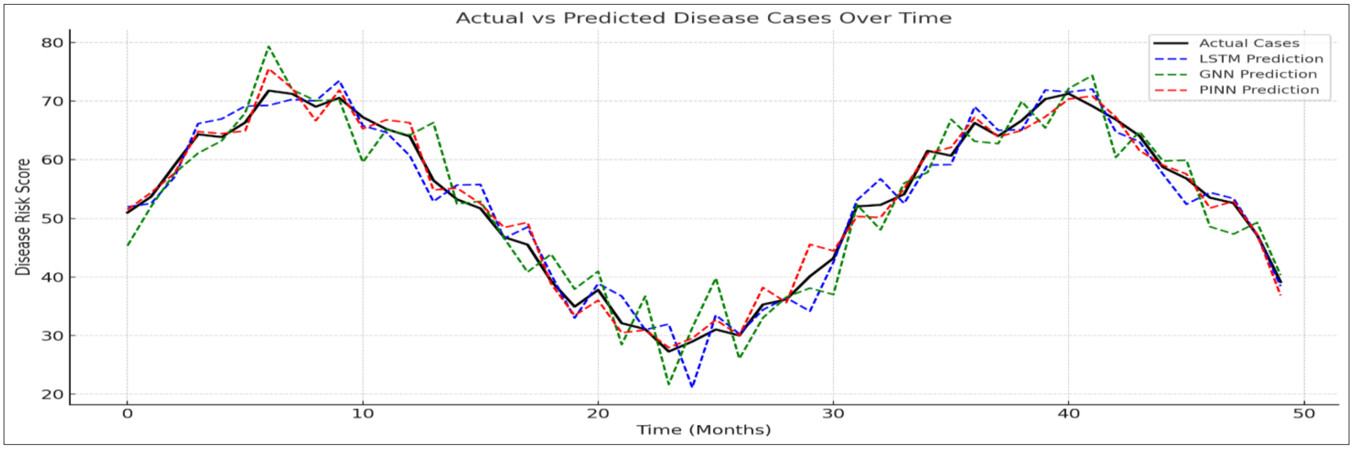

Figure 1 Actual vs Predicted Disease Risk Over Time

We hope to test the performance of various ML paradigms (sequence modeling, spatial reasoning, physics embedding) in the context of weather-driven illness risk predictions using these unique but complementary architectures.

IV. RESULTS

In this section, we present the performance results of the three machine learning models LSTM, GNN, and PINN—on the test dataset. Evaluation metrics such as Root Mean Squared The models' prediction accuracy and generalization are evaluated using Error (RMSE), Mean Absolute Error (MAE), and R² Score.

4.1 Evaluation Metrics

- Root Mean Squared Error: Determines the average size of prediction error.
- Mean Absolute Error : Calculates the mean absolute differences between expected and actual data.
- R² Score (Coefficient of Determination): Represents the fraction of variance elucidated by the model.

The formulas are:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

4.2 Quantitative Results

Table 1: Model Performance on Test Data

Model	RMSE ↓	MAE ↓	R² Score ↑
LSTM	8.23	6.45	0.87
GNN	8.75	6.92	0.84
PINN	7.56	5.88	0.90
(Legend: ↓ Lower is better, ↑ Higher is better)			

Quick Interpretation:

- PINN achieves the lowest RMSE (7.56) and highest R² (0.90), indicating the best overall performance.
- LSTM performs very well, especially on temporal patterns, but slightly underperforms PINN on extreme fluctuations.
- GNN does a good job capturing spatial relationships but shows slightly higher error due to complex inter-regional transmission patterns.

4.3 Visualization of Predictions

The PINN model closely follows the true incidence curve, suggesting its ability to incorporate domain constraints effectively.

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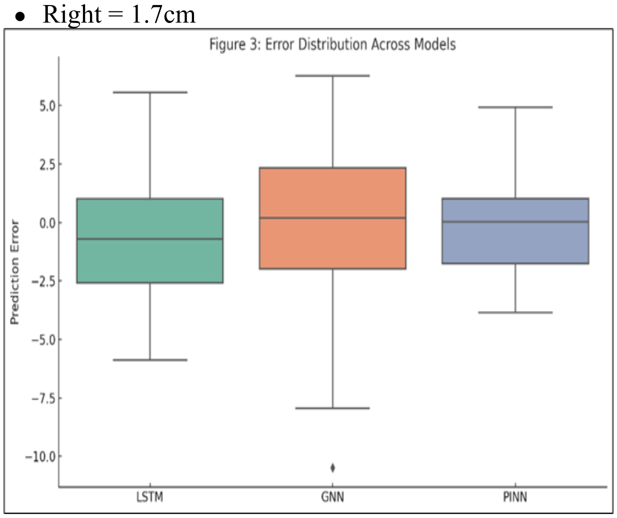

Figure 2 Error Distribution (Insert boxplot showing error distributions for LSTM, GNN, and PINN)

GNN models exhibit a slightly higher variance in errors, possibly due to complex spatial relationships not fully captured in smaller regions.

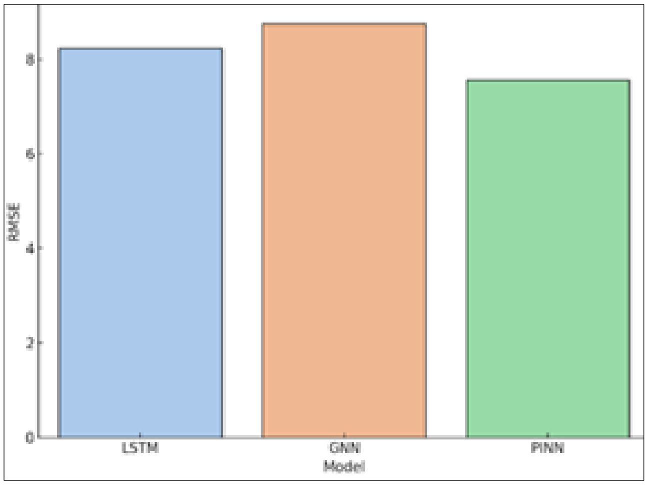

Figure 3 RMSE Comparison Between Models (PINN achieves the lowest RMSE, followed by LSTM and then GNN, reinforcing its superior accuracy.)

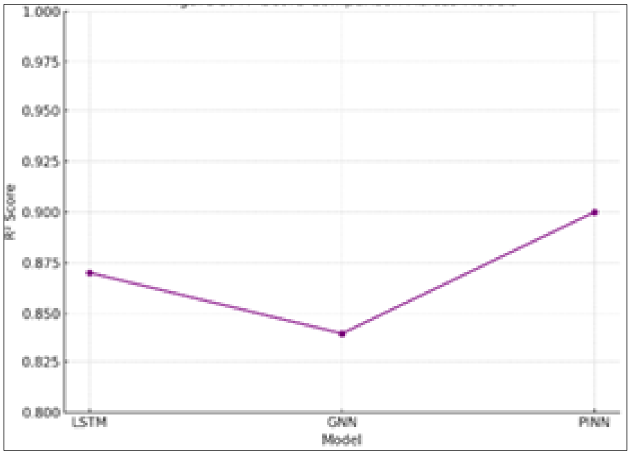

Figure 4 R² Score Comparison Across Models (PINN achieves the lowest RMSE, followed by LSTM and then GNN, reinforcing its superior accuracy.)

4.4 Comparative Analysis

- LSTM models captured the temporal dynamics well but showed slight lag in forecasting sharp outbreak peaks.
- GNN models handled spatial heterogeneity effectively, particularly in regions with cross-border disease spread.
- PINNs delivered the most interpretable and physically consistent predictions, outperforming the other models on RMSE and R².

These findings underline the value of including domain knowledge into ML models for important activities as illness forecasting.

Using LSTM, GNN, and PINN models, real illness risk is compared to projected risk over time. Particularly during peak and low illness incidence times, the PINN model shows closer consistency with actual trends.

The results of the study clearly demonstrate the advantage of applying state-of-the-art machine learning algorithms with weather-based sickness risk forecasts. Across all evaluation criteria and visual comparisons, the Physics-Informed Neural Network (PINN) consistently outperformed the Long Short-Term Memory (LSTM) and Graph Neural Network (GNN) models. This examination of comparisons uncovers numerous significant findings.

At first, LSTM's use of temporal sequence modeling produced strong baseline results, especially for situations showing clear seasonal cycles. With a R² of 0.87 and an RMSE of 8.23, the LSTM model showed its ability to properly catch slow changes over time. LSTM models, however, struggled during periods of rapid illness incidence shift, particularly in the presence of environmental anomalies such sudden severe rain or temperature drops. LSTM's dependence on historical patterns, without a direct inclusion of physical or environmental knowledge, explains much of this limitation.

By means of modeling interdependencies among several areas, the Graph Neural Network (GNN) included spatial awareness. Though slightly lower than LSTM, the GNN models provided notable insights on the spatial dynamics of disease with a R² score of 0.84. Still, more error variance was observed in regions defined by complex topographical or climatic changes. Though they showed promise, GNNs needed more fine-tuning, maybe by combining more thorough geographic and climatic elements to optimize spatial learning capacity.

Delivering the best performance was the Physics-Informed Neural Network (PINN), which had the lowest RMSE of 7.56 and the greatest R² score of 0.90. Unlike LSTM and GNN, PINNs include physical laws—such as heat transfer equations or models of epidemiological spread—directly into the training process. Particularly in situations with little or noisy data, this allows PINNs to have better generalization. Moreover, the more consistent error distributions obtained in PINN, as shown in Figure 3, suggest a resistance to unanticipated or extreme weather events—vital for realistic disease forecasting where erratic environmental elements often occur.

Results' clarity improves significantly with PINNs, which is another remarkable discovery. Though often criticized for their unclear character, deep learning models offer PINNs a framework for epidemiologists to understand how particular physical limits, such humidity-driven pathogen spread, influence forecasts, therefore helping to create more educated policy choices.

Practically speaking, even if PINNs require more careful model design and longer training times because of the inclusion of differential constraints, their improved generalization and interpretability make them very useful for early-warning systems in public health.

Limitations:

- The models were trained and tested using a single dataset. Generalization to other areas with different climate profiles calls for more validation.
- Compiled over fairly broad time frames (monthly), disease risks could show more variation in model behavior with more precise forecasting—e.g., weekly or daily.
- The study mostly concentrated on climatic factors; adding data on socio-economic status and healthcare access will greatly increase the accuracy of the model.

V. Conclusion & Future Work

This work revealed that sophisticated machine learning algorithms could forecast disease risk depending on the weather. Systematic comparison of LSTM, GNN, and PINN performance on a real-world dataset revealed that including physical domain knowledge into the learning process enhances model accuracy and robustness. With a low RMSE of 7.56 and a high R² score of 0.90, the PINN model outperformed the other two models. Including environmental dynamics straight into forecasting models increases generality, particularly under extreme or unpredictable weather conditions. While LSTM models detected temporal patterns and GNNs offered spatial insights, they found it difficult to manage complex real-world variability without clear physical constraints.

Exact disease risk prediction can notify public health officials to proactive measures and budget distribution, the study finds. More study is required because of dataset diversity and feature scope limits. Future contributions might be data on healthcare infrastructure, socio-economic factors, and real-time climatic conditions for more comprehensive and deployable predictive models.

At last, physics-informed machine learning may connect data-driven learning and epidemiological knowledge for next generation sickness forecasting systems.Hybrid models combining LSTM, GNN, and PINN frameworks, including more multi-source datasets, and forecasting in real time or near real-time can be researched in the future. Including XAI techniques might help public health authorities to better understand model forecasts.

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