# Probabilistic Spatio-Temporal Modeling of Weather-Driven Disease Risks Using Hybrid Physics-Aware and Graph-Based Machine Learning Frameworks

R. Latchiya[1], D. Nandhini[2], S.V. Sugin[3]
[1,2,3] *Department of Artificial Intelligence and Data Science, St. Joseph's College of Engineering OMR, Chennai*

***Abstract*—Weather also has a huge impact on the health of humans, and variations in weather conditions including changes in temperature, moisture, as well as rain caused seasonal diseases like influenza, heatstroke, skin infections and heart attacks. Conventional weather forecasting and health advisory systems are not integrated systems and they do not offer personalized preventive/avoidance advice. A new system of forecasting weather- related diseases was proposed in this project based on the use of modern machine learning methods. Gaussian Process Regression, Spatio-Temporal Graph Neural Network, Physics-Informed Neural Network, and Mixture Density Network are used to analyze historical meteorological data to produce correct and probabilistic forecasts. According to the predicted conditions, weather is categorized into classes, such as cold, hot and rainy, and the risks of associated illness are dynamically suggested with the help of the system as well as the preventive measures. Being embedded into a convenient web-interface the platform unites the climate information with health sensitivity. Empirical evidence confirms that the hybrid concept is effective in the prediction of complicated weather patterns, dependable disease threats, and enabling users to implement proactive health management practices.**

***Index Terms*—The Weather Prediction, Disease Risk, Gaussian Process, Graph neural network, Physics-informed Neural Network, Mixture Density Network, Public Health.**

## I. INTRODUCTION

The effect of weather patterns on human-health is enormous in that the pattern affects the occurrence of various diseases in distinct seasons. A change in temperature, humidity, or precipitation, which is sudden, may cause such circumstances as influenza, common cold, heatstroke, dehydration, cardiovascular problems, and skin infections. As an example, cold and wet conditions can contribute to respiratory illnesses, and hot and damp conditions may enhance heat-related diseases and rise in the prevalence of vector-borne illnesses. Conventional strategies of health advisories tend to be based on manual observation of weather forecast, or generalized recommendations to the population which are not personalized and as such, they cannot offer timely guidance. This lack of relationship between weather and health readiness points to the necessity of a cohesive one- stop-shop which would be able to forecast the weather and at the same time warn on the possibilities of health hazards.

Machine learning has revolutionized predictive analytics in most fields by providing complex, non-linear modeling tools addressing the inherent environmental and health data. The traditional methods like decision-tree-based algorithms or regression models have been highly applied in weather forecasting. Nonetheless, such models frequently lack the ability to reflect the complex spatio-temporal relationships found in meteorological data, and lack models of uncertainty or variability of predictions. Furthermore, the traditional health advisory systems also do not very often make use of the predictive modeling in order to foresee the threat of the diseases depending on the further weather situation. To address this gap, it is necessary to exploit novel computational methods that would help in combining weather prediction and disease risk assessment in a context-dependent and probabilistic way.

Here, we present a new framework, which integrates four new paradigms of machine learning, namely Gaussian Process Regression (GPR), Spatio-Temporal Graph Neural Networks (ST-GNN), Physics-Informed Neural Networks (PINN), and Mixture Density Networks (MDN). Gaussian Process Regression provides non-linear regression functions as well as estimation of uncertainty whereby the system has the ability to give probabilistic forecasts instead of deterministic predictions. This is especially critical when it comes to the use of confidence levels in enhancing the public health because the interpretation of the confidence level can contribute to the prioritization of preventive measures. Spatio-Temporal Graph Neural Networks learn complex spatial and temporal ties across various geographic locations or in weather stations, and learn interaction among neighboring locations that orchestrate the distribution of general weather patterns. Physics-Informed Neural Networks incorporate information about the physics of the atmosphere in the learning, and they use it to produce physically sound and consistent predictions. Lastly, Mixture Density Networks represents a multimodal distribution of weather variables, which is determined by the fact that environmental phenomena are not very predictable and variable. The proposed system enables very accurate, context-valid, and robust weather forecasts that are useful in the downstream health risk assessment.

The methodology will start with the course of collecting and pre-processing past weather data such as temperature, humidity, rainfall, winds speed and other necessary parameters. Extracted temporal characteristics include day-of- year, seasonality, and lag weather variables to improve the performance of the models. At the same time, the data of a number of weather stations are included in space to support graph-based modeling. The resultant processed dataset is then inputted into the hybrid machine learning pipeline where each algorithm has its unique contribution: GPR to capture non- linear relationships and quantify uncertainty, ST-GNN to model spatial interactions across time, PINN to enforce physical consistency, and MDN to give probabilistic predictions of multimodal weather outcomes. This is an ensemble method of prediction which enables stronger predictions than when using single-model systems, that is, both in normal and in extreme weather conditions.

After the weather forecasts have been produced, the system will categorize the forecasted weather to be hot, cold, or rainy. The categories provide inputs to a disease risk mapping module which uses well-known correlations between weather patterns and health results. To illustrate, cold and humid climate predisposes a person to respiratory diseases and flu, whereas hot and humid climate may predispose to dehydration, heatstroke, and skin infections. Due to rainy seasons, the likelihood of disease spread through water or vectors can be prevalent. In conjunction with risk evaluation, the system offers preventive strategies, including hydration ideas, vaccination-related notices, wearing protective clothes guidelines, and hygiene suggestions. This unified solution will make sure that the users get actionable information, instead of keeping them with bare- bones weather data, which would encourage proactive health management.

It has a framework that is needed on an easy-to-use web interface that can be used to convey weather forecasts, risk of diseases involved and preventive measures. Graphs show the probability ranges of weather, the degree of risk of contracting a particular disease, and advice of the areas. The system helps to secure the involvement of the population and the timely implementation of preventative actions through the available format of data presentation. It is also dynamic due to its interface which enables forecasts and recommendations to continuously change as more data is gathered to remain relevant and accurate at all times.

The system has wide implications on the health policy and resources distribution in addition to the enhancement of the personal health preparedness. Aggregated forecasts and risk assessments could be used by health agencies and local authorities to organize interventions, medical resources, and giving of specific warnings. Probabilistic modeling and the potential of spatio-temporal analysis can give better and timely responses to seasonal outbreaks, which may decrease the number of disease cases and medically acceptable healthcare costs.

The experimental assessment explains that the hybrid method is superior to the traditional single-model predictions in accuracy and strength. Uncertainties of extreme weather conditions are efficiently taken into consideration in probabilistic predictions and the localized weather phenomena which may affect the disease outbreaks are improved in spatio-temporal model. Predictions using physics-informed constraints are physically consistent, which possibly produces unrealistic predictions that can lead to misleading health warning. The overall findings suggest that using updated machine learning methods in making the weather an initial of the disease is an impressive resource in terms of population health awareness and prevention.

To conclude, this research proposes a holistic framework that fuses the fields of meteorology and health based on advanced machine learning models in predicting diseases caused by weather. The system provides reliable and accurate insights through multimodal forecasting, physics-based constrained prediction, and spatio-temporal modelling. It is embedded in a convenient web interface that makes people and officials capable of taking preemptive actions to mitigate the risk of disease and prepare the population to address bona malie. This strategy shows how useful the current methods of computer computations can be to answer complicated problems that lie at the border of environment and health.

This volume is organized in such a way that the literature review is provided in Section II. Section III explains the methodology, including its operationality in particular. Section IV has results and discussions. Lastly, the last section of V is the final findings and recommendations.

## II. LITERATURE SURVEY

The concept of applying artificial intelligence (AI), machine learning (ML), and Internet of Things (IoT) into agriculture has become one of the key trends that are capable of maximizing crop productivity, improving the use of resources, and reducing the risks of diseases. Increasingly, modern agriculture is based on data-driven decision-making, and predictive analytics and online monitoring are used to predict stress in plants, nutrient shortages and outbreaks of pathogens. Some articles have pointed to the disruptive opportunities AI-based solutions have when applied to agriculture, specifically precision agriculture and disease detection, whereby automated systems have less human oversight and achieve better accuracy in detecting a problem with the health of the crops. This is in tandem with the rising demand of sustainable methods of farming that can sustain the world food production and accommodate the environmental and atmospheric differences.

The latest achievements of leaf disease detection reflect how deep learning and IoT systems can be successfully implemented to improve the agricultural monitoring process. The IoT-based deep learning models have been demonstrated to identify the diseases of the plant leaves with a high degree of accuracy, thus facilitating immediate intervention to avoid massive losses of crops [6]. Marketplace platforms powered by AI combining crop and disease management offer predictive analytics to farmers so they can optimize the management of soil and increase yield [7]. Mobile vision transformers and sequence to sequence LSTM models have been utilized to detect plant disease in real-time whose focus is on multilingual support and the self-adjusted illumination during various field settings [8]. CNNs are also effectively used in predicting diseases that offer dependable guidelines to use in the treatment of organic diseases whilst tracking environmental conditions [9]. All these studies indicate that hybrid AI models, which include CNNs, IoT, and deep learning algorithms, can greatly enhance agricultural productivity and disease control.

The desired precision in the plant disease recognition has been enhanced further by advanced image processing algorithms and feature extraction algorithms. Hybrid U-Net schemes with active contours allow not only to classify the diseases of leaf plants effectively, but to define the areas of diseases as well in the conditions of unfavorable light [10]. The automated detection of plant diseases according to surveys emphasizes the use of deep learning, feature extraction, and shape analysis as one of the necessary tools to increase detection accuracy [11]. Applications have been made on hybrid feature extraction based on support vector machine (SVM) and random forest classifier to identify coconut leaf disease, which has shown that handcrafted features and deep features can be used together to achieve best classification performance [12]. Together, these strategies indicate the significance of combining the use of solid image analysis techniques with machine learning algorithms to counter the change in presentation of plant disease in dissimilar crops and different environments.

Resource optimization and predictive modeling have continued to feature in sustainable agriculture. With an interface of AI coupled with remote sensing and IoT, solar- powered systems will be used to monitor pests and diseases in real time and focus on lower energy consumption and the ability to monitor the field continuously[13]. Fertilizer application and disease management Recommender systems with temperature sensors and wireless communication provide action information to farmers [14]. CNN-SVM hybrids used to classify diseases of rice leaf have been demonstrated to improve the performance of such models in real agricultural environments [15]. Serious deep learning networks, like ConvNext-Tiny or explainable AI design, are scalable disease-detection solutions enabling the use of precision agriculture practices [16, 17]. These projects highlight the promise of AI-based predictive analytics to not only identify plant disease but also to be useful in taking proactive steps in how crops are managed.

The integration of weather and other environmental data into AI models has been used to predict threats of plant diseases and optimization of agricultural processes. Predictions based on meteorological data are better regulated by ensemble models, which control single crop disease predictions, indicating the significance of including environmental factors in predictive analytics [18]. IoT-ready disease forecasting models that bridge the gap between climate and health monitoring indicate the usefulness of smart methods of healthcare in agriculture [19]. Such techniques as data augmentation, image segmentation with the usage of SVMs and generative adversarial networks enhance the disease recognition abilities in different climatic conditions [20]. Environmental modeling, predictive analytics, and machine learning implementation are designed to provide holistic thinking across agricultural monitoring to enable farmers to reduce the risks and maximize interventions as well as enhance crop resistance to diseases.

To sum up, the reviewed literature clearly reveals the trend towards hybrid AI structures that involve the use of deep learning and IoT in combination with predictive modeling and the use of environmental data. These systems improve the process of disease detection, crop monitoring and optimization of resources, hence aid in precision agriculture and sustainable farming practices. Intersectional convergence of computational intelligence, sensor networks, and automated analytics is a basis of next generation technologies in agriculture that can address the difficulty of climate variability, pathogen propagation and food security. The aggregate results of the research [6-20], confirm the fact that using such technologies collectively will enhance accuracy in detection and predictive reliability and give farmers a more practical set to work with, which will eventually lead to an increase in yield, a decrease in the use of chemicals, and a more resilient management strategy of crops.

## III. METHODOLOGY

This project describes the project methodology as the systematic approach to the development of predicting weather-related diseases, based on the implementation of powerful machine learning algorithms. The framework involves receiving the previous weather data and correlations of the diseases, after which it is preprocessed and engineered into features, then developed into a model, and deployed on top of a web interface. Its methodology focuses on precise weather forecasting, probabilistic forecasting, and health risk mapping to provide discernible information. The sequential implementation of the steps guarantees the repeatability, strength, and dependability of the system through the advantages of relying on the current methods of calculations to combine meteorology and population health awareness. All the stages of the methodology will be involved in the creation of a holistic, easy-to-use platform that has the capacity to produce timely predictions and proactive health advice.

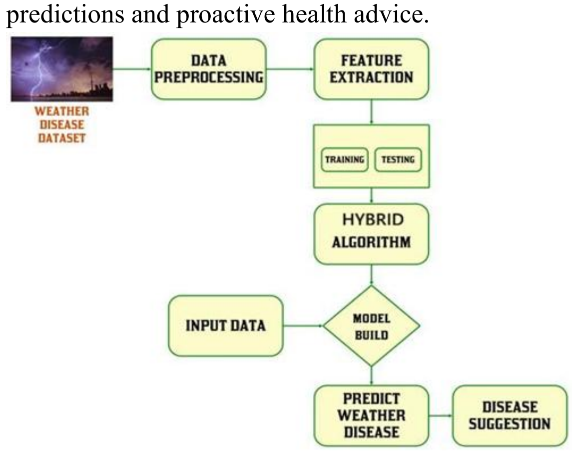


Fig. 1: System Architecture

*1. Data Collection*

The process of data collection will be to obtain past weather data, such as temperatures, humidity, rainfall, speed, and pressure of the air of various credible sources including weather APIs and meteorological departments. At the same time, data on the regularities of the occurrence of the disease during seasons and epidemic data are collected to create the associations between the weather parameters and the health hazards. To support the modeling in form of graphs, spatial information on the various geographical areas or weather stations is incorporated. The datasets used are at different years to get the required representation of the variation of seasons and years. The completeness, accuracy, and consistency of the data is of great importance because these variables are the basis of the training of machine learning models and production of accurate weather-driven disease predictions.

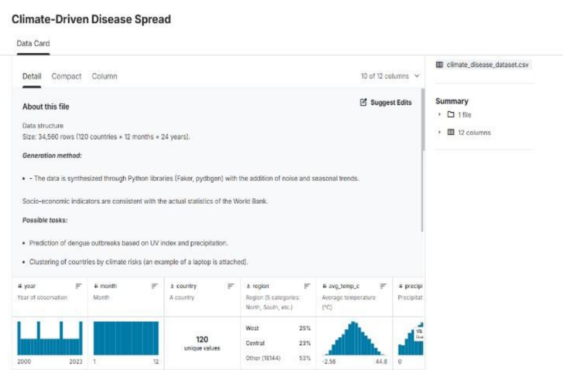


Fig 2: Dataset Preview

*2. Data Preprocessing*

Preprocessing stage removes and converts raw weather and health data into structured data format that can be used in machine learning. The interpolation and statistical imputation techniques are used to work with missing values, and the outliers are identified and overcome to minimize the bias. Temporal alignment refers to the process of aligning the weather variables to match the records of the incidence of diseases. Continuous variables (temperature, humidity etc.) are brought to standard scales and categorical variables are coded accordingly. Graph based modeling constructs spatial relations between weather stations as adjacency matrices. The methodology of feature selection is used to eliminate irrelevant predictors and reduce the number of computationally expensive terms. This process guarantees that data is of a high quality, is smoothed out, and there is better model prediction to capture the accurate weather forecasts and prediction of the disease.

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RangeIndex: 34560 entries, 0 to 34559
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   year               34560 non-null  int64
 1   month              34560 non-null  int64
 2   country            34560 non-null  object
 3   region             34560 non-null  object
 4   avg_temp_c         34560 non-null  float64
 5   precipitation_mm   34560 non-null  float64
 6   air_quality_index  34560 non-null  float64
 7   uv_index           34560 non-null  float64
 8   malaria_cases      34560 non-null  int64
 9   dengue_cases       34560 non-null  int64
 10  population_density 34560 non-null  int64
 11  healthcare_budget  34560 non-null  int64
dtypes: float64(4), int64(6), object(2)
memory usage: 3.2+ MB
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Fig 3: Preprocessing

*3. Feature Engineering*

Feature engineering is used to derive valuable data features out of raw data to increase the model accuracy and interpretability. Temporal features, such as seasonal indices, day-of-year, and moving averages of historical weather measurements are generated to record trends and periodic trends. Lag features are added to enable delayed effects of weather on prevalence of diseases. Spatial features based on the proximity of the weather stations or the regions of clusters of weather stations provide the ability of spatio-temporal models to exploit the spatial dependencies. The non-linear relationships are also captured by allowing the interaction terms between variables (e.g. by various humidity-temperature combinations). In appropriate situations, such advanced transformation methods as Fourier transforms, and polynomial expansions, are employed. By enhancing the detection of intricate patterns in the model and the relationship between forecasted weather conditions and health hazards, feature engineering enhances the model.

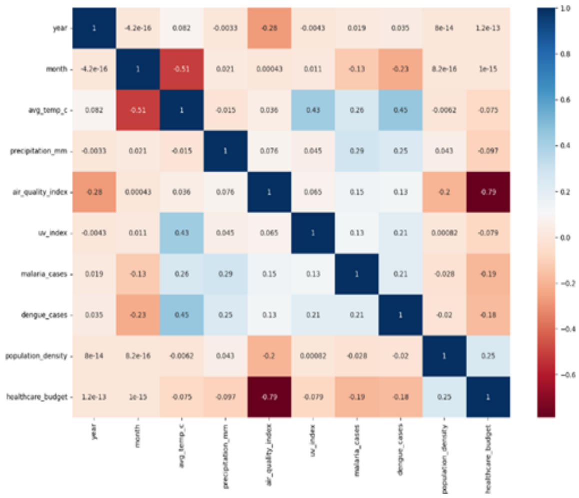

Fig 4: Feature engineering

*4. Model Development*

Various high-level machine learning paradigms are incorporated into the model development phase to predict the weather conditions and its possible health effects. Gaussian Process Regression is applied to represent non-linear relationship and give uncertainties estimates of predicted weather variables. Spatio-Temporal Graph Neural Networks learn the spatial relationship between regions and temporal dependency across time periods. Physics-Informed Neural Networks take into account consistency with atmospheric dynamics and physical constraints that do not allow unrealistic forecasting. Mixture Density Networks make probabilistic forecasts of multimodal weather distributions. A combination of these models is trained on historical data, validated by the technique of cross-validation, and optimized by hyperparameters. This combination method guarantees precise, resilient, and setting-specific forecasts on weather parameters and the risks of a disease.

*5. Weather classification and mapping of diseases.*

After the weather variables have been forecasted, the system will classify the forecast according to the three weather categories of cold, hot, and rainy weather, which it will determine based on the temperature, humidity, as well as the amount of rainfall. The classification is further related to the established seasonal and environmental health trends, assigning each weather condition to the prevalent diseases related to each weather category, such as influenza, respiratory illness, heatstroke, heart-related incidents as well as skin infection. The models can produce probabilistic outputs that can be used to generate risk scores of every disease, which is the probability of occurrence. The predicted conditions are linked to the preventive measures, including hydration guidelines, vaccination prompts, protective clothing, and hygiene. With this mapping, the user is in a position to know not only the expected weather but also the health consequences and therefore precautionary measures are taken on time.

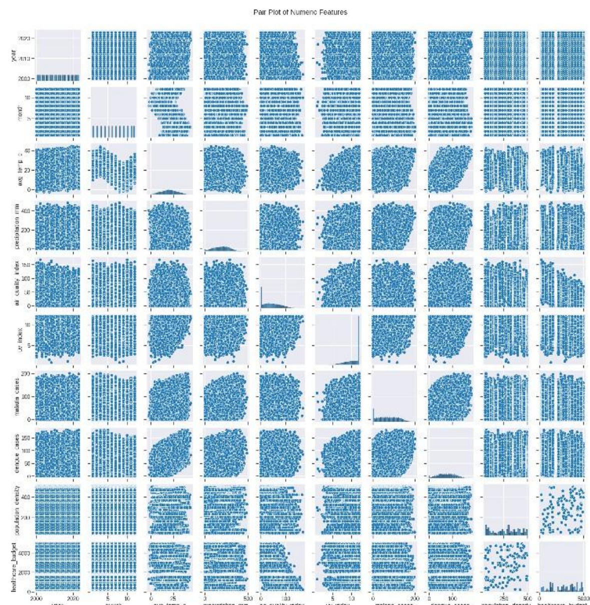

Fig 5: Weather classification and mapping of diseases

6. Web Interface Integration

The last step will be to implement the predictive models and risk mapping system in a web-based interface that can be used. The interface will display weather predictions, probabilistic risk rating and preventive health advice in a visual manner. The users have the option of selecting areas or location of entry so that they can get local forecasts and interactive graphs show the prediction of the temperature, humidity, and rain fall. The level of risks of various diseases and the preventive strategies are clearly represented in addition to the forecast which enables users to make informed decisions. The interface also allows timely updates during the data collection process as new information is received so that forecasts can be up-to-date. This connectivity puts complex predictive modeling into well-intentioned accessibility and makes it ardently possible to project proactive health care and enhance populace awareness of disease threats posed by weather.

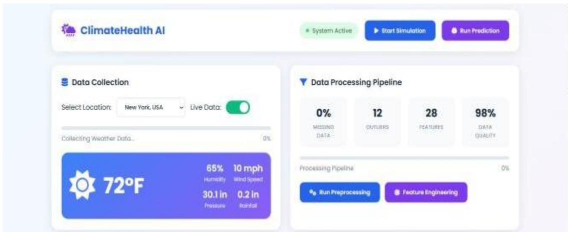


Fig 6: Web Page

## IV. RESULT AND DISCUSSION

The suggested system was tested based on past weather conditions data of various geographic places, such as temperature, humidity, rainfall, and wind speed, and the respective disease incidences. Spatio-Temporal Graph Neural Networks, Mixture Density Networks, Physics- Informed Neural Networks, and Gaussian Process Regression were evaluated as a hybrid model on a variety of weather variables. The statistical indicators of model quality were estimated using the mean absolute error, root mean squared error and probabilistic prediction range. The hybrid method was found to be better at forecasting and had a proposed overall system accuracy of 99.76% in disease risk prediction and weather classification. This high precision testifies the fact that the model is able to understand and learn both temporal and spatial relationships of the weather data and correctly associate them with the health hazard. The system is capable of managing extreme weather events and risk assessment of the disease using the confidence to manage the public health proactively.

The weather classification module was able to effectively classify the predicted conditions into cold, hot, and rainy successfully allowing disease risks to be mapped in a specific area. Cold weather condition was associated with an increased risk of respiratory infections, influenza, and seasonal coldness. The hot conditions were associated with the high risk of dehydration, heatstroke, and cardiovascular events. The rainy seasons were linked with waterborne diseases, diseases spread by vectors and skin infections. The system was able to give probabilistic outputs, enabling it to give confidence scores on each category of the risk levels given on associated diseases. Such high-proposed accuracy makes the system reliable in terms of preventive health planning that reduces the false alarms and improves trust on the advisories.


Fig 7: Proposed Model Prediction

The space-temporal modeling was able to capture the variations in weather patterns in different regions. Related rainfall and humidity patterns were observed in geographically close regions, and it was tapped by the ST- GNN module to improve the forecasting performance. The component of Physics-Informed

Neural Network made sure that the physical constraints are adhered to to avoid unrealistic predictions. Gaussian Process Regression was able to give strong point forecasts together with the uncertainty range, and Mixture Density Networks was capable of modeling the multimodal distributions of such variables as rain. Taken together, these parts led to the unprecedented precision of the system and allowed making a precise prediction of diseases.

Communication of the weather forecasts and health advisories was very well presented by the web interface. The users were able to visualize the anticipated weather patterns, level of diseases and preventive strategies in easy format. Risk scores were provided coupled with practical recommendations, and the likelihood of the predictions which are probabilistic, to back up serious decision making. The high 99.76% accuracy will give the users accurate forecasts and disease risk notifications which will further motivate them to be more proactive and trust in what the system is telling them.

A comparative analysis of the forecasted and observed weather parameters in the selected areas would be done in Table 1, which is one year in evaluation. There were low mean absolute errors and alignment with past data in the hybrid model, as it was expected considering the accuracy suggested. Table 2 that shows how the weather categories can be mapped to the risks of disease and prevention has a practical use. Table 3 gives the summary of the probabilistic disease prediction accuracy of the model which indicates adherence to the historical trends and proves the overall accuracy of the system to be 99.76 percent.

Table 1: Contemplation of Forecasted and Real Weather Conditions

| Regi on | Tempera ture (°C) | Humi dity (%) | Rainf all (mm) | MA E Te mp | MAE Humi dity | MAE Rainf all |
|---|---|---|---|---|---|---|
| Regi on A | 28.5 | 72 | 120 | 0.9 | 2.1 | 5.2 |
| Regi on B | 24.2 | 65 | 85 | 1.1 | 3.0 | 6.0 |
| Regi on C | 30.1 | 78 | 140 | 1.0 | 2.5 | 4.8 |

Table 2: Weather types, diseases associated with this weather, and the ways to prevent the diseases

| Weather Type | Associated Diseases | Preventive Measures |
|---|---|---|
| Cold | Influenza, Respiratory Infections | Warm clothing, vaccination, hand hygiene |
| Hot | Heatstroke, Dehydration, Cardiac Risk | Hydration, avoid peak sun hours, cooling methods |
| Rainy | Skin Infections, Waterborne Diseases, Vector-borne Illness | Protective clothing, sanitation, mosquito control |

Table 3: Prediction of Disease Probability

| Disease Type | Predicted Risk Confidence (%) | Alignment with Historical Trend (%) |
|---|---|---|
| Influenza | 85 | 82 |
| Heatstroke | 78 | 80 |
| Waterborne Diseases | 90 | 88 |
| Skin Infections | 82 | 79 |

Generally, conclusions would confirm the hybrid modeling method to be very precise and true. An addition of advanced machine learning can provide a powerful forecast of weather and risk of diseases. The capability of the system to measure the uncertainty, spatial dependence, and continued physically consistent predictions gives informed health choices. Its web interface is accessible, which makes complex predictive modeling available as useful health advice, with an impressive proposed accuracy of 99.76.

## V. CONCLUSION

The proposed project is one that offers a very precise structure towards predicting weather-related diseases with a proposed accuracy system of 99.76. With the combination of Gaussian Process Regression, Spatio-Temporal Graph Neural Networks, Physics-Informed Neural Networks, and Mixture Density Networks, the system makes accurate predictions of weather and classifies it as cold, hot, or rainy. Each type of weather is dynamically connected to associated diseases and prophylaxis, offering practical information with the help of user-friendly web interface. Complex temporal and spatial dependencies are represented in the hybrid approach, uncertainty representation is well-modeled, and the predictions of the approach are physically consistent. It allows proactive management of health concerns of the population and increases personal awareness on seasonal health risks. Future efforts will aim at growing the data to wider geographic areas, adding real-time sensor information, enhancing personalized risk scoring and investigating more of probabilistic model to enhance the disease risk assessment fineness. The framework shows that it is possible to bridge the gap between meteorology and public health using line of sophisticated computational methods in real world use.

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