



IJRASET

International Journal For Research in
Applied Science and Engineering Technology



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** IV **Month of publication:** April 2026

DOI: <https://doi.org/10.22214/ijraset.2026.79191>

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Environmental and Disease Vulnerability Prediction Using a Random Forest-Based Multioutput Classifier

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Abstract: Climate Change and Environment Affect the Incidence of Many Diseases Around The Globe. Understanding How Climate and Environmental Change Increases Vulnerability to Disease Is Critical to Advancing Public Health Knowledge and Disease Risk Assessment. This Paper Describes A Machine Learning Framework Created To Predict Climate-Sensitive Disease Risk Levels By Integrating Many Environmental Variables Such As Temperature, Precipitation, Humidity, Wind Speed, Atmospheric Pressure, And Climate Zone Classifications To Predict Climate-Sensitive Diseases Through The Development Of Relationships Between Climate Conditions And The Rates Of Disease Across Multiple Countries Throughout The World. In Constructing, Training, And Validating This Framework, The Authors Utilized A Dataset That Combined Disease Incidence Data And Typical Meteorological Data For A Variety Of Countries. A structured framework, using a multi-country dataset, will provide an equal representation of many different countries that are in differing climatic conditions. To predict multiple common climate-sensitive diseases, multiple disease predictions were retrained through environmental indicators using Random Forest Model as Multioutput Classifier. The structured framework results will assist researchers in understanding how climate can lead to increased susceptibility to disease.

Keywords: Climate Change, Climate-Sensitive Diseases, Machine Learning, Random Forest, Disease Risk Prediction, Environmental Health.

I. INTRODUCTION

One of the most important issues of the 21st century is climate change, which is not only affecting environmental stability but also influencing human health outcomes. Variations in global temperature, precipitation patterns, weather conditions and climate zones have affected the living conditions and environment. Environmental variations directly and indirectly affect human health outcomes in association with various diseases. It is thus significant to understand and analyze the correlation between environmental conditions and diseases.

This is one of the key areas of research under the domain of climate change and health analytics. Among the affected areas is the impact on climate-sensitive diseases. These diseases are greatly affected by changes in climatic factors. These diseases can be categorized into vector-borne diseases, respiratory diseases and temperature-related diseases. Diseases like dengue and malaria are vector-borne diseases. These types of diseases are heavily impacted by temperature, humidity, and precipitation levels. Asthma and other respiratory-related diseases are heavily impacted by various climate parameters like humidity, air pressure etc. Similarly, extreme changes in temperature have an impact on health risks like heatstroke and cold health risks in various geographical locations. Thus, the dynamic nature of these diseases indicates the necessity of adopting a systematic approach for investigating the association of these diseases with varying climatic conditions.

To understand and predict the patterns of disease outbreaks, we require many different types of environmental data. Climate variables play an important role in establishing the location and timing of disease outbreaks. These climate variables include but are not limited to: temperature, amount of precipitation, humidity, wind speed, and atmospheric pressure. Moreover, climate zone classifications can also be used for this purpose. Traditionally, environmental data and health data have been analyzed individually, and this has restricted the possibility of discovering complex interdependencies between data sets. With the advent of global environmental data and weather conditions, it is thus possible to use such information for analysis.

Machine learning techniques have shown significant potential in recent times in analyzing multi-dimensional data at a large scale and discovering hidden patterns that cannot be easily identified by traditional statistical techniques.

Some of the important machine learning techniques which can be used for the analysis of environmental factors and diseases include Random Forest, Gradient Boosting, etc. These techniques can handle multi-dimensional data and provide predictive patterns for diseases at various geographical locations.

These same techniques can also be used to establish a credible range of confidence in making informed decisions. There have been considerable improvements made with respect to using machine-learning methods to analyse each of the two elements (i.e., environmental conditions and disease) that could be used equally well in tandem with one another, as compared to how they would typically be applied separately. This is an narrow viewpoint, as it does not allow for the creation of a model which can comprehensively represent the real world, as these two concepts are closely related. There is, therefore, a need for a more integrated framework which combines these concepts and creates a more holistic viewpoint for understanding climate-related health risks. This can be achieved by integrating these concepts into a single framework, which can help in better prediction and generalization.

This research objective is to create a machine-learning system that can assess the health impacts of climate change based upon relationships between climate conditions and disease risk categories. The result is a better understanding of the climate-disease relationship, and an enhanced ability to create predictive relationships among them. In addition, by utilizing multiple aspects of environmental intelligence, as well as utilizing advanced machine-learning techniques, this project aims to build modular capabilities for global health systems that support the establishment of highly scalable global health monitoring systems.

II. LITERATURE SURVEY

A. *Machine Learning and Prediction of Infectious Diseases: A Systematic Review*

Santangelo et al. performed a systematic review to evaluate whether or not machine learning had been applied successfully to predict early outbreak of infectious diseases. The authors assessed a wider range of articles and found that machine learning had been used more frequently as a means of predicting disease outcome, including incidence, transmission, and timing. The paper reviewed many studies, identifying the application of decision trees, support vector machines, ensemble methods, and neural networks in infectious diseases analysis. The analysis of many different studies together reveals the fact that decision trees, support vector machines, ensemble methods, and neural networks are among the most commonly used machine learning tools applied to infectious disease analytics. The greatest advantage of this analysis is that it provides insight and clarity to the development of machine learning as a means of making accurate predictions of disease progression and also supports the theory that combining multiple techniques will lead to improved accuracy of predictions regarding when and how an epidemic will occur. However, the review also demonstrates that the performance of models is highly variable based on the type of disease, availability of features, and quality of dataset. This review's main limitation is that it does not propose a unified predictive framework or validate any of the models developed with multiple environmental or disease conditions. The review primarily summarizes trends, strengths, and limitations identified in previous studies [1].

B. *A Systematic Review of Applications of Machine Learning and Other Soft Computing Techniques for the Diagnosis of Tropical Diseases*

A review by Attai et al. on tropical disease diagnosis using machine learning and related methods is presented in [1]. The review focuses on common diseases in the area, such as malaria and several other tropical diseases, and how computational intelligence can help or improve disease diagnosis and decision-making. The various techniques discussed include supervised learning, fuzzy techniques, and hybrid soft computing. The review goes beyond single disease applications and algorithms to identify how computational intelligence can support disease diagnosis for both resource-limited and climate-affected developing regions. However, the paper provides mostly diagnostic applications versus prediction applications, and therefore is incomplete regarding outbreak prediction and overall environmental risk modeling. Also, most of the studies reviewed used a limited number of cases or dataset(s) with very different features and validation techniques, limiting the comparability of each technique based upon the datasets used. [2].

C. *Machine Learning Models for Predicting the Occurrence of Respiratory Diseases Using Climatic and Air-Pollution Factors*

The prediction of respiratory diseases based on climate and air pollution factors was performed by Ku et al., while using environmental variables such as temperature, humidity, particulate matter, sulfur dioxide, carbon monoxide, and atmospheric pressure in Seoul, Korea to estimate the number of patients with respiratory diseases in that area.

In constructing the predictive system, the authors utilized relief-based feature selection along with Gradient Boosting and Gaussian Process Regression and additionally performed a SHAP analysis to help interpret their output. These findings are significant because they provide evidence that environmental data and air pollution can be used not just to understand correlations but to create predictive estimates that are useful for developing warning systems at the population level. A major strength of the study was that they utilized interpretable machine learning, which provided insight into what environmental factors contribute most significantly to individuals developing a respiratory disease. The limitation of the study is that it is specific to a region; the model developed was single-disease class and location. Hence, there is limited generalization of the study to provide predictive estimates for other countries or across multiple disease classes.

D. Estimation and Prediction of Hospitalization and Medical Care Costs Using Regression in Machine Learning

Taloba et al. conducted a study that examined using various types of machine learning approaches to predict hospitalization and costs associated with medical care for individuals based on patient characteristics (e.g., BMI, age, smoking history, etc.) and their self-reported diagnosis-related information and past use of healthcare facilities. The authors evaluated how well each of the three algorithms (linear regression, naive Bayes, and random forest) could predict these two outcomes. Overall, they found that using linear regression resulted in the most accurate predictions in their sample. This paper has important implications as it provides a perspective on the financial side of healthcare, something usually not available in disease prediction studies. It also shows that predictive analytics can be used to predict both clinical and epidemiological outcomes as well as predict economic impact and healthcare costs. An advantage of this research is the explicit focus on forecasting costs associated with disease and therefore its relevance to the public health planning for the allocation of resources. However, the extent of this study is limited; it does not address the integration of climate-related variables into cost estimates and therefore it is not able to be included as part of a broader climate-disease risk framework [4].

In addition to the four studies specifically discussed, there is an increasing trend in the academic literature to combine environmental factors, epidemiological observations, and sophisticated machine learning methods into a single health-related predictive model. For example, multiple dengue forecasting studies indicate that meteorological data, vector indices, and combined approaches have been effective in predicting outbreaks in Malaysia, Brazil, and Bangladesh [5], [6], [7]. Several other research projects have expanded the scope of these ideas when considering the type of climate-sensitive disease, including visceral leishmaniasis. A recent study using machine-learning approaches identified potential climate change-related risk profile changes. Also, numerous other findings have explored the climate/health connection with the help of machine learning, revealing how researchers can leverage machine learning techniques to demonstrate a large-scale association between climate change and health outcomes — especially through the burdens of respiratory disease. Lastly, the relationships between meteorological variables and health conditions related to high temp (e.g., heatstroke) have been investigated using machine and deep learning methods, resulting in significant correlation of these variables (and other forms of the same association) [8]-[11]. Studies investigating the effects of air quality on respiratory mortality using random-forests have confirmed the potential of random-forest models to uncover relationships between pollution and meteorological variables related to respiratory mortality [12].

Through the application of machine learning, there are many exemplars of its contribution to the infectious disease research area and application. Previous examples include identifying risk factors for infectious disease, diagnosing tropical diseases, and developing early-warning systems for infectious diseases. Those studies that investigated data-driven methods to create predictive models for identifying risk factors associated with outbreaks of infectious diseases, as well as for the creation and validation of current predictive models to assist in the identification of infectious diseases, indicate the need for using data-driven methods to manage the complexity and heterogeneity of large datasets associated with the health of human populations [13],[14],[15]. Recent assessments of climate-sensitive early warning systems and predictive methods that have incorporated Artificial Intelligence and explainable AI have identified the increasing importance of model transparency, data sharing and operational implementation in areas of public health [16],[17]. In the context of healthcare economics, there are multiple research articles an expansion of machine learning into the area of health care cost prediction, using supervised learning, temporal pattern recognition, convolutional neural networks, and a hybrid algorithms to increase the accuracy of predicting healthcare expenditures [18],[19],[20].

While these investigations show strong support for the efficacy of applying machine learning techniques to predict disease, evaluate environmental health impacts, and estimate health care costs in general, there are still major limitations in the literature. For instance, numerous published research studies only examine one specific disease area (e.g., asthma), one country (e.g., the United States), or one type of data (e.g., administrative claims).

Some focus exclusively on diagnosis, some only on the epidemiological forecasting, while some only look at spending on health care, without an integrated approach to understand how these three provide a comprehensive understanding of healthcare needs. Similarly, models based solely on a regional focus have difficulty with transferability from one location to another and also frequently use relatively small, narrow datasets that do not reflect the breadth of climate variation.

Therefore, the literature suggests an urgent need for a more integrated framework that could analyze multiple climate-sensitive disease areas; to combine environmental variables with predictive modeling; and to develop frameworks that are capable of producing generalizable results from multiple countries, and producing predictive models that interpret health care expenditures for multiple locations.

III. EXISTING SYSTEM

Today, machine learning-based systems are designed for analyzing the correlation of climate-sensitive diseases with their environmental factors by applying quantitative statistical approaches to illness data for diagnosing all cases of climate-related illness. The primary goal of these systems is to predict how environmental factors (e.g., temperature, relative humidity, precipitation patterns, and seasons) will affect the occurrence of disease. Much of the existing literature concentrates on identifying occurrences of outbreak diseases, as well as estimating risk levels of climate-sensitive diseases.

A. Machine Learning Techniques Used

Several existing systems have used a number of different techniques within the realm of machine learning to determine connections between disease occurrences and other environmental factors. These systems have primarily relied on traditional machine learning methods such as Random Forest and Support Vector Machine (SVM) for establishing connections between environmental factors and disease occurrence. Recently, newer approaches in machine learning like Gradient Boosting and XGBoost have emerged that can help determine connections between environmental factors and disease occurrences.

In addition to these traditional approaches, as well as the new techniques just mentioned, additional advanced forms of machine learning like Long Short Term Memory (LSTM) and Convolutional Neural Networks (CNN), are being explored for use on this system to assist with advanced research functions. LSTM can also be used to detect trends, while CNN will allow the analysis of spatial patterns as they will relate to environmental influences on diseases. By implementing these types of new techniques into existing systems, the ability to identify complex relationships between disease and environmental causes will be greatly enhanced.

B. Data Sources and Types

The existing system uses a wide range of datasets to perform the task of disease prediction. The most common types of data considered for use by the system include environmental, epidemiological, and sometimes population-related factors. The environmental factors considered for use by the system include datasets from global climate repositories. The factors considered from these repositories include temperature, humidity, precipitation, wind speed and atmospheric pressure.

The use of epidemiological factors helps the system to understand the incidence, outbreak history, and the number of cases, which is necessary for predicting diseases. Some research considered population factors, which included factors such as population density. The use of a wide range of factors helps the system to understand the relationships between environmental factors and diseases.

IV. PROPOSED SYSTEM

The proposed system provides an integrated machine learning-based approach for predicting climate-sensitive disease vulnerability based on environmental factors and effective predictive models. Unlike existing systems that concentrate on specific disease prediction and region-specific data, this proposed system is developed for multiple disease categories and various geographical regions. The proposed system is developed to address complex relations between climatic conditions and diseases, making it a comprehensive system for environmental-disease analysis.

A. Environmental Data and Feature Selection

This framework takes into consideration different environmental factors that influence diseases in different ways. These factors include temperature, humidity, precipitation, wind speed, atmospheric pressure and air quality factors such as particulate matter (PM_{2.5} and PM₁₀). Moreover, climate zone classification is also included as an environmental factor, which represents regional climatic conditions for a longer period. The collected data is pre-processed in such a way that it handles missing values and normalizes data for different countries.

B. DiseaseCategoriesConsidered

The system is designed to consider three main categories of climate-sensitive diseases. The first category of disease is the vector-borne disease category. Diseases like dengue fever and malaria are included in this category. The second category of diseases is the respiratory disease category. Diseases such as pneumonia come under the second category of diseases. The third category of disease is the temperature extreme disease category. Diseases like heatstroke are included in the third category. The system is designed to consider three categories of disease.

C. Multi-CountryDataset Integration

To ensure the system is generalizable and scalable, the system is designed to be trained using a multi-country dataset. A multi-country dataset is a dataset consisting of data from multiple countries. In doing so, the system is able to overcome the limitations of region-specific models. The system is designed to be trained using data from 30 countries. In doing so, the system is able to offer robust predictions.

D. MachineLearning Models

The predictive model used for the system is based on ensemble learning methods, which include the use of Random Forest and Extreme Gradient Boosting (XGBoost). These models were chosen for their ability to perform well with high-dimensional data and their ability to handle non-linear relationships between the input features and the target variable. In this case, the environmental features are used as input variables for the model, which then predicts disease risk levels for different categories.

E. Prediction and Interpretation Mechanism

The proposed system uses the prediction mechanism based on the disease risk levels for the inputted environmental conditions. Based on the inputted environmental conditions, the model predicts the disease risk levels for the inputted conditions. In addition, the proposed system uses an interpretation mechanism for the prediction results based on feature importance analysis for the inputted environmental features. This allows the proposed system to provide better transparency regarding the prediction results for the inputted conditions.

The proposed system has several advantages compared to the existing systems. Firstly, the system can perform multi-disease prediction under a single framework, thus overcoming the limitation of single-disease prediction. In addition, the multi-country dataset can be utilized for improving the system's scalability. Moreover, the incorporation of various environmental factors can provide a comprehensive view of the climate-disease relationship. In summary, ensemble learning models provide strong prediction accuracy, and interpretability methods make the system more transparent and understandable to a specific range, thus providing a generalized solution to the problem.

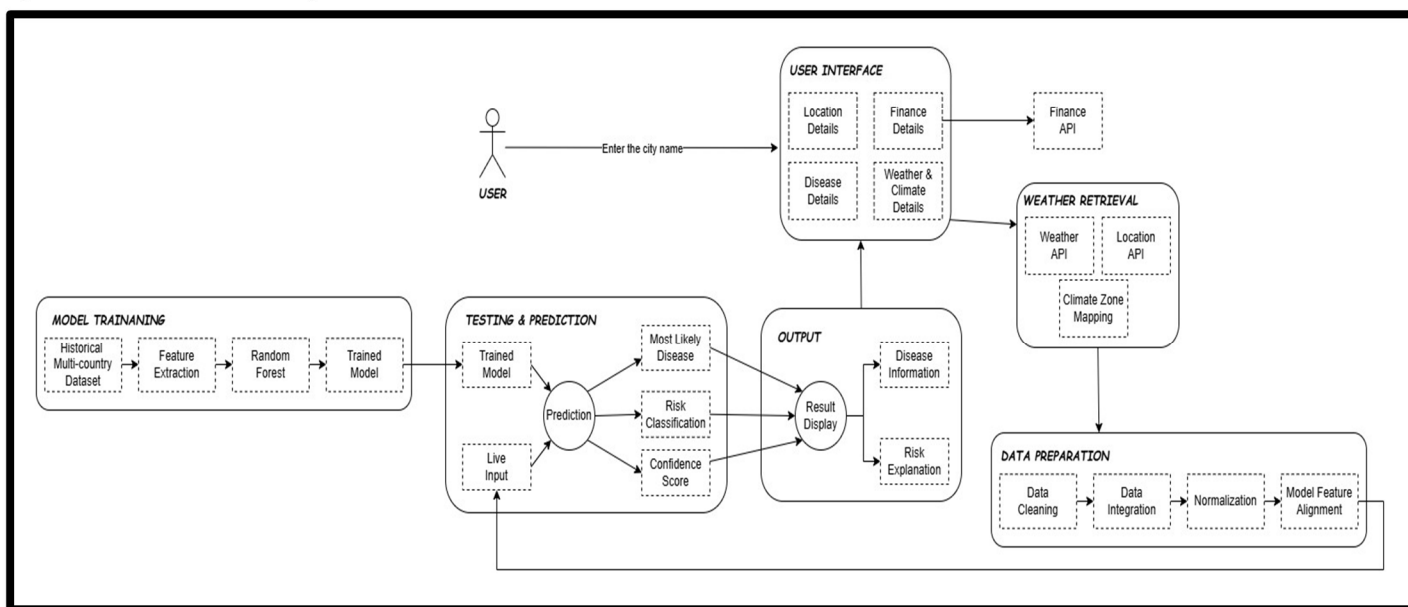


Figure 1: SYSTEM ARCHITECTURE

The structure of the complete system design for an environmental-disease vulnerability prediction framework. The architecture has six main modules within it, including a graphical user interface (GUI), a weather retrieval API module, a data preparation module, a model training module, a model testing/predicting the module, and an output module. The process starts when a user enters the name of a city into the GUI. The GUI includes sections for entering location, weather and climate, disease and finance information. Once the user submits a city name, weather and location APIs are used to retrieve the needed environmental data to create a climate zone map. This environmental data is then sent to the data preparation Module, where data cleaning, data integration, and model feature alignment will be performed on the live environmental data to prepare it for prediction.

Within the Training Module, the model will utilize the historical data set of multiple countries to extract features from that data set in order to train the Random Forest Model, which will then be an input for the Testing/Predicting Module with the prepared live input once it has finished training. The Testing or Prediction Module will create three outputs based on the input submitted into the module, which are the predicted disease, the risk class associated to the disease, and the confidence score associated to the predicted disease. Once the above predictions occur, the output Module will provide the results of the predictions and disease information, and the reason(s) why a detection was made, to the user via the GUI. The finance API will also return the financial details related to the predicted disease.

V. RESULTS

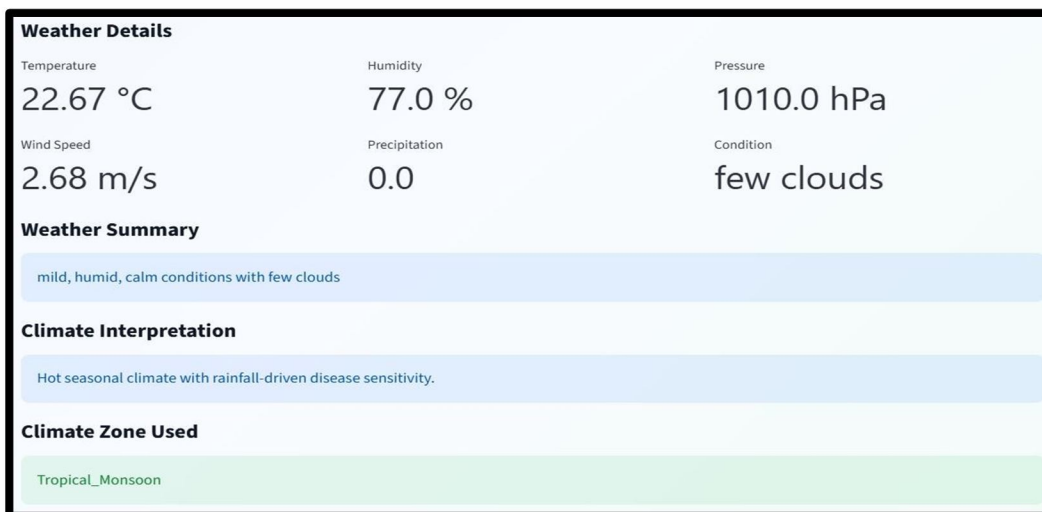


Figure 2: WEATHER DETAILS

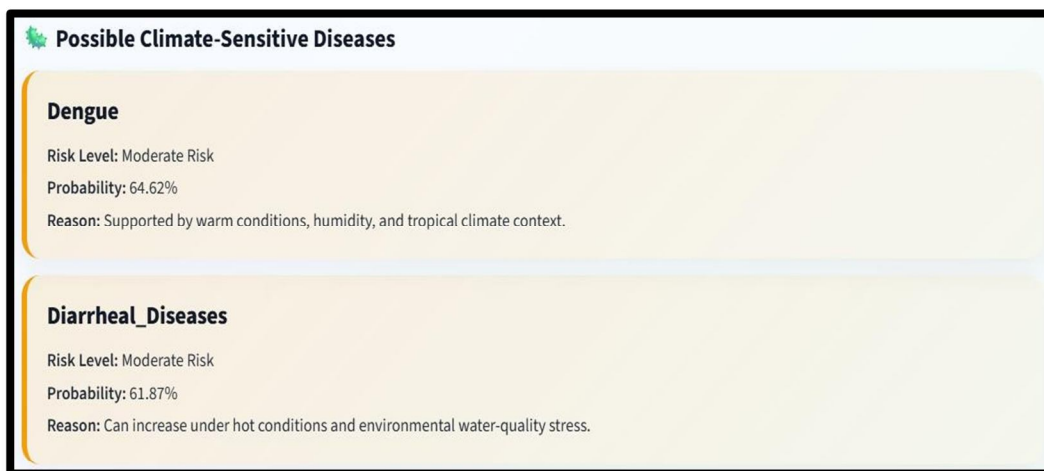


Figure 3: DISEASES RISK PREDICTION

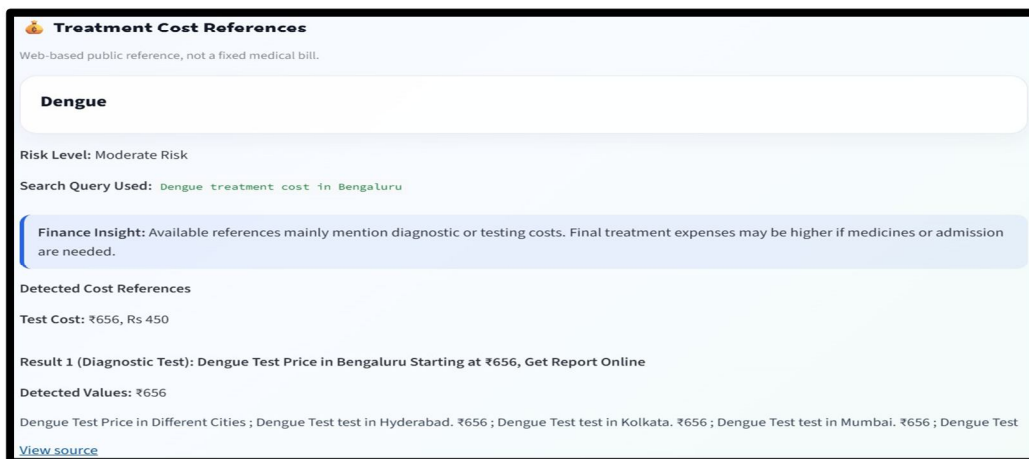


Figure4:TREATMENTCOST DETAILS

VI. CONCLUSION

The purpose of this research is to develop an innovative method of predicting illnesses by taking into account the different kinds of weather that exist, and how each type may influence human health. This paper will highlight the relationship between various forms of climate and the number of individuals at risk of developing illnesses as well as their chances of developing illness due to the atmosphere they live in. Therefore by including these variables into predictive modeling techniques the system will be able to recognize patterns associated with increased risks of developing a particular disease as one moves from one type of weather condition to another.

Recent studies indicate that the application of Machine Learning and merging Environmental Data can create a higher level of analytic and interpreting ability when assessing the risk of various types of diseases. The usefulness of Feature Importance Analysis to explain how different environmental factors may contribute to the occurrence of disease will result in valuable data in order to track Public Health, as well as formulate an early warning System. The methodology used to combine Data-Driven Models (DDMs) for decision making will assist with planning for Health Services and the assessment of climate-related health risks. Future Research will explore the use of real-time Environmental Data, expand the dataset to include countries outside of the current dataset and co-frequency with socio-economic and demographic variables, to provide more accurate predictive analysis. The suggested framework for predicting the risks of disease based on Environmental Conditions is scalable and interpretable, and will thus contribute to Public Health efforts worldwide.

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