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Environmental and Disease Vulnerability Prediction Using a Random Forest-Based Multi output 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 CriticaltoAdvancing Public HealthKnowledgeand DiseaseRiskAssessment.ThisPaperDescribesA Machine Learning Framework CreatedToPredict Climate-Sensitive Disease Risk Levels By Integrating ManyEnvironmentalVariables SuchAs Temperature,Precipitation,Humidity,WindSpeed, 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 ThroughoutTheWorld.InConstructing,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,multiplediseasepredictionsweretrained through environmental indicators using Random Forest Model as Multioutput Classifier. The structured frameworkresultswillassist researchers inunderstandinghowclimatecanleadtoincreased 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 globaltemperature, precipitationpatterns, weather conditions and climate zones have affected the living conditionsand 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. Amongtheaffectedareasis theimpactonclimate-sensitive diseases. These diseases are greatly affectedbychangesinclimaticfactors.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 areheavilyimpactedbytemperature,humidity,and precipitation levels. Asthmaand other respiratory-related diseases are heavily impacted by various climate parameters like humidity, air pressure etc. Similarly,extremechangesintemperaturehavean 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 ofthese 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 thispurpose.Traditionally,environmentaldataand 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.

Someoftheimportantmachinelearningtechniques whichcanbeused fortheanalysisofenvironmental 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.

Thesesametechniquescanalsobeusedtoestablish acrediblerangeofconfidenceinmakinginformed decisions. There have been considerable improvementsmadewithrespecttousingmachine-learning methods to analyse each of the two elements (i.e., environmental conditions and disease) that could be used equallywell intandem with one another, as compared to how theywould typicallybeappliedseparately.Thisisanarrow viewpoint,asit doesnotallow forthecreationofa 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 advancedmachine-learningtechniques,thisproject aimstobuildmodularcapabilitiesforglobalhealth 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 reviewto evaluatewhetherornotmachine learning had been applied successfully to predict early outbreak of infectious diseases.Theauthorsassessedawiderange ofarticlesandfoundthatmachinelearning had beenused more frequentlyas 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 advantageofthisanalysisisthatitprovides insight and clarity to the development of machine learning as a means of making accuratepredictionsofdiseaseprogression andalsosupportsthetheorythatcombining multipletechniqueswillleadtoimproved accuracy of predictions regarding when andhowanepidemicwilloccur.However, the review also demonstrates that the performance of models is highly variable basedonthetypeofdisease,availabilityof features, and quality of dataset. This review's main limitation is that it does not propose a unified predictive framework or validate anyofthe models developed with multiple environmental or disease conditions. The review primarily summarizes trends, strengths, and limitations identified in previous studies [1].

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

Areview byAttaiet al. ontropicaldisease diagnosis using machine learning and related methods is presented in [1]. The review focusesoncommondiseases 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, fuzzytechniques, 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 applicationsversuspredictionapplications, and therefore is incomplete regarding outbreak prediction and overall environmentalriskmodeling.Also,mostof thestudiesreviewedusedalimitednumber of cases or dataset(s) with very different featuresandvalidationtechniques,limiting the comparability of each technique based upon the datasets used. [2].

C. Machine Learning Models for Predicting the Occurrence of RespiratoryDiseasesUsingClimaticand Air-Pollution Factors

The prediction of respiratory diseases based on climate and air pollution factors was performed by Ku et al., while using environmentalvariablessuchas 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.

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In constructing the predictive system, the authors utilized relief-based feature selectionalongwithGradientBoostingand Gaussian Process Regression and additionallyperformedaSHAPanalysisto help interpret their output. These findings are significant because they provide evidence that environmental data and air pollutioncanbeusednotjusttounderstand correlations but to create predictive estimates that are useful for developing warningsystemsatthepopulationlevel.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 pastuseofhealthcarefacilities.Theauthors evaluated how well each of the three algorithms (linear regression, naive Bayes, and randomforest) 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 providesaperspectiveonthefinancialside of healthcare, something usually not available in disease predication studies. It also shows that predictive analytics can be used to predict both clinical and epidemiologicaloutcomesaswellas 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 variablesintocostestimatesandthereforeit is not able to be included as part of a broaderclimate-diseaseriskframework[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,includingvisceralleishmaniasis.Arecent 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].

Throughtheapplicationofmachinelearning,there are many exemplars of its contribution to the infectious disease research area and application. Previous examples include identifying risk factors forinfectiousdisease,diagnosingtropicaldiseases, anddevelopingearly-warningsystemsfor infectiousdiseases.Thosestudiesthatinvestigated data-drivenmethodstocreatepredictivemodelsfor identifying risk factors associated with outbreaks of infectious diseases, as well as for the creation andvalidationofcurrentpredictivemodelstoassist intheidentificationofinfectiousdiseases, indicate the need for using data-driven methods to manage the complexityand heterogeneityof 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 IntelligenceandexplainableAIhaveidentifiedthe increasing importanceofmodeltransparency, data sharingandoperationalimplementationinareasof publichealth[16],[17].Inthecontextofhealthcare 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].

Whiletheseinvestigationsshowstrongsupportfor 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 limitationsintheliterature.Forinstance,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 focusexclusivelyon 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 comprehensiveunderstandingofhealthcareneeds. Similarly, modelsbased solelyona regionalfocus have difficulty with transferability from one location to another and also frequently use relativelysmall,narrowdatasetsthat do not reflect the breadth of climate variation.

Therefore,theliteraturesuggestsanurgentneedfor 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,andseasons)willaffect theoccurrenceof disease. Much of the existing literature concentrates on identifying occurrences of outbreak diseases, aswellasestimating risk levels of climate-sensitive diseases.

A. MachineLearningTechniquesUsed

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

In addition to these traditionalapproaches, 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 useonthissystemto assist withadvancedresearch functions.LSTMcanalso beusedto detecttrends, 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. DataSourcesand Types

The existing system uses a wide range of datasets toperformthetaskofdiseaseprediction.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.Thefactorsconsideredfromthese repositories include temperature, humidity, precipitation, wind speed and atmospheric pressure.

Theuseofepidemiologicalfactorshelpsthesystem 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 environmentalfactorsthatinfluencediseasesin different ways. These factorsinclude temperature, humidity,precipitation,windspeed,atmospheric pressure and air quality factors such as particulate matter(PM2.5andPM10).Moreover,climatezone classification is also included as an environmental factor, whichrepresentregional climatic conditionsforalongerperiod.Thecollecteddatais pre-processedinsuchawaythatithandlesmissing 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 inthis 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 considerthreecategoriesofdisease.

C. Multi-CountryDataset Integration

Toensurethesystemisgeneralizableandscalable, the system is designed to be trained using a multi-countrydataset.Amulti-countrydatasetisadataset consistingofdatafrommultiplecountries.Indoing so, the system is able to overcome the limitations ofregion-specific models. The system is designed tobetrainedusingdatafrom30countries.Indoing so, the system is able to offer robust predictions.

D. MachineLearning Models

The predictive modelused 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 betweenthe input features and the target variable. In this case, the environmental features are used as input variables for the model, whichthenpredictsdiseaserisklevelsfordifferent categories.

E. Prediction and Interpretation Mechanism

The proposed system uses the prediction mechanismbasedonthediseaserisklevelsfor 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 resultsbasedonfeatureimportanceanalysisforthe 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 systemcanperformmulti-diseasepredictionunder asingleframework,thusovercomingthelimitation ofsingle-diseaseprediction. Inaddition,themulti-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 andunderstandabletoaspecificrange, thus providing a generalized solution to the problem.

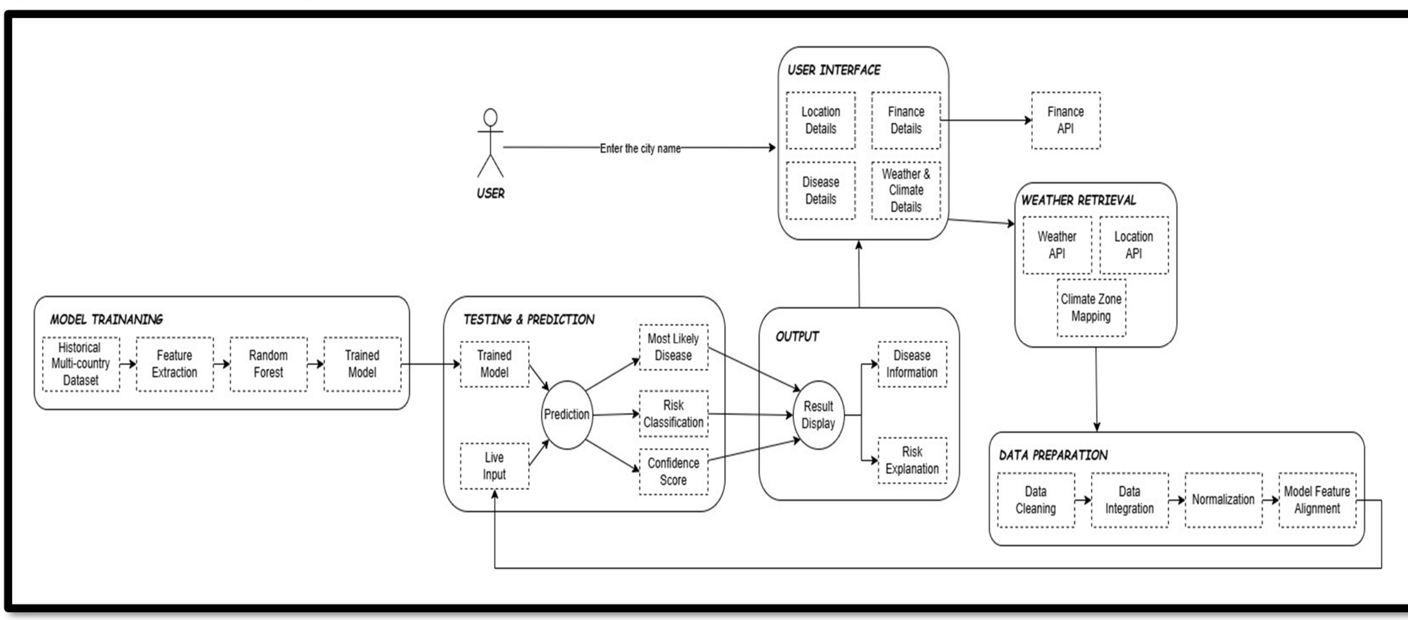

Figure1:SYSTEMARCHITECTURE

The structureofthecomplete systemdesignfor an environmental-disease vulnerability prediction framework.Thearchitecturehassixmainmodules withinit,includingagraphicaluserinterface(GUI), aweatherretrievalAPImodule,adatapreparation 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 sectionsforenteringlocation,weatherandclimate, disease and finance information. Once the user submitsacityname,weatherandlocationAPIsare used to retrieve the needed environmental data to createaclimatezonemap.Thisenvironmentaldata 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.

WithintheTraining Module,themodelwillutilize thehistoricaldatasetofmultiplecountriestoextract features from that data set in order to train the RandomForestModel, whichwillthenbe aninput fortheTesting/PredictingModulewiththeprepared liveinputonceithas finishedtraining.TheTesting orPredictionModulewillcreatethreeoutputsbased ontheinputssubmittedintothemodule,whichare thepredicteddisease,therisk classassociatedtothe disease, andthe confidence score associatedto the predicteddisease.Oncetheabovepredictionsoccur, the output Module will provide the results of the predictions and disease information, and the reason(s)whyadetectionwasmade,totheuservia the GUI. The finance API will also return the financial details related to the predicted disease.

V. RESULTS

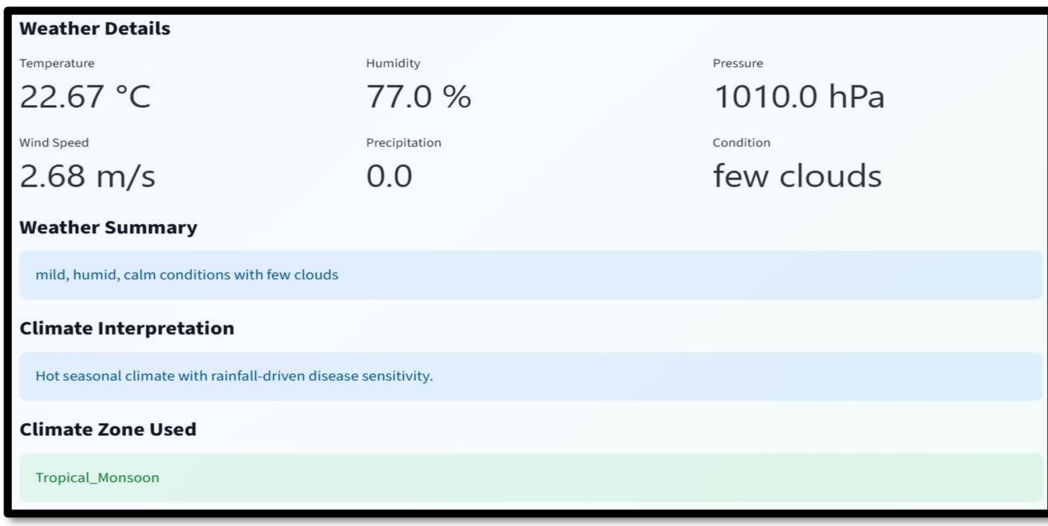

Figure2:WEATHER DETAILS

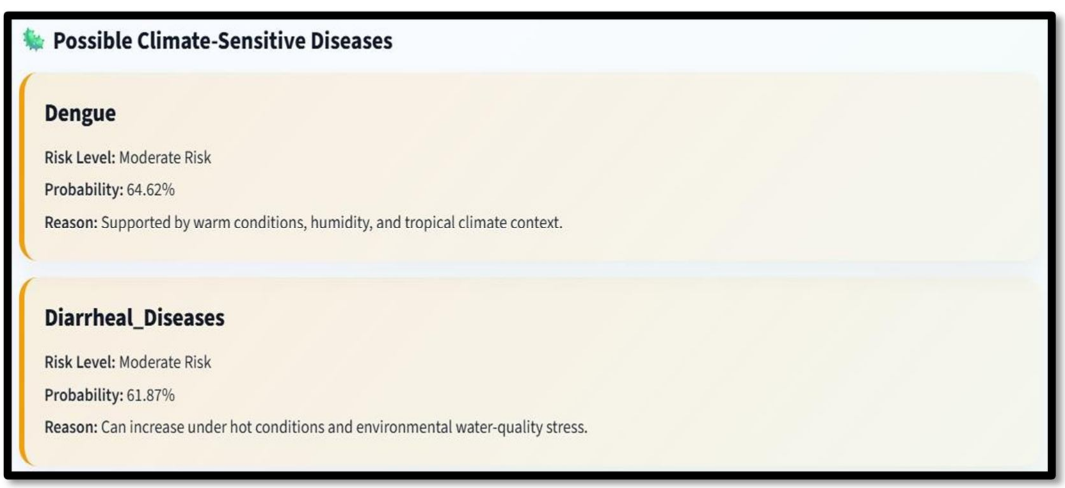

Figure3:DISEASESRISKPREDICTION

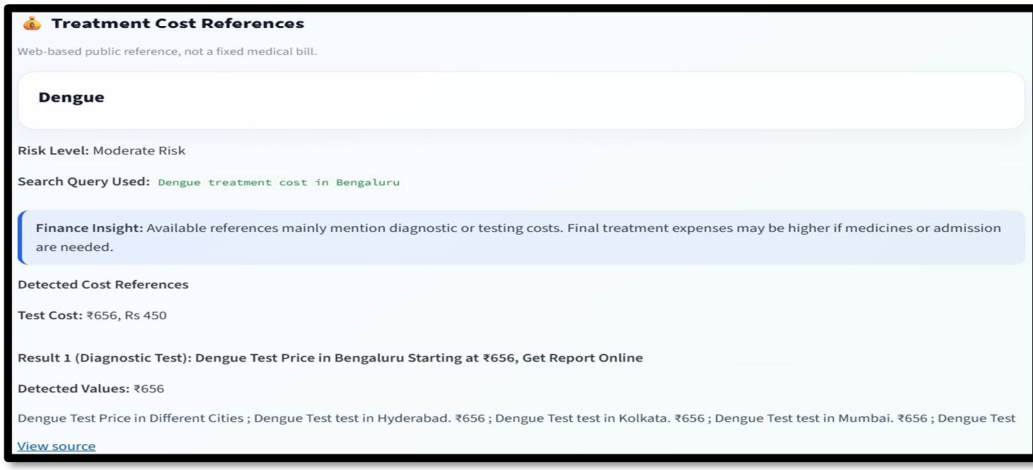

Figure4:TREATMENTCOST DETAILS

VI. CONCLUSION

The purpose of this research is to develop an innovativemethodofpredictingillnessesbytaking into accountthedifferent kindsofweatherthatexist, and how each type may influence human health. This paper will highlight the relationship between various forms of climate and the number of individualsatriskofdevelopingillnessesaswellas their chances of developing illness due to the atmosphere they live in. Therefore by including thesevariablesintopredictivemodelingtechniques 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 varioustypesofdiseases.TheusefulnessofFeature Importance Analysis to explain how different environmental factors may contribute to the occurrenceofdiseasewillresultinvaluabledatain ordertotrackPublicHealth,aswellasformulatean early warning System. The methodology used to combineData-DrivenModels(DDMs)fordecision makingwillassistwithplanningforHealthServices and the assessment of climate-related healthrisks.

Future Research will explore the use of real-time EnvironmentalData,expandthedatasetto include countries outside of the current dataset and co-frequency with socio-economic and demographic variabls,toprovidemoreaccuratepredictive analysis. The suggested framework for predicting the risks of disease based on Environmental Conditions is scalable and interpretable, and will thuscontributetoPublicHealtheffortsworldwide.

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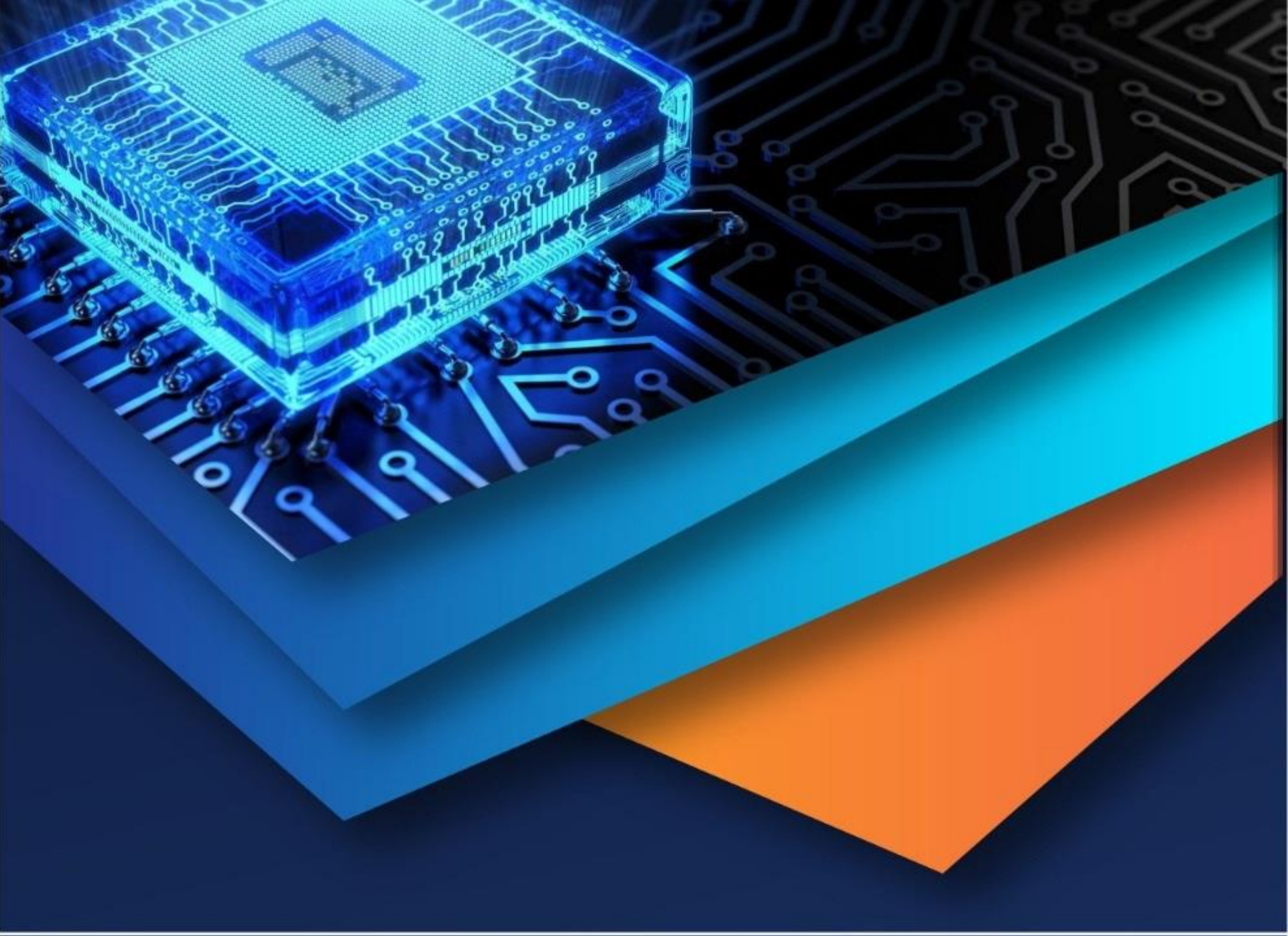

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