Anuman Malaria

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CONTENTS

ABSTRACT

India, where one in every seventh person on the planet lives, has no major national study on the impact of climate change, although about 600 million people are at risk from its effects. The life cycles and transmission of most infectious agents are inextricably linked with climate.

This research revolves around analysing how the factors of climate influence its developments and spreading. Extreme weather increased temperature, and air quality poses a direct risk to human vector-borne disease. Air quality affects the survival rates of pathogens, while the temperature influences the life cycle of mosquitoes and transmitters. The further warmer temperature and humidity favour the breeding of insects. On the other hand, a Rapidly increasing population enhances the transmission of vector-borne diseases (like dengue, malaria), as indirect risks are mediated through social processes (e.g., human-vector contacts).

Despite the global implications of this problem, the research is very limited in this domain. Towards the end, this research aims to show whether a single or combined weather variable has any significant association with the observed disease prevalence.

CHAPTER 1

INTRODUCTION

Malaria has persisted for a long period of time as one of the leading global health challenges, primarily prevalent in tropical and sub-tropical countries of the world. It is one of the major causes of illness and death in India and also remains as a serious obstacle to socio-economic development in India.

It was estimated that about 90% of the deaths occurred in India, where various factors such as ecosystem and climate conditions are favorable to species of mosquitoes transmitting the malaria parasite. In recent years, a lot of investments have been made to enhance malaria control and research programs, of which the World Health Organization (WHO) Global Technical Strategy (GTS) has the target to achieve a 90% decrease in malaria incidence and mortality rates by 2023.

The importance of meteorological variables in genesis and survival of mosquitoes have been known for a long time, although the relative roles of these variables and various aspects are still being investigated. However, fairly sharp and well-defined ranges of meteorological variables, especially temperature, are required for the genesis and survival of malaria vectors, although these thresholds also depend on the mosquito species.

Malaria disease is transmitted to humans through the bite of female mosquitoes of the genus Anopheles. These vectors feed on human blood for their egg production. During the process of feeding, they transmit the plasmodium parasite. The growth and maturity of this parasite mostly depend on climatic factors, which include temperature, rainfall, relative humidity, and thus, any change in climate factors would certainly exert an effect on the mosquito ecology.

This is why the influence of climatic and environmental variables over malaria incidence has been a predominant research focus. The key contribution of this paper is to find key factors responsible for malaria outbreaks based on climatic and population factors.

1.1 PROBLEM STATEMENT

An increase in temperature, rainfall, and humidity may cause a proliferation of the malaria-carrying mosquitoes at higher altitudes, resulting in an increase in malaria transmission in areas in which it was not reported earlier.

Human health is vulnerable to climate change. The changing environment is expected to cause more heat stress, an increase in waterborne diseases, poor air quality, and diseases transmitted by insects and rodents. Extreme weather events can compound many of these health threats.

This research aims at analysing how the factors of climate influence on developments and spreading of vector-borne diseases.

1.2 DATASET

Study Area

28 states of India, characterized by wide ranges of temperature, humidity, population, air pollution and rainfall.

Collection of Vector-Borne Disease Data

The data was collected from the Directorate of Health, State Govts of India, based on cases reported from Primary Health Centers (PHCs) from all the states. These data contain case counts and rates for malaria that met the surveillance case definition for that disease.

The National Vector Borne Disease Control Programme (NVBDCP) is an umbrella programme for the prevention and control of vector-borne diseases viz. Malaria, Japanese Encephalitis (JE), Dengue, Chikungunya, Kala-azar and Lymphatic Filariasis.

The Epidemiological data on vector diseases are available online in the National Vector Borne Disease Control Programme(NVBDCP), Ministry of Health & Family Welfare, Govt. of India.

Collection of Meteorological Data

Weather instruments collect data from all over India at thousands of weather stations. Thermometers measure temperature, radar measures rain or snow locations and movements, barometers measure air pressure, rain gauges measure amounts of rain, wind vanes measure wind direction, anemometers measure wind speed, transmissometers measure visibility, and hygrometers measure humidity.

Weather prediction is extremely valuable for reducing property damage and even fatalities. If the proposed track of a hurricane can be predicted.

The dataset was used with the help of the worldweatheronline.com API and the wwo_hist package.

Collection of Rainfall Data

Rainfall data generally are collected using electronic data loggers that measure the rainfall in 0.01- inch increments every 15 minutes using either a tipping-bucket rain gauge or a collection well gauge.

The dataset contains district wise rainfall calculated with the data for the period 1951 - 2000.

Collection of Air pollution Data

Air pollution refers to the release of pollutants into the air that is detrimental to human health and the planet as a whole.

India's air pollution levels over the years As mentioned in the WHO report 7 million premature deaths annually linked to air pollution, air pollution is the world's largest single environmental risk. The dataset contains air quality data and AQI (Air Quality Index) at an hourly and daily level of various stations across multiple cities in India.

The data has been made publicly available by the Central Pollution Control Board

1.3 TECHNOLOGIES AND TOOLS USED

A programming tool is a computer program that software developers use to create, debug, maintain, or otherwise support other programs and applications. Technology is the collection of techniques, skills, methods, and processes used in the production of goods or services or in the accomplishment of objectives. The tools and technologies used in the project are detailed in this section.

1.3.1 PYTHON

Python is an interpreted high-level general-purpose programming language. Python's design philosophy emphasizes code readability with its notable use of significant indentation. Its language constructs as well as its object-oriented approach aim to help programmers write clear, logical code for small and large-scale projects.

Python is a programming language that enables the application of machine learning algorithms and concepts in a simpler and faster manner.

1.3.2 REACT JS

React (also known as React.js or ReactJS) is an open-source, front end, JavaScript library for building user interfaces or UI components. It is maintained by Facebook and a community of individual developers and companies. React can be used as a base in the development of single-page or mobile applications.

1.3.3 GITHUB

GitHub, Inc. is a provider of Internet hosting for software development and version control using Git. It offers the distributed version control and source code management (SCM) functionality of Git, plus its own features. It provides access control and several collaboration features such as bug tracking, feature requests, task management, continuous integration and wikis for every project.

CHAPTER 2

RELATED WORK

Background & Objectives

The influence of temperature on the life cycle of mosquitoes as well as on development of malaria parasites in mosquitoes is well studied. Most of the studies use outdoor temperature for understanding the transmission dynamics and providing projections of malaria. As the mosquitoes breed in water and rest usually indoors, it is logical to relate the transmission dynamics with temperature of micro-niche.

Global Warming

Global warming has various effects on human health. The main indirect effects are on infectious diseases. Although the effects on infectious diseases will be detected worldwide, the degree and types of the effect are different, depending on the location of the respective countries and socio economic situations.

Among infectious diseases, water- and foodborne infectious diseases and vector-borne infectious diseases are two main categories that are forecasted to be most affected. The effect on vector-borne infectious diseases such as malaria and dengue fever is mainly because of the expansion of the infested areas of vector mosquitoes and increase in the number and feeding activity of infected mosquitoes. There will be an increase in the number of cases with water- and foodborne diarrhoeal diseases. The effect of global warming on human health is divided into two categories: direct effect on the illness such as heat shock and increased mortality in the population with other diseases and indirect effect on diseases such as infectious diseases and allergy.

Example: Extreme precipitation such as the flooding described here may pose significant challenges to malaria control programs, and will demand timely responses to mitigate deleterious impacts on human health.

CHAPTER 3

RELATED TERMINOLOGIES

Climate Change and Human Health

Although low- and middle-income countries are responsible for only a small percentage of global greenhouse gas emissions, the adverse health effects associated with climate change will likely fall disproportionately on their populations. This inequity will further exacerbate global health disparities (McMichael et al. 2003; Patz and Olson 2006; Patz et al. 2007; Wiley and Gostin 2009). High-risk areas include those already experiencing a scarcity of resources, environmental degradation, high rates of infectious disease, weak infrastructure, and overpopulation (Patz et al. 2005; Wiley and Gostin 2009).

In particular, tropical regions will experience significant changes in human–pathogen relationships because of climate change (Sattenspiel 2000). Changing temperatures and precipitation patterns linked to climate change will further affect health by changing the ecology of various vector-borne diseases, such as malaria, dengue, chikungunya, Japanese encephalitis, kala-azar, and filariasis (Bhattacharya et al. 2006; Dhiman et al. 2008).

Heat stress and air pollution:

The summer of 2010 was the hottest summer on record in India, with temperatures approaching 50°C (122°F); the effects were far-reaching, including hospitalization because of heatstroke, the suffering of livestock, and severe drought in some regions that affected health as well as agriculture (Burke 2010).

Vector-borne disease:

India has approximately 2 million confirmed cases of malaria per year (Kumar et al. 2007). Like most infectious diseases, prevalence varies by region (Figure 1C, D). Although WHO concludes that approximately 15,000 individuals die from malaria each year in India

(WHO 2008), a recent study by Dhingra et al. (2010) estimates approximately 200,000 malaria deaths per year in India before 70 years of age and 55,000 in early childhood.

Little is known about the influence of climate variability or climate change on the prevalence of malaria in Indian urban areas (Kumar et al. 2007). The issue of urban malaria becomes even more important when considering the rapid expansion of urban and peri urban environments, water storage techniques, and rising poverty levels.

The need for adaptation:

Although adaptation to climate impacts has attracted substantial attention recently, the effectiveness of specific strategies in relation to the greater resilience of public health systems remains under-investigated. Adapting to climate change will be necessary and will occur at physiological, behavioural, social, institutional, and organizational scales.

CHAPTER 4

DATA VISUALIZATION

RAINFALL ANALYSIS

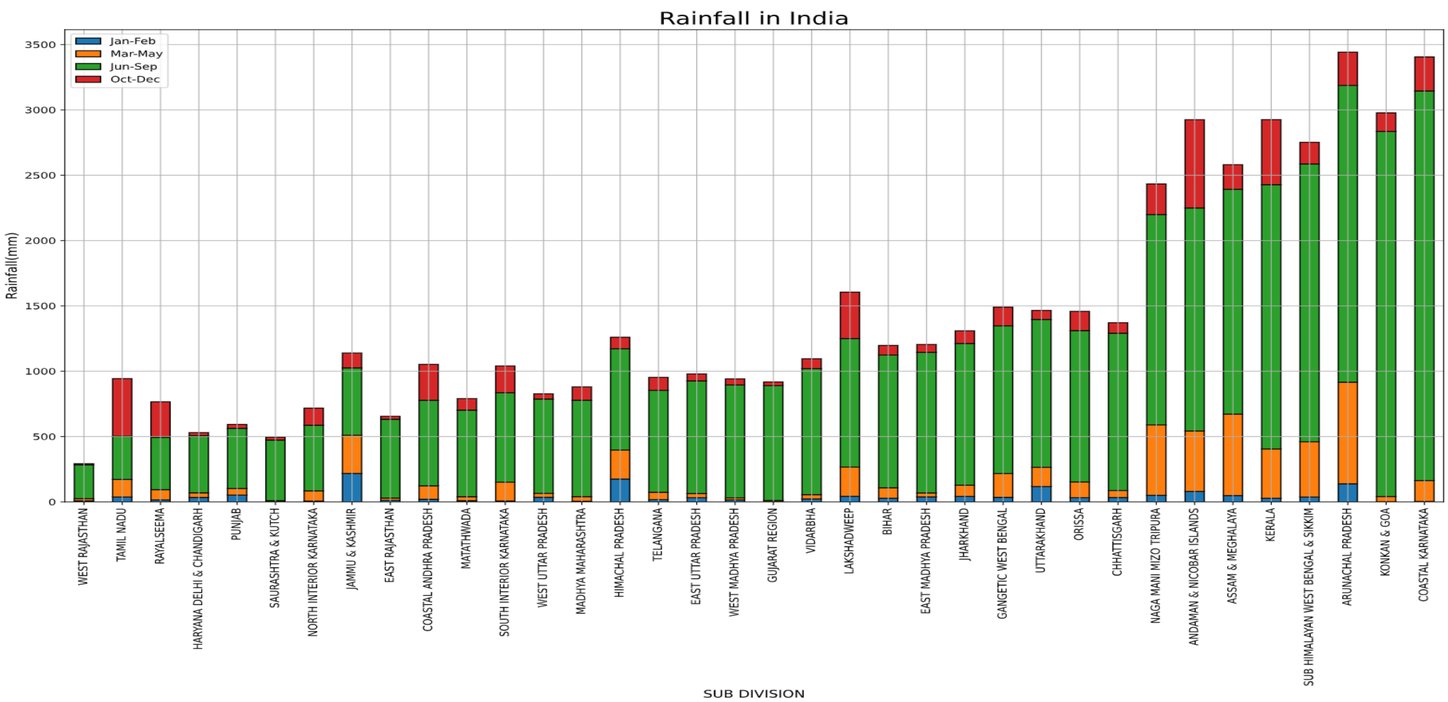


Table 4.0 Rainfall Distribution Across States

The average rainfall in India is 125 cm. The South-west monsoon constituted 75% of the total rainfall (June to September), 13% of it by north-east monsoon (October to December), 10% of it by pre monsoon cyclonic rainfall (mainly in April and May and 2% of it by western disturbances (December to February).

Table 4.0 shows that the Rainfall during the month of June to September is significantly higher than other times of the year. It can also be seen that Coastal Karnataka received the highest rainfall during this period of 5 years. Over 80% rainfall is received in the four rainy months. During cold weather, India receives about 25 cm of rainfall. The amount of rainfall however decreases rapidly in the interior of the peninsula.

AIR POLLUTION ANALYSIS

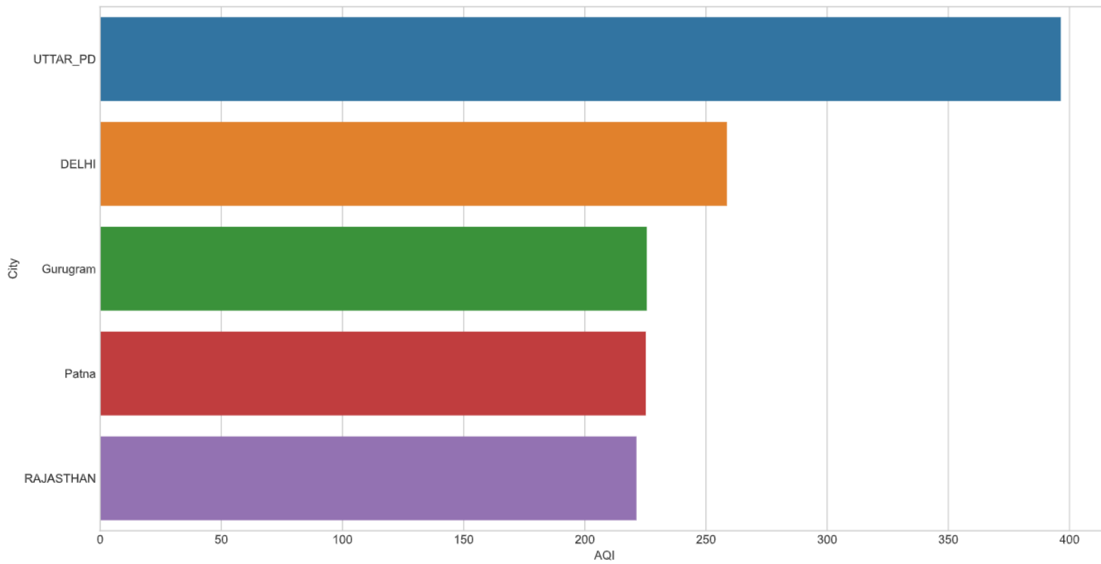


Table 4.1Air Pollution Quality across states

Air pollution in India is a serious health issue. Of the 30 most polluted cities in the world, 21 were in India in 2019. Here it can seen that Uttar Pradesh had the worst AQI. Since it is a serious cause, Air pollution is also included in our variables.

TEMPERATURE ANALYSIS

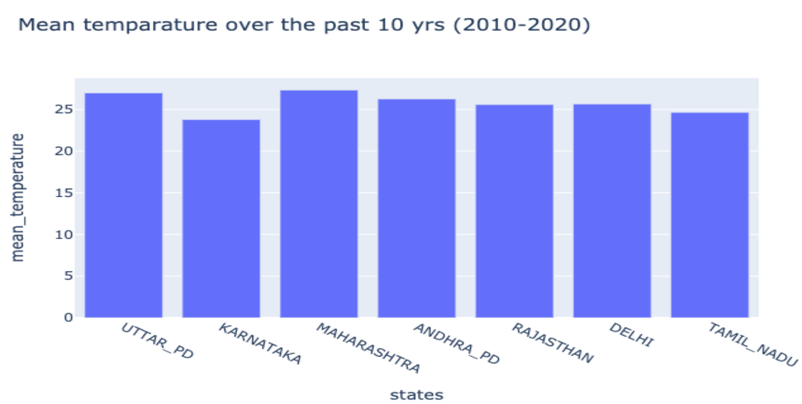


Table 4.2 Temperature Across States

Temperature is particularly critical. For example, at temperatures below 20°C (68°F), Plasmodium falciparum cannot complete its growth cycle in the Anopheles mosquito, and thus cannot be transmitted. Thus, temperature finds a place in our variables list.

MALARIA DISTRIBUTION

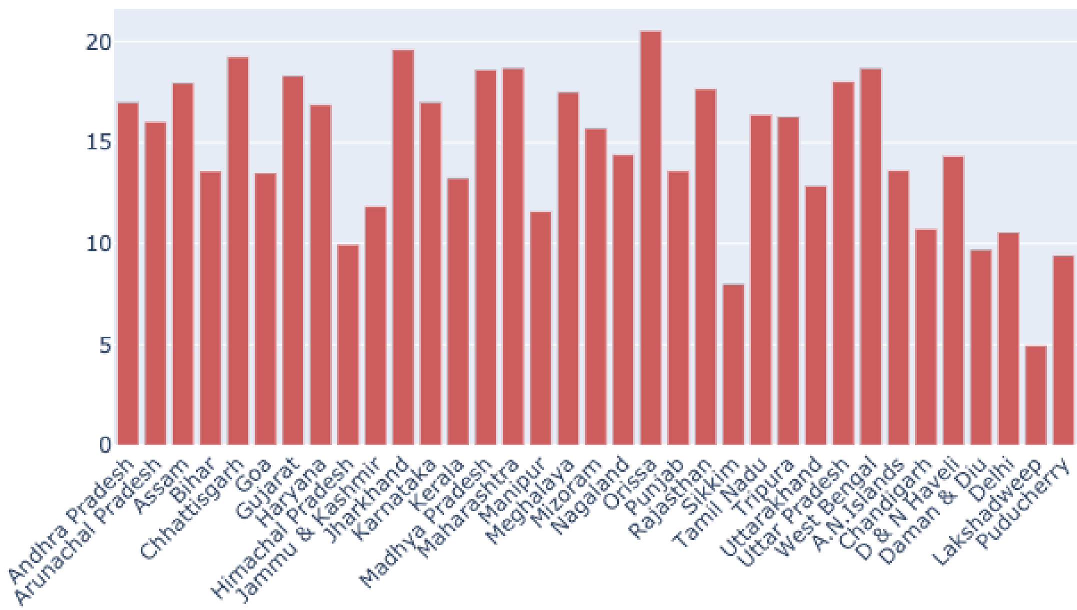


Table 4.2 Malaria Distribution Across States

The majority of malaria in India is reported from the eastern and central part of the country and from states which have large forest, hilly and tribal areas. These states include Odisha, Chhattisgarh, Jharkhand, Madhya Pradesh, Maharashtra and some north-eastern states like Tripura, Meghalaya and Mizoram.

Malaria has been a problem in India for centuries. Details of this disease can be found even in ancient Indian medical literature like the Atharva Veda and Charaka Samhita. In the 30's there was no aspect of life in the country that was not affected by malaria.

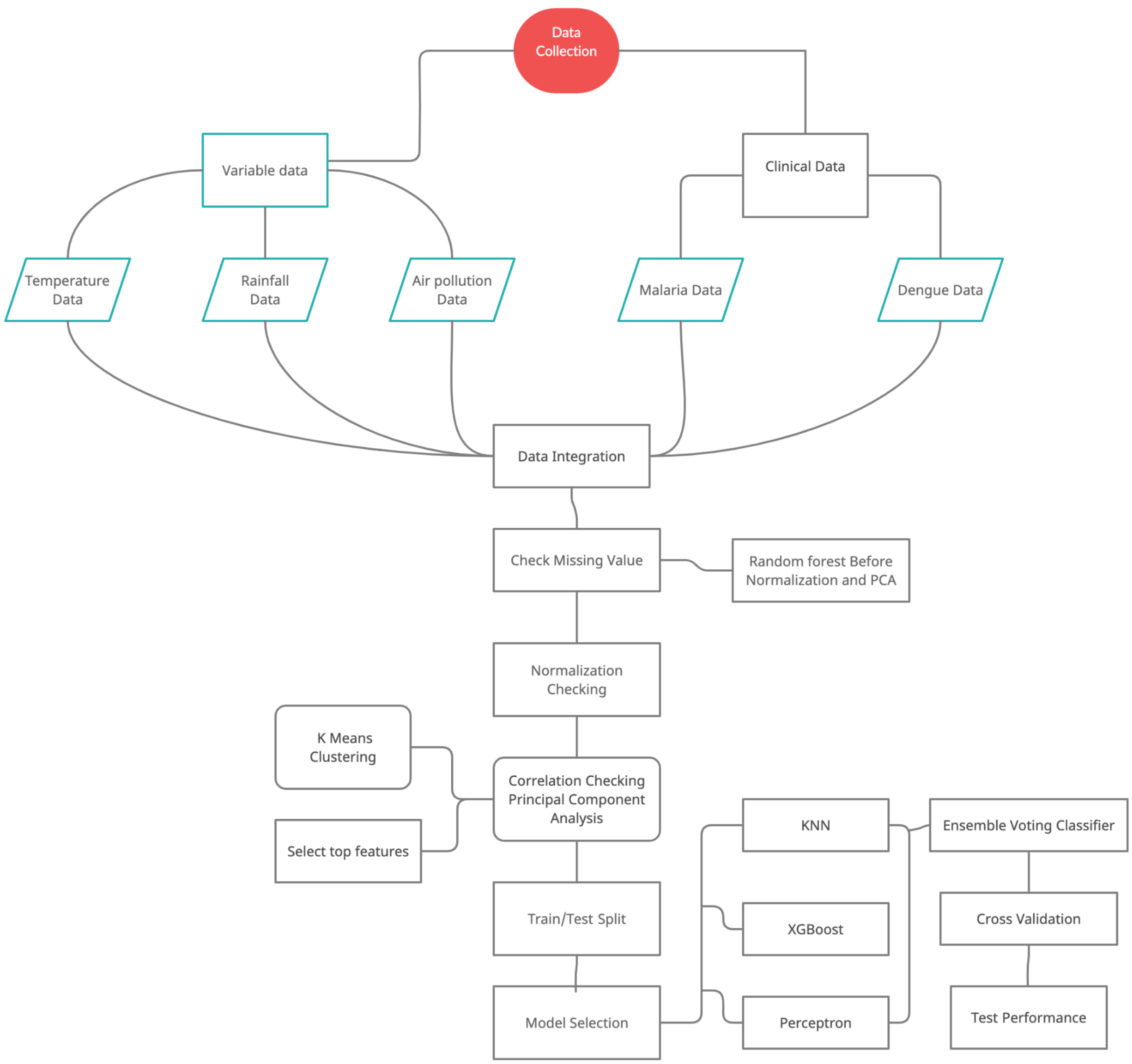
According to the World Malaria Report 2014, 22% (275.5m) of India's population lived in high transmission (> 1 case per 1000 population) areas, 67% (838.9m) lived in low transmission (0–1 cases per 1000 population) areas and 11% (137.7m) lived in malaria-free (0 cases) areas.

Here our sole aim is to find variables which act favourably for malaria. Thus we can take steps to minimize them.

CHAPTER 5

MODEL ARCHITECTURE

The implementation of the malaria incidence classification (MIC) model was done using Anaconda 3 that supports Python 3.8 programming language. It is open-source software that contains some packages supporting machine learning and data science applications. The design flow of the MIC is explained below with a flow chart.



CHAPTER 6

PROPOSED METHODOLOGY

The proposed methodology makes use of both qualitative and quantitative perspectives, and includes a broad array of approaches such as literature reviews, expert opinions, focus groups, and content validation. It also involves sophisticated assessment of construct validity including substantive and structural aspects.

6.1 DATA COLLECTION

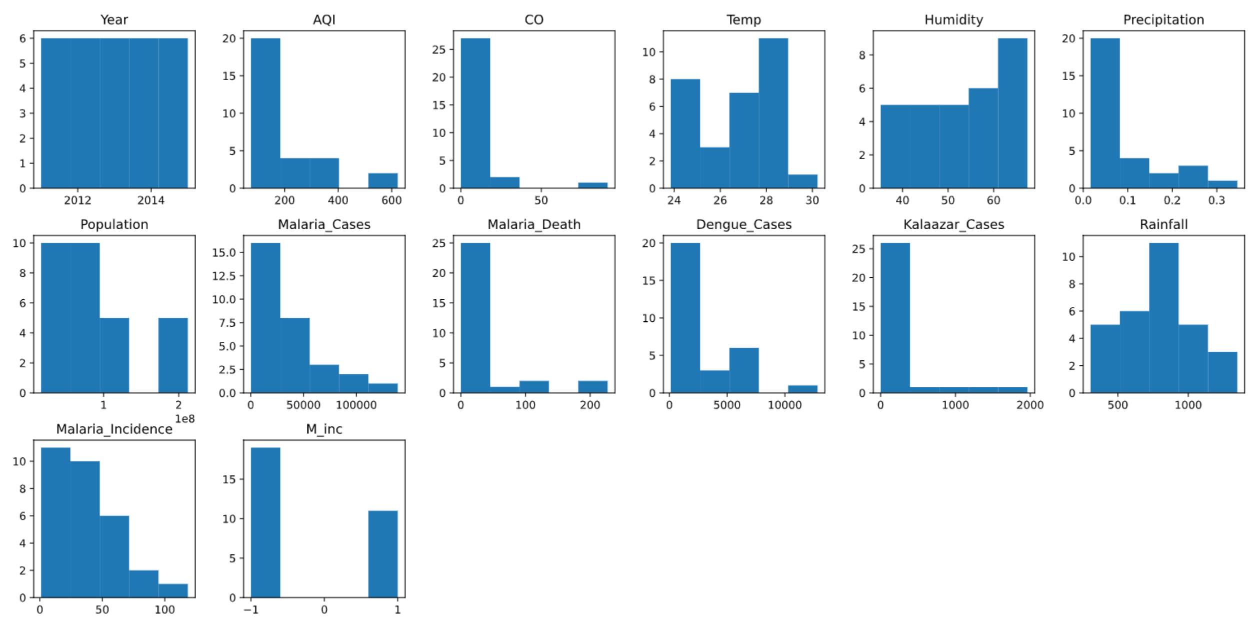


Table 6.0 Data Summary

Data collected from multiple sources are processed and collected together for the final data processing to develop a model based on the architecture explained above.

This Finalized collection of data consists of all the variables including AQI ,CO ,Temp, Humidity, Precipitation, Population, Rainfall.The malaria incidence rate (I) is the number of new cases of malaria (M) divided by the total population (Pop) and multiplied by 100,000.

Whereas, M_inc is calculated from malaria incidence threshold = xb + 0.45(SD).

Where,

xb = population mean

n = total number of years

SD = Standard Deviation

Whenever the number of malaria incidence rises above these thresholds, it is regarded as a high incidence and vice versa. The target variable was divided into two output classes, namely 1 and -1 to signify high and lower incidence.

6.2 DATA PREPROCESSING

6.2.1 NULL Value Removal

Removing null values from the dataset is one of the important steps in data wrangling. These null values adversely affect the performance and accuracy of any machine learning algorithm. So, it is very important to remove null values from the dataset before applying any machine learning algorithm to that dataset.

Feature	Null Values count
Year	0
AQI	0
CO	0
Temp	0
Humidity	0
Precipitation	0
Population	0
Malaria_Cases	0
Malaria_Death	0
Dengue_Cases	0
Kalaazar_Cases	0

Table 6.1 NULL Value Count

6.2.1 Visualization & Analysis

Since most of the data is already cleaned during initial processing of variables individually, The final dataset is mostly clear from any discrepancies and is safe to work.

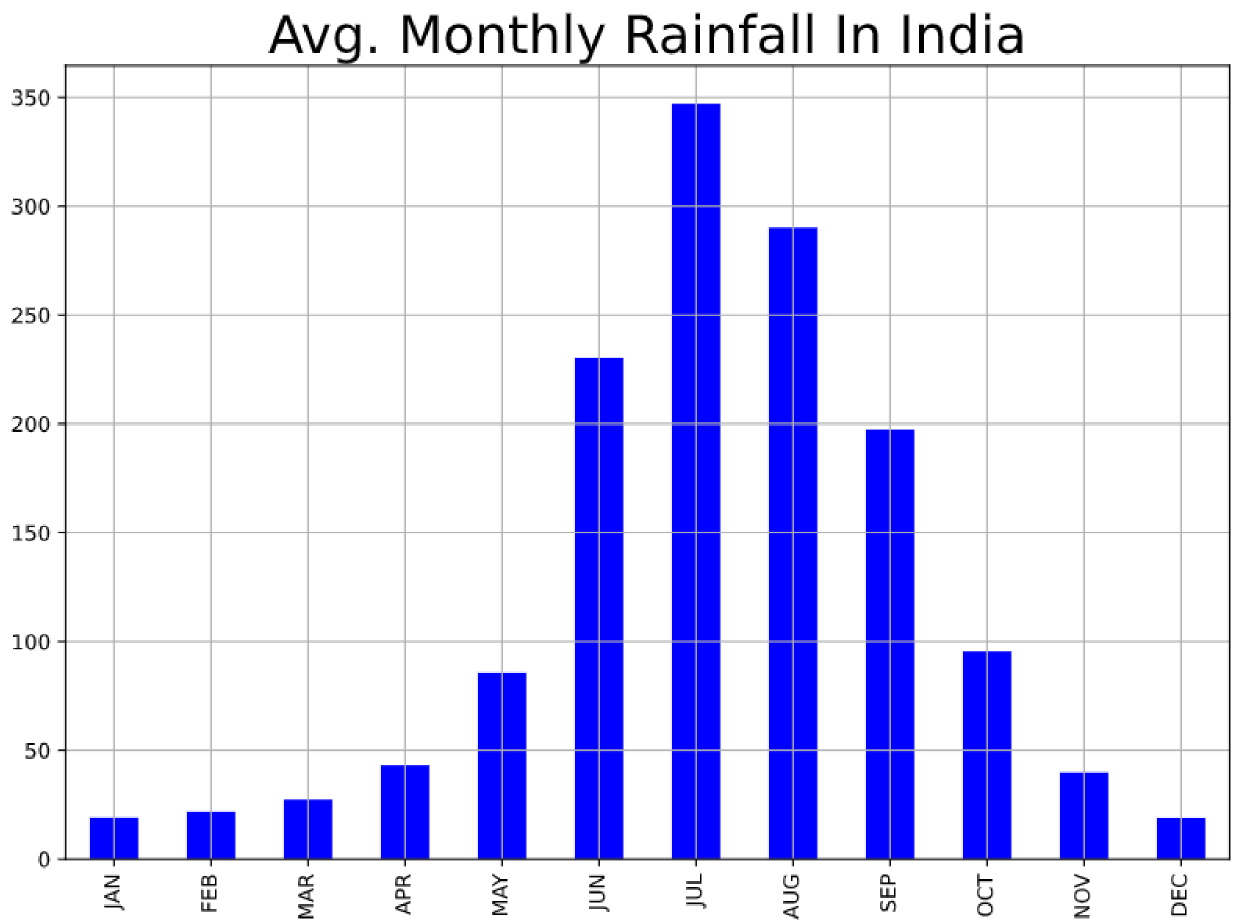


Table 6.3 Month wise Average Rainfall in India

6.3 DATA ANALYSIS

6.3.1 Feature Scaling

Is a technique to standardize the independent features present in the data in a fixed range. If feature scaling is not done, then a machine learning algorithm tends to weigh greater values, higher and consider smaller values as the lower values, regardless of the unit of the values.

BEFORE FEATURE SCALING

Feature	Min	Mean	Max	Std. Dev
M_inci	-1	-0.267	1	0.980
AQI	73.758	181.808	622.551	134.776
CO	0	6.938	91.218	17.707
Temp	23.849	26.730	30.223	1.665
Humidity	35.197	53.492	67.409	10.239
Precipitation	0.016	0.096	0.346	0.083
Population	16787941	87896594.933	2.121e+08	61416452.214
Rainfall	305.500	806.837	1348.500	258.264

AFTER FEATURE SCALING

Feature	Min	Mean	Max	Std. Dev
M_inci	-1	-0.267	1	0.980
AQI	-0.815	0	3.326	1.017
CO	-0.399	0	4.841	1.017
Temp	-1.760	0	2.133	1.017
Humidity	-1.817	0	1.382	1.017
Precipitation	-0.981	0	3.068	1.017
Population	-1.178	0	2.056	1.017
Rainfall	-1.974	0	2.133	1.017

Table 6.4 Before and After Feature Scaling

As seen from Table 6.4, it is evident that the scattered values are now normalized and are better suited for data processing and fitting. This would benefit us in getting better results.

6.3.2 Correlation Analysis

To get in depth knowledge about the relationship between features and to check if PCA should be used or not. From Table 6.4 we can understand that some features are highly correlated to each other and hence PCA is essential in our case.

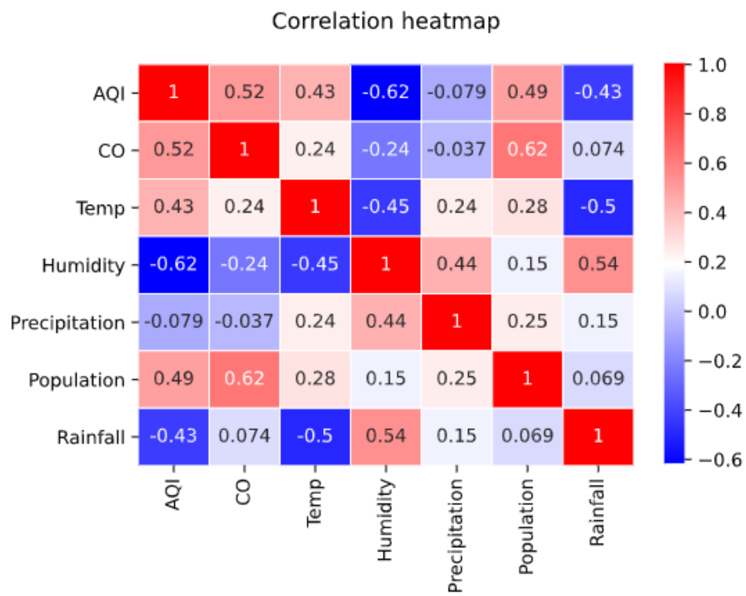


Table 6.4 Correlation between variables

In trying to plot the feature importance, we found that 3 variables are the most responsible for spread of malaria and these 3 combined together almost reached 90 percent suggestions. Hence it is more proper to only consider those 3 variables than considering all.

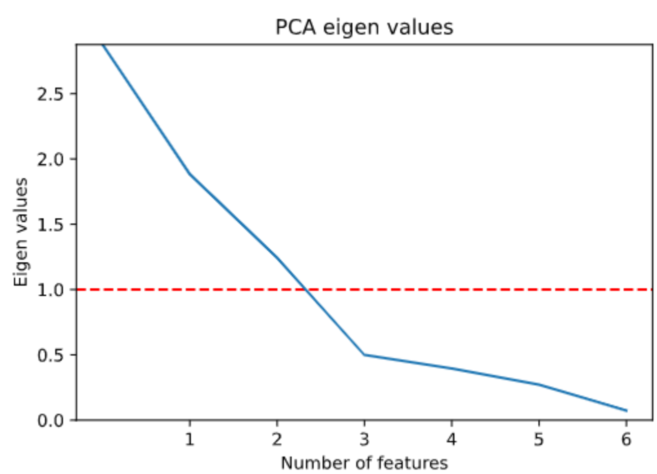


Table 6.5 Impact of features

6.4 CLUSTERING

Clustering partitions a large number of data points into a small number of clusters. It groups the objects in such a way that objects with similar characteristics are in one group by measuring their similarity in terms of distance. K-means clustering was used in this study to detect outliers and clean the dataset.

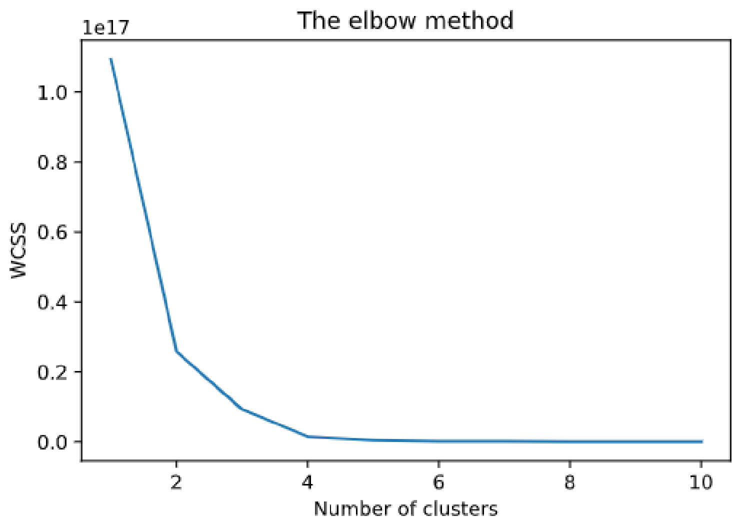


Table 6.6 K Means Cluster Performance

K means performs best with 2 clusters in case of AQI and malaria incidence. Similarly Malaria incidence is checked with Rainfall, Temperature and compared.

6.5 CLASSIFICATION

6.5.1 Perceptron

A Perceptron is an algorithm used for supervised learning of binary classifiers. Binary classifiers decide whether an input, usually represented by a series of vectors, belongs to a specific class. In short, a perceptron is a single-layer neural network.

There are two types of Perceptrons: Single layer and Multilayer. Single Layer is used here for faster analysis.

6.5.2 XGBoost

Extreme Gradient boosting, popularly referred to as XGBoost, is a machine learning method that is used to solve regression and classifi- cation problems. It provides results in a prediction model, mostly in the form of trees. It is scalable and efficient in memory usage and drives fast learning through parallel and distributed computing. This model is suitable for the nature of our dataset as it is important to improve the accuracy in the classes having fewer samples. The proposed MIC model is implemented using the XGBoost model.

6.5.2 KNN

k-NN is a type of classification where the function is only approximated locally and all computation is deferred until function evaluation. Since this algorithm relies on distance for classification, if the features represent different physical units or come in vastly different scales then normalizing the training data can improve its accuracy dramatically.

Both for classification and regression, a useful technique can be to assign weights to the contributions of the neighbors, so that the nearer neighbors contribute more to the average than the more distant ones. For example, a common weighting scheme consists in giving each neighbor a weight of 1/d, where d is the distance to the neighbor samples. The proposed MIC model is implemented using the XGBoost model.

6.5.2 ENSEMBLE VOTING CLASSIFIER

Voting Classification is a selection method used to vote the models according to accuracy score, with highest ranking accorded to model with the highest accuracy score. The majority voting approach allows the selection of models that can provide the best accuracy score. The formula for the ensemble voting classification.

Majority voting-based ensemble classifier is a simple ap- proach. In this approach, each classifier assigns equal weight, which represents all classifiers equally.

Hard voting is the simplest case of majority voting, which is widely used in classification tasks.

6.6 VALIDATION

To minimise the out-of-sample error and improve the precision of the model, Cross-Validation is performed on the training and testing data by using multiple test sets and averaging the out-of-sample errors.

This is a common approach whereby the training and testing data are further randomly separated into folds that evenly stratified the train/test sets, either 10 folds. Every point in the sets of data will occur exactly once, resulting in identical training and test sets. One important feature of cross-validation is to ensure that each test set is randomly assigned to avoid systemic biases in the data; this in turn allows estimation for the out of sample error in the predictions.

6.7 PERFORMANCE METRICS

The following performance metrics were used to test the perfor- mance of the MIC model

Accuracy :-

Accuracy is defined as the percentage of correct predictions for the test data. It can be calculated easily by dividing the number of correct predictions by the number of total predictions. The benefits of improving model accuracy help avoid considerable time, money, and undue stress.

Precision & Recall:-

In pattern recognition, information retrieval and classification (machine learning), precision (also called positive predictive value) is the fraction of relevant instances among the retrieved instances. While recall (also known as sensitivity) is the fraction of relevant instances that were retrieved. Both precision and recall are therefore based on relevance.

F1 Score:-

The F1 Score is the 2*((precision*recall)/(precision+recall)). It is also called the F Score or the F Measure. Put another way, the F1 score conveys the balance between the precision and the recall.

CHAPTER 7

EXPERIMENTAL RESULTS

A controlled experiment often compares the results obtained from experimental samples against control samples, which are practically identical to the experimental sample except for the one aspect whose effect is being tested.

7.1 FEATURES CONCLUDED

During the feature selection process, the 3 variables including Rainfall, Temperature and Humidity constructed 90 percent of the data, Hence those features are of direct relation with the spread of Malaria. On further analysis, it was found that temperature plays a major role in spread of Malaria than any other components as it mattered for 40 percent of the impact on itself.

```
    #Temp, Humidty and Rainfall takes the top place

Column: 0, Selected False, Rank: 5.000
Column: 1, Selected True, Rank: 1.000
Column: 2, Selected False, Rank: 3.000
Column: 3, Selected False, Rank: 2.000
Column: 4, Selected True, Rank: 1.000
Column: 5, Selected False, Rank: 4.000
Column: 6, Selected True, Rank: 1.000
```

Table 7.1 Selected Features

7.2 ACCURACY ANALYSIS

From the observations, it can be seen that Ensemble Voting is the most efficient machine learning algorithm. However, we may need to further evaluate the results with a larger dataset. It is highly recommended for models such as XGBoost to optimize the hyper parameters setting before building into the baseline of the ensemble. It is scalable and efficient in memory usage and drives fast learning through parallel and distributed computing.

PREDICTION RESULTS

1. PERCEPTRO
2. XGBOOST
3. KNN (K-NEAREST NEIGHBOR)
4. ENSEMBLE VOTING CLASSIFIER

Model	Acc	Prec	Recall	F1
1	66.670	0.520	0.530	0.520
2	65	0.920	0.860	0.880
3	51.670	0.720	0.710	0.710
4	71.670	0.840	0.650	0.630

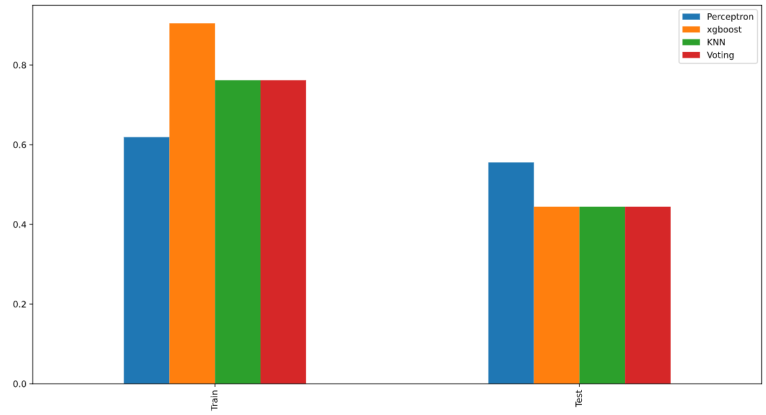


Table 7.2 Performance Analysis

Table 7.2 gives an overall view of how our data fared when made to fit in different models, Ensemble voting overtakes all other models and gives a better result. Computational time is not an area of concern as our dataset is limited to 5 states and 5 years.

7.3 FINAL MODEL

Prior to the training of models, the dataset has to be pre-processed and scaling has to be done so that each feature contributes approximately proportionately to the final distance. This is followed by PCA feature extraction to transform the set of values to linearly uncorrelated principal components. To minimize the overfitting problem, we used a 10-fold cross validation technique which splits the data into 90% for training and 10% for validation test for each baseline model. The process is repeated a few times until we get a stable accuracy score from the average 10-fold. The number of k-fold is subjective to debate and the most widely used numbers are k = 5 or 10.

CHAPTER 8

WEB IMPLEMENTATION

Home Page

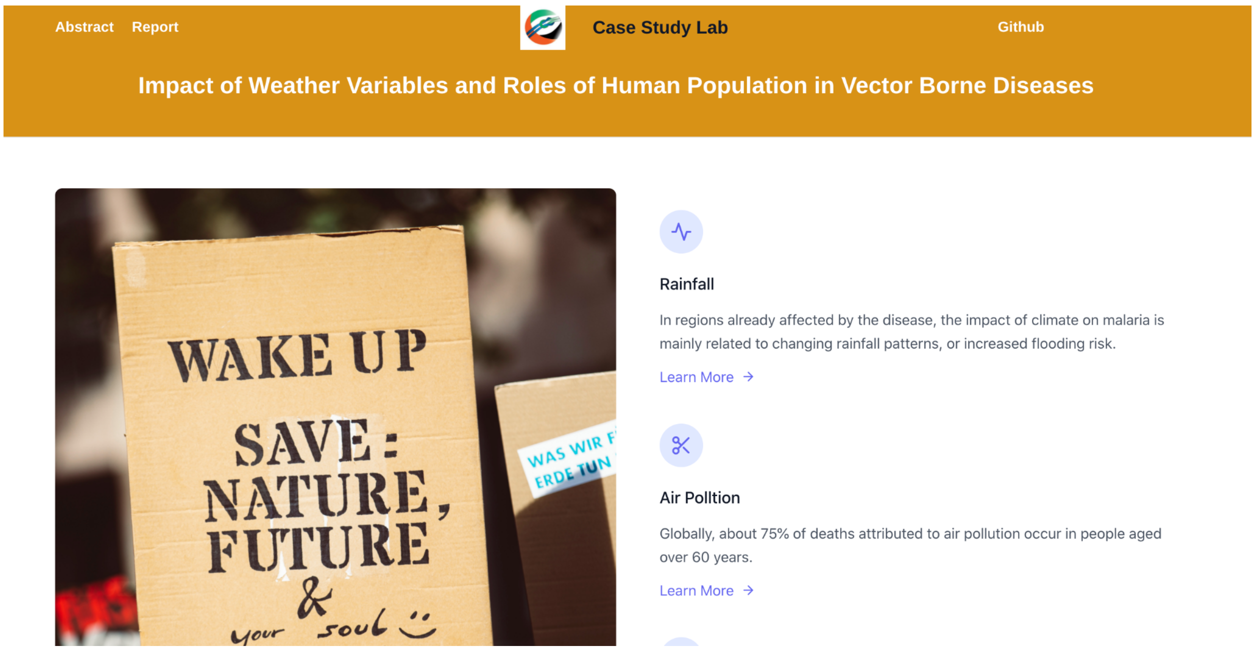


Fig 8.1 Home Page

A home page (or homepage) is the main web page of a website. Over here we have provided links to “Abstract” and “Report” on the header and users can download them for their reference. We have also provided a link to our GitHub where users can find datasets and different ML models that we have tried. We have also placed links to other pages where different visualizations have been used to analyze Air quality, Climate and Rainfall in major states of India.

Air Quality Analysis

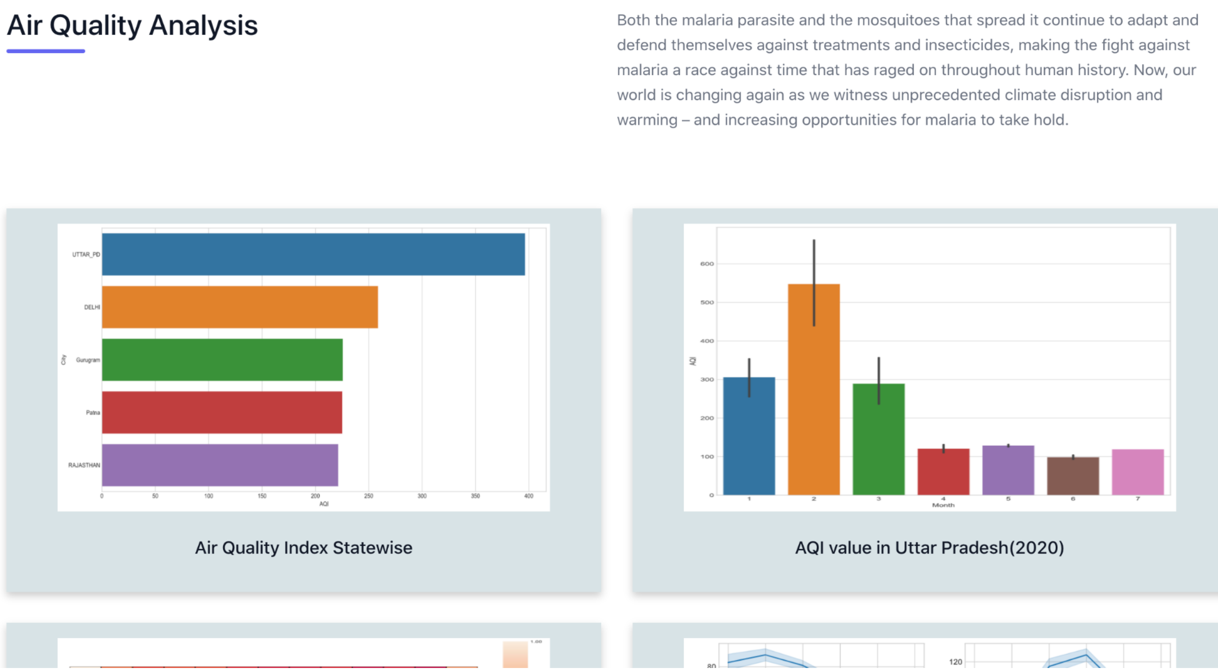


Fig 8.2 Air Quality

In this page we have shown different Air Quality Index (AQI) in different states. AQI really helps in knowing how hazardous the air is. The higher the AQI value, the greater the level of air pollution and the greater the health concern. For example, an AQI value of 50 or below represents good air quality, while an AQI value over 300 represents hazardous air quality. And we have shown visualization for different air elements and their values fron 2015 to 2020.

Different air elements include:

- PM2.5
- PM10
- NO2
- NOx
- NH3
- CO
- SO2
- O3
- Benzene

Rainfall Analysis

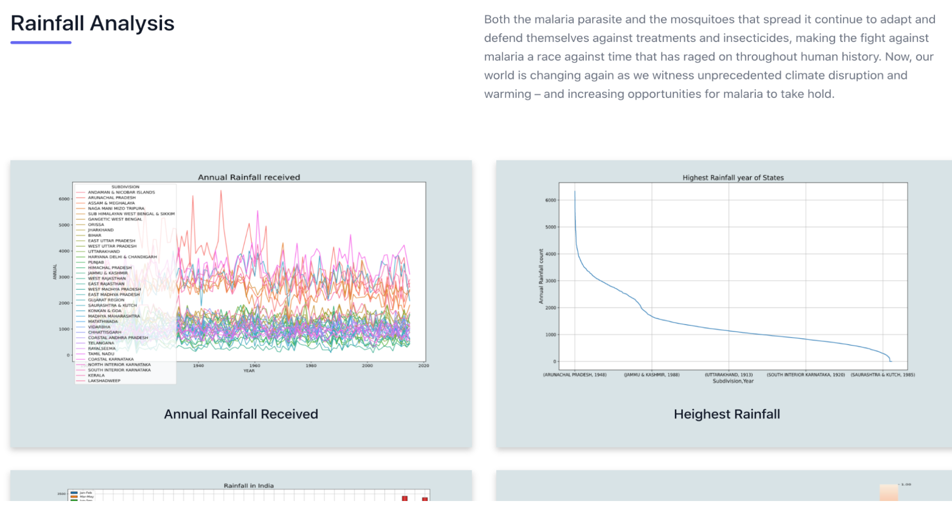


Fig 8.3 Rainfall

Rainfall analysis page shows annual rainfall received in different states. Then we have the highest rainfall year for each state. A Bar chart which shows average rainfall in India monthly wise. And other types of charts to better understand rainfall in different states and rainfall is a major factor when it comes to predicting malaria and other diseases similar to that.

CLIMATE ANALYSIS

Fig 8.4 Climate

CHAPTER 9

CONCLUSION

It will be critical for India to invest in improvements in information infrastructure that are innovative and that promote interdisciplinary collaborations while embarking on adaptation strategies. This will require unprecedented levels of collaboration across diverse institutions in India and abroad. The data can be used in research on the likely impacts of climate change on health that reflect India's diverse climates and populations. Local human and technical capacities for risk communication and promoting adaptive behavior must also be enhanced.

The association between vector-load and daily values of weather variables is robust and holds for different climatic regions (states of India). Thus use of all the three weather variables provides a reliable means of proactive and efficient vector sanitation and control as well as assessment of impact of climate change on malaria.

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