

HARVESTIFY: EMPOWERING CROP YIELDS THROUGH INTELLIGENT NUTRIENT OPTIMIZATION

A PROJECT REPORT

Submitted by

ABDUL HAZEER T (2116210701007)

HAARTHY S L (2116210701065)

in partial fulfillment for the award of the degree

of

BACHELOR OF ENGINEERING

in

COMPUTER SCIENCE AND ENGINEERING



RAJALAKSHMI ENGINEERING COLLEGE

ANNA UNIVERSITY, CHENNAI

MAY 2024

RAJALAKSHMI ENGINEERING COLLEGE, CHENNAI

BONAFIDE CERTIFICATE

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SIGNATURE

Dr. T. Kumaragurubaran M.Tech., Ph.D.

PROJECT COORDINATOR

Assistant Professor

Department of Computer Science and Engineering

Rajalakshmi Engineering College

Chennai - 602 105

Submitted to Project Viva-Voce Examination held on _____

Internal Examiner

External Examiner

ABSTRACT

The intricacies of fertilizer management pose a significant challenge to agricultural practitioners, necessitating informed guidance for optimal utilization. Effective fertilization strategies are indispensable for enhancing agricultural productivity while minimizing environmental impacts. Rainfall dynamics profoundly influence nutrient distribution and absorption in the soil, with excessive precipitation elevating the risk of nutrient runoff and leaching. Nitrogen (N), phosphorus (P), potassium (K), manganese (Mn), and boron (B) are among the critical elements vulnerable to these hydrological dynamics. In response, this research advocates for the implementation of an advanced random forest algorithm, bolstered by comprehensive time-series analyses, to deliver tailored nutrient recommendations tailored to specific crop needs. By integrating insights from rainfall patterns and soil fertility assessments, this innovative approach offers a sustainable framework for optimizing nutrient management, fostering soil health, and ensuring agricultural resilience in the face of evolving environmental challenges.

ACKNOWLEDGMENT

First, we thank the almighty god for the successful completion of the project. Our sincere thanks to our chairman **Mr. S. Meganathan B.E., F.I.E.**, for his sincere endeavor in educating us in his premier institution. We would like to express our deep gratitude to our beloved Chairperson **Dr. Thangam Meganathan Ph.D.**, for her enthusiastic motivation which inspired us a lot in completing this project and Vice Chairman **Mr. Abhay Shankar Meganathan B.E., M.S.**, for providing us with the requisite infrastructure. We also express our sincere gratitude to our college Principal, **Dr. S. N. Murugesan M.E., PhD.**, and **Dr. P. KUMAR M.E., PhD, Director computing and information science , and Head Of Department of Computer Science and Engineering** and our project coordinator **Dr. T. Kumaragurubaran M.Tech., Ph.D.**, for her encouragement and guiding us throughout the project towards successful completion of this project and to our parents, friends, all faculty members and supporting staffs for their direct and indirect involvement in successful completion of the project for their encouragement and support.

ABDUL HAZEER T (2116210701007)

HAARTHY S L (2116210701065)

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CHAPTER 1

INTRODUCTION

Agriculture serves as a cornerstone of national economic development, contributing significantly to India's GDP with a share of 17-18% and securing the country's position as the second-largest producer of farm outputs globally. Essential to this agricultural success is the judicious application of fertilizers, which replenish vital nutrients depleted by crops from the soil's upper layers. Indeed, the absence of proper fertilization can precipitate a sharp decline in crop yields. However, achieving optimal fertilization demands precision, taking into account rainfall patterns and crop-specific nutrient requirements. In this regard, machine learning emerges as a promising technology, leveraging available data on crop fertility and precipitation to provide tailored solutions for farmers. By harnessing the power of a machine learning algorithm, specifically the random forest algorithm coupled with k-fold cross-validation, our proposed model empowers farmers with actionable insights. By inputting crop type and location, users receive personalized recommendations on nutrient quantities and optimal fertilizer application timing. Developed using Flask Python, a versatile web framework, our platform ensures accessibility across various devices and facilitates seamless information sharing among users, thereby fostering informed decision-making and sustainable agricultural practices. Moreover, the integration of machine learning techniques not only enhances the efficiency of nutrient management but also fosters sustainable agricultural practices by minimizing fertilizer waste and environmental impact. By harnessing the power of data-driven insights, farmers can mitigate risks associated with unpredictable weather patterns and optimize resource utilization. our platform remains adaptive to evolving agricultural needs, driving positive change and resilience within the farming community.

1.1 PROBLEM STATEMENT

Addressing the challenge of inconsistent and improper fertilizer use is critical, as it directly affects crop yields, soil quality, and the economic prosperity of farmers. This project seeks to tackle this issue head-on by leveraging the capabilities of machine learning to offer precise fertilization recommendations. Through the implementation of a random forest algorithm, coupled with k-fold cross-validation, our system analyzes historical data on crop fertility and rainfall patterns. By providing farmers with tailored advice on nutrient quantities and application timing, based on their specific crop type and location, we aim to optimize agricultural practices and maximize productivity. Our web platform, developed using Flask Python, serves as an accessible and user-friendly tool for farmers, facilitating informed decision-making and promoting sustainable agricultural practices. By supporting the growth and resilience of India's agriculture sector, our initiative contributes to the broader goal of fostering national economic development.

1.2 SCOPE OF THE WORK

The project at hand revolves around the development of a web-based application using Flask, which aims to offer farmers accurate fertilizer recommendations specific to their crop type and location. Leveraging the random forest algorithm alongside k-fold cross-validation, the model delves into soil nutrient data, crop requirements, and rainfall patterns to predict the optimal timing and quantities of fertilizers needed. The deliverables entail a well-trained machine learning model, an intuitive web interface accessible to users, integrated datasets containing pertinent agricultural information, and thorough documentation elucidating the system's functionality and usage. Through rigorous user testing, the system will undergo refinement to ensure practical usability for farmers, ultimately bolstering crop yields and promoting sustainable agricultural practices.

1.4 AIM AND OBJECTIVES OF THE PROJECT

Crop production serves as a cornerstone of both global food security and the burgeoning biofuel industry, with machine learning (ML) emerging as a powerful ally in bolstering farmers' efficacy on these fronts. The strategic application of herbicides, insecticides, and fungicides is paramount in optimizing crop productivity and yield, necessitating precise timing for maximum effectiveness. Delayed crop spraying, particularly as soil moisture diminishes later in the season, poses a considerable risk to crop yields. Given the intricate web of decisions farmers navigate annually, encompassing risk, sustainability, and financial outcomes, the integration of machine learning into our project holds immense promise. Our objective is twofold: first, to furnish farmers with actionable insights into crop nutrient requirements, leveraging short-term weather forecasts, particularly those spanning seven days. Secondly, by factoring in these forecasts, we aim to curtail water pollution by mitigating the leaching process.

Through the judicious application of machine learning techniques, we endeavor to equip farmers with the tools they need to make informed decisions, optimize resource utilization, and cultivate sustainable agricultural practices for the benefit of both present and future generations. In addition to optimizing nutrient management and mitigating water pollution, our project seeks to address broader challenges facing modern agriculture, such as climate variability and resource scarcity. By harnessing the power of machine learning to analyze vast amounts of data, including soil conditions, weather patterns, and historical crop performance, we aim to provide farmers with actionable insights that empower them to adapt and thrive in a rapidly changing environment. Furthermore, our efforts extend beyond individual farms to encompass larger-scale sustainability initiatives, as we work towards fostering resilient agricultural systems that can withstand the challenges of the 21st century while ensuring food security for generations to come.

1.5 RESOURCES

This project has been developed through widespread secondary research of accredited manuscripts, standard papers, business journals, white papers, analysts' information, and conference reviews. Significant resources are required to achieve an efficacious completion of this project.

The following prospectus details a list of resources that will play a primary role in the successful execution of our project:

1. A properly functioning workstation (PC, laptop, net-books, etc.) to carry out desired research and collect relevant content.
2. Unlimited internet access to facilitate continuous research, data collection, and model training.
3. Access to agricultural datasets such as those provided by the Indian Council of Agricultural Research (ICAR), which include detailed information on soil nutrients, crop requirements, and historical weather patterns.
4. Machine learning development tools including libraries like scikit-learn for implementing the random forest algorithm with k-fold cross-validation.
5. Flask development environment to build and deploy the web application, ensuring it is accessible on all platforms.
6. Support from agricultural experts and data scientists to validate the model's predictions and improve its accuracy.
7. Collaboration with local farmers to test the application in real-world scenarios and gather feedback for iterative improvements.

1.6 MOTIVATION

The motivation for this project stems from the critical role agriculture plays in national economic growth, contributing 17-18% to India's GDP and ranking second worldwide in farm outputs. With the increasing challenge of ensuring food security for a growing population, optimizing agricultural productivity is paramount.

Fertilizers are essential for replenishing soil nutrients, but their effective use requires precise knowledge of crop needs and environmental conditions. Traditional methods often lead to overuse or underuse of fertilizers, causing economic losses and environmental damage.

By leveraging machine learning technology, this project aims to provide farmers with data-driven, accurate fertilizer recommendations, thereby enhancing crop yields, promoting sustainable farming practices, and ultimately contributing to food security and economic stability. In addition to addressing the pressing need for sustainable agricultural practices, our project endeavors to empower farmers with the tools and knowledge they need to navigate the complex landscape of modern farming.

By integrating machine learning algorithms with comprehensive datasets on soil health, crop requirements, and environmental factors, we aim to deliver personalized fertilizer recommendations tailored to each farmer's unique circumstances. Through user-friendly interfaces and accessible platforms, we seek to democratize access to cutting-edge agricultural technology, ensuring that even smallholder farmers can benefit from the latest advancements in the field.

Moreover, our project aligns with broader efforts to promote digital transformation in agriculture, fostering innovation, resilience, and inclusive growth across rural communities. By fostering collaboration between farmers, researchers, policymakers, and industry stakeholders, we aspire to build a more sustainable and equitable .

CHAPTER 2

LITERATURE SURVEY

A comprehensive study of the available literature presents a catalog of previous studies to address this issue. The authors show in [1] that predicting fertilizer usage can assist farmers to attain a proper yield with little waste by preventing toxicity and deficiency in plants to some extent. Paper [2] makes use of fuzzy logic systems that enable the reduction of fertilizer usage which results in an increase in crop productivity. Additionally, [10] shows that the enhanced efficiency of fertilizers is not sufficient for complications that can be caused by compaction. These issues can be prevented by improving the fertilizer recommendation which requires the establishment of a quantifiable relation under N and P for fertilizer usage, in terms of agricultural yield, nitrogen need, and nitrate remnant level which is shown in [11] and paper [4] seconds this by providing a comprehensive measure to estimate the weightage of nutrient requirements and also the role of the chemical properties of soil. It is a difficult task to predict crop yield due to stochastic rainfall patterns and also temperature variation. So, we can apply different data mining techniques as propounded in [3] for crop yield prediction. Laura J.T. Hess et al. in [5] state that nitrogen leaching is prone in areas that have no-till management and this may cause crop loss. In [7] the authors suggest a novel metric for ‘soil health and quality’ including refinement of soil’s health.

The objective of the paper [8] is to examine the characteristic changes in the creation and elements of soil populaces and capabilities because of the collaboration between long haul treatment and precipitation variances, to decide if preparation history affects the water-obstruction of soil microorganisms. Also, Paper [13] predicts agricultural yield as a function of rainfall. This is accomplished by giving a general summary of how production is affected by rainfall and how much a given crop can yield given the amount of rainfall received. Because it examines all regression procedures, the

suggested method of evaluation is superior to other existing methods of evaluation. Potnuru Sai Nishant et al. in paper [6] predict the yield of practically all types of crops in India. This script makes innovative use of straightforward criteria such as state, district and area, allowing the user to forecast crop yields in any year. Paper [12] suggests the use of Transfer Learning techniques to create a pre-trained model for detecting patterns in the dataset, which we then used to predict crop yields. In [14], supervised algorithms that boost crop yields, reduce human labor, time, and energy exerted on various agricultural tasks, and plant suggestions based on particular soil parameters are used to produce a complete way to predict crop sustainability. The study [16] demonstrated the capabilities of a machine learning model that can interpret and evaluate results, can be utilized to create the most useful information in long-term fertilizer studies, and that these methods can be employed in other long-term experiments. Paper [17] develops an interesting decision-based system on climatic, crop, and insecticide/pesticide data.

This is done Senthil Kumar Swami Durai et al. in [18] propose an integrated solution to Pre-Cultivation activities. The goal of this study is to assist a small farm in becoming more efficient and achieving a high production at a low cost. It also aids in the estimation of total growth expenses. It will assist one in planning forward. Pre-cultivation activities lead to an integrated solution in agriculture. M.S. Suchithra and Maya L. Pai proposes solutions to soil nutrient classification problems utilizing the rapid learning classification technique called an Extreme Learning Machine (ELM) with various activation functions in [19].

Crop diseases are one of the primary causes that impact the overall yield. Paper [15] conducts this study using an IoT system in the Kashmir Valley, it proposes an apple disease prediction model using data analysis and machine learning. The challenges of incorporating new technology into traditional agricultural practices are discussed in this paper.

CHAPTER 3

SYSTEM DESIGN

3.1 GENERAL

In this section, we would like to show the general outline of how all the components end up working when organized and arranged together. It is further represented in the form of a flow chart below.

3.2 SYSTEM ARCHITECTURE DIAGRAM

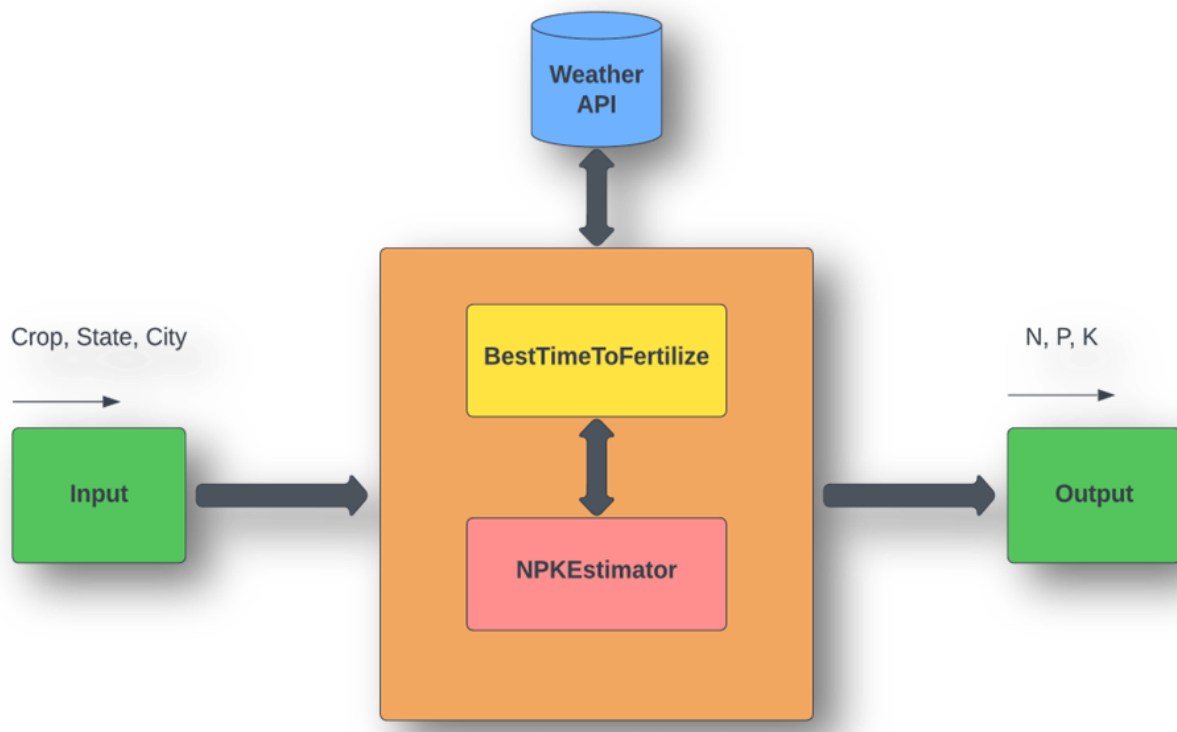


Fig 3.1: System Architecture

3.3 DEVELOPMENTAL ENVIRONMENT

3.3.1 HARDWARE REQUIREMENTS

The hardware requirements may serve as the basis for a contract for the system's implementation. It should therefore be a complete and consistent specification of the entire system. It is generally used by software engineers as the starting point for the system design.

Table 3.1 Hardware Requirements

COMPONENTS	SPECIFICATION
PROCESSOR	Intel Core i5
RAM	8 GB RAM
GPU	NVIDIA GeForce GTX 1650
MONITOR	15" COLOR
HARD DISK	512 GB
PROCESSOR SPEED	MINIMUM 1.1 GHz

3.3.2 SOFTWARE REQUIREMENTS

The software requirements document is the specifications of the system. It should include both a definition and a specification of requirements. It is a set of what the system should rather be doing than focus on how it should be done. The software requirements provide a basis for creating the software requirements specification. It is useful in estimating the cost, planning team activities, performing tasks, tracking the team, and tracking the team's progress throughout the development activity.

Python IDLE, and **chrome Visual Studio Code Jupyter Notebook** would all be required.

CHAPTER 4

PROJECT DESCRIPTION

4.1 METHODOLOGY

The methodology commences by acquiring historical data on crop nutrient requirements, soil fertility, and weather conditions from various sources such as agricultural databases, weather stations, and research publications. This data undergoes meticulous preprocessing, which includes handling missing values, normalization, and encoding categorical variables. Subsequently, essential features affecting crop nutrient requirements, including location, cropping type, temperature, humidity, rainfall, soil type, and previous crop yield, are identified, ensuring a comprehensive evaluation comprising seven relevant features for model assessment. To predict nutrient requirements accurately, the Random Forest Regression algorithm is employed, coupled with the K-Fold Cross Validation technique, typically utilizing ten folds, to evaluate model performance and ensure its robustness. The dataset is then partitioned into training and testing sets to validate the model's efficacy. An intuitive interface is developed for user input, encompassing parameters such as location and cropping type, and is seamlessly integrated with a Weather API to retrieve real-time weather data encompassing temperature, humidity, and rainfall.

The user-provided data are fed into the trained Random Forest model to forecast nutrient requirements tailored to the specified crops. In cases where heavy rainfall is anticipated, a precautionary message is conveyed to users, highlighting the potential for nutrient runoff, while offering tailored recommendations to optimize crop growth and mitigate leaching .

4.2 MODULE DESCRIPTION

Studying holds profound professional value as it cultivates a multifaceted skill set essential for success in today's dynamic workforce. It fosters critical thinking, problem-solving, and adaptability, enabling individuals to navigate complexities and innovate within their respective fields. Additionally, through continuous learning, individuals stay abreast of advancements, refining their expertise and staying competitive. Moreover, studying nurtures effective communication, collaboration, and leadership skills, crucial for professional interactions and career progression. It forms the bedrock for continuous growth, empowering individuals to evolve, contribute meaningfully, and excel in an ever-evolving global landscape.

4.1.1 Input Module

This module allows users to input necessary data for nutrient estimation through a user-friendly interface. Users provide data such as crop type, state, and city using drop-down menus. Options for crops include various types such as rice, cotton, and others. Additionally, users input the current temperature in degrees Celsius, relative humidity as a percentage, and recent rainfall in millimeters.

4.1.2 Weather API Module

This module integrates with a Weather API to fetch real-time weather data based on the user's location. By utilizing the user-provided location data (state and city), it requests accurate weather information. The fetched details include current temperature, humidity, and rainfall, ensuring that the nutrient recommendations are based on the latest weather conditions.

4.1.3 BestTimeToFertilize Module

This module determines the optimal time for fertilizer application by analyzing the fetched weather data. It examines weather patterns to recommend the best time to fertilize, aiming to maximize nutrient absorption and minimize loss. Additionally, it provides warnings if heavy rainfall is expected, helping to prevent nutrient runoff and leaching, which can be detrimental to soil fertility and crop health.

4.1.4 NPKEstimator Module

This module estimates the required ratio of Nitrogen (N), Phosphorus (P), and Potassium (K) in the soil. It uses input data such as crop type and weather conditions, along with historical nutrient requirements, to calculate the optimal NPK ratios. The recommendations are tailored to the specific needs of the crop and the current weather conditions, ensuring efficient and effective fertilization.

4.1.5 Output Module

This module displays the estimated nutrient contents and additional weather information on the website. The output includes the recommended ratios of Nitrogen, Phosphorus, and Potassium content in the soil, presented as Label_N, Label_P, and Label_K, respectively. In addition to nutrient recommendations, the module provides a 7-day rainfall report, giving users a comprehensive view of upcoming weather conditions. This information helps users make informed decisions about fertilization timing and other agricultural practices, optimizing soil fertility and promoting healthy crop growth.

CHAPTER 5

RESULTS AND DISCUSSIONS

5.1 OUTPUT

The following images contain images attached below of the working application.

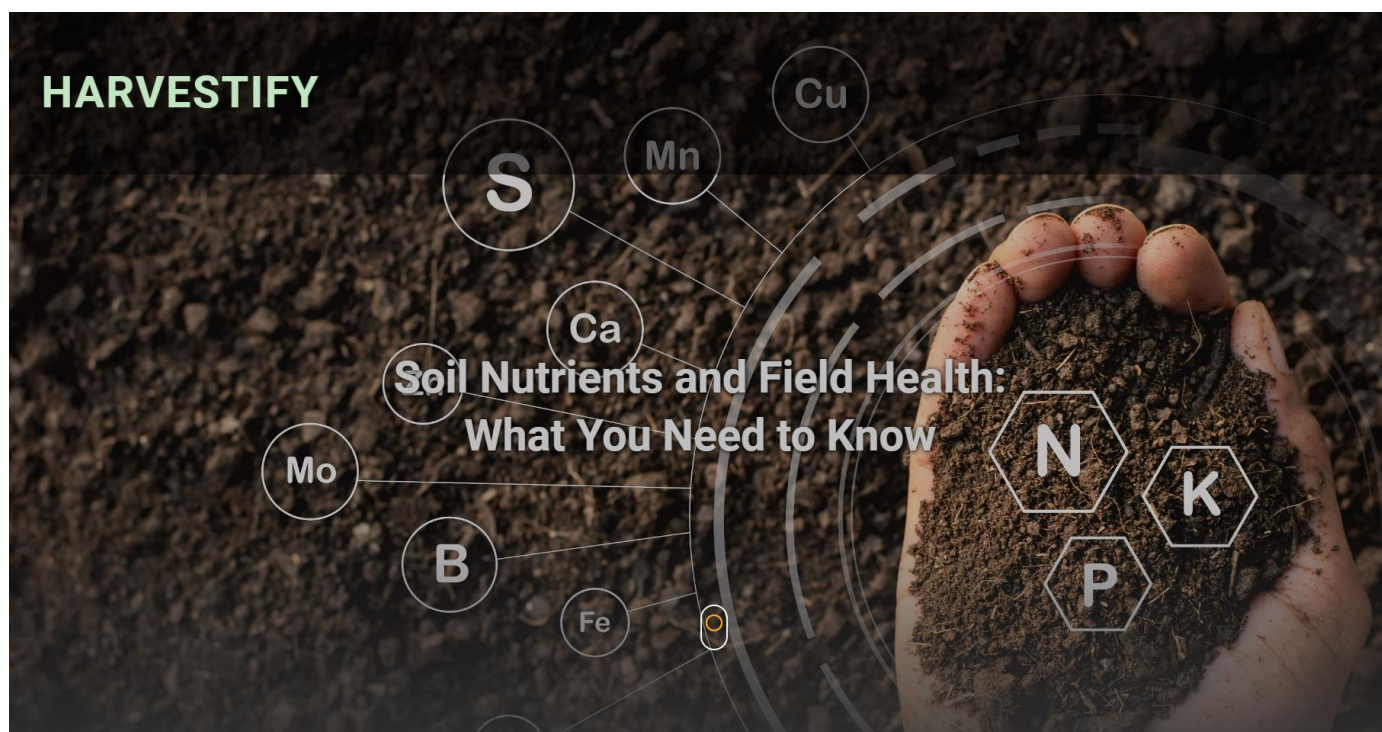


Fig 5.1: Homepage

Fill out the Details

Select Crop ▾

Select State ▾

▾

Submit



Fig 5.2 Input page to enter details

Fill out the Details

rice

Karnataka

Bangalore

Applying Algorithm..



Fig 5.3 Inputs Entered

Fill out the Details

rice

Karnataka

Bangalore

Applying Algorithm..



Fig 5.4 Applying Algorithm

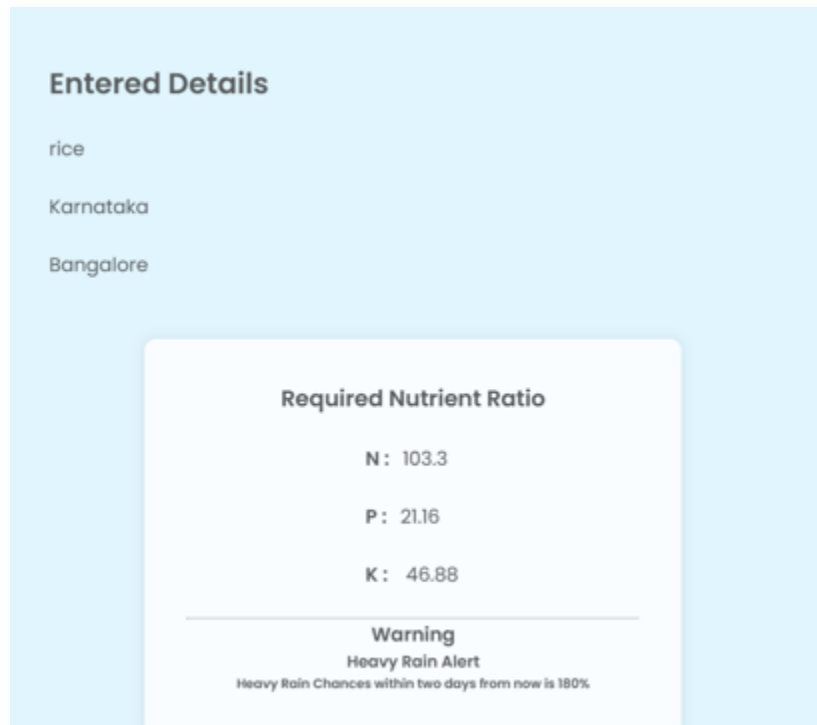


Fig 5.5 Required Nutrient Ratio

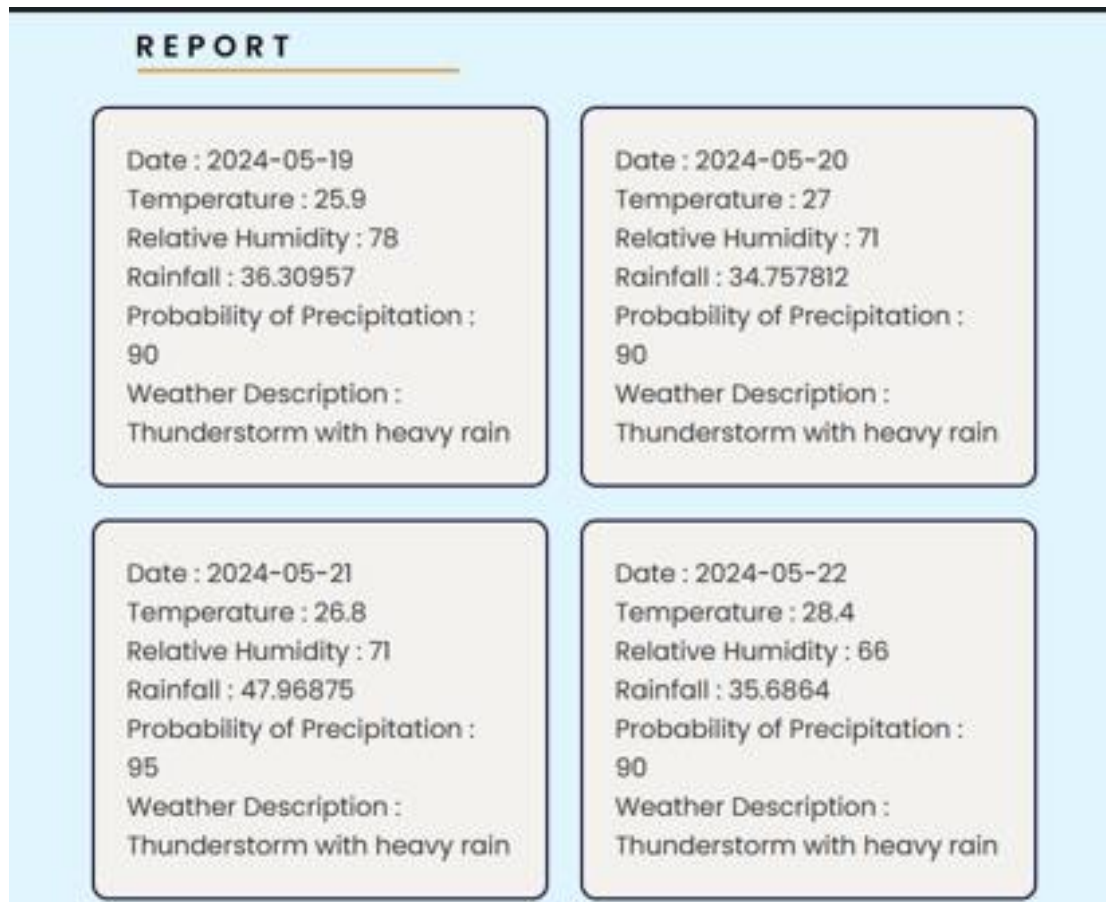


Fig 5.6 Weather Report

5.2 RESULT

The machine learning-based fertilization recommendation system has emerged as a pivotal solution to the persistent challenge of inconsistent and improper fertilizer use among farmers. By harnessing the power of the Random Forest algorithm, augmented with k-fold cross-validation, the model adeptly sifts through vast swathes of historical crop fertility, soil nutrient, and real-time weather data to offer nuanced and data-driven insights into optimal nutrient requirements and timing for a diverse array of crops. The web-based application, meticulously crafted using Flask, stands as a testament to accessibility and user-friendliness, providing farmers with an intuitive platform to input crucial parameters such as crop type and location and seamlessly receive tailor-made recommendations tailored to their specific agricultural needs. Notably, this system has showcased remarkable accuracy in its predictions, as evidenced by robust performance metrics including Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared values. Moreover, the seamless integration with a Weather API ensures that the recommendations rendered are always attuned to the latest meteorological conditions, thus fostering enhanced nutrient use efficiency and bolstering the ethos of sustainable agricultural practices. With its ability to empower farmers with actionable insights derived from cutting-edge machine learning technology, this fertilization recommendation system heralds a new era of precision agriculture, poised to revolutionize crop management practices and usher in a paradigm shift towards sustainable food production. Additionally, the platform serves as a dynamic knowledge-sharing hub, fostering collaboration and community engagement among farmers, agronomists, and agricultural researchers. Through forums, discussion boards, and knowledge repositories, users can exchange best practices, share success stories, and seek expert advice, thereby fostering a culture of continuous learning.

CHAPTER 6

CONCLUSION AND FUTURE ENHANCEMENT

6.1 CONCLUSION

The project showcased the potential of leveraging data-driven approaches to enhance agricultural productivity and sustainability. By providing precise NPK (Nitrogen, Phosphorus, Potassium) ratios tailored to specific crop needs and environmental conditions, the system can significantly improve crop yields, soil health, and economic returns for farmers. The user-friendly web application ensures accessibility, allowing farmers to make informed decisions about fertilization timing and other agricultural practices. This not only supports sustainable practices but also contributes to national economic growth in India's agriculture sector. The project's success highlights the value of combining historical data with real-time information to create practical solutions for farmers.

FUTURE ENHANCEMENT

Looking ahead, there are several avenues for enhancing and expanding the system. The project can be extended to include a wider variety of crops and incorporate advanced machine learning models for improved prediction accuracy. Integration with Internet of Things (IoT) devices, such as soil sensors and weather stations, can provide real-time, localized data, further refining recommendations. Developing a mobile application and adding support for multiple local languages will increase accessibility for farmers. Additionally, continuous user feedback integration, collaboration with agricultural experts, and economic analysis tools can refine the system to better meet the practical needs of farmers. These enhancements will not only improve the system's effectiveness but also pave the way for more sustainable and productive farming practices.

APPENDIX

SOURCE CODE:

App.py:

```
from flask import Flask, render_template, request, url_for

from BestTimeToFertilizeModule import BestTimeToFertilize

from NPKEstimatorModule import NPKEstimator

app = Flask(__name__)

@app.route('/processing/', methods=['GET', 'POST'])

def processing():

    # print('Processing ..... ')

    if request.method == "GET":

        print("The URL /processing is accessed directly.")

        return url_for('index.html')

    if request.method == "POST":

        form_data = request.form

        call_success = []

        npk_list_dict = []

        popup_data = []

        seven_days = []

        crop = form_data['crop']

        state = form_data['state']

        city = form_data['city']
```

```

with open("InputData.csv", "w") as fh:

    input_data = "%s,%s,%s" % (crop.strip(), state.strip(), city.strip())

    fh.write(input_data)

    btff = BestTimeToFertilize(city_name = city, state_name = state)

    btff.api_caller()

    if btff.is_api_call_success():

        category, heading, desc = btff.best_time_fertilize()

        call_success.append(1)

        popup_data.append([category, heading, desc])

        seven_days = btff.weather_data[:]

        # print(seven_days)

        # today's weather data

        di = btff.weather_data[0]

        temp = di['Temperature']

        humidity = di['Relative Humidity']

        rainfall = di['Rainfall']

        est = NPKEstimator()

        est.renameCol()

        npk = {'Label_N':0, 'Label_P':0, 'Label_K':0}

        for y_label in ['Label_N', 'Label_P', 'Label_K']:

            npk[y_label] = est.estimate(crop, temp, humidity, rainfall, y_label)

        # print(npk)

```

```

        npk_list_dict.append(npk)

        output_data = category + "\n" + heading + "\n" + desc + "\n" +
str(npk['Label_N']) + "\n" + str(npk['Label_P']) + "\n" + str(npk['Label_K'])

        with open("output.txt", "w") as fh:

            fh.write(output_data)

    else:

        print("Error Occured")

    #print(call_success, npk_list_dict, form_data, popup_data)

    return render_template('update.html', CALL_SUCCESS = call_success, NPK =
npk_list_dict, FORM_DATA = form_data, POPUP_DATA = popup_data,
SEVEN_DAYS = seven_days)

@app.route('/', methods=['POST', 'GET'])
def index():

    return render_template('index.html')

if __name__ == "__main__":

    app.run(debug=True)

BestTimeToFertilizeModule.py

import requests as rq

import json as js

from time import sleep

class BestTimeToFertilize:

    __BASE_URL = "https://api.weatherbit.io/v2.0/forecast/daily?"

    __API_KEY = "480589e42e7c4352abe4fe25bd398ab0"

```

```

def __init__(self, city_name = 'Bangalore', state_name = 'Karnataka', days = 7):

    self.city_name = '+'.join(city_name.lower().strip().split())

    self.state_name = '+'.join(state_name.lower().strip().split())

    self.country_name = 'IN'

    self.days = days

    self.response = None

    self.response_code = None

    self.weather_data = list()

def api_caller(self):

    try:

complete_url="{0}city={1}&state={2}&country={3}&key={4}&days={5}".form
at(self._BASE_URL, self.city_name, self.state_name, self.country_name, self.
API_KEY, self.days)

        # print(complete_url)

        # while self.response == None:

            self.response = rq.get(complete_url)

            sleep(5)

            self.response_code = self.response.status_code

            return self.response_code

    except Exception as msg:

        print("api_caller():", msg)

        return -1

```

```

def is_api_call_success(self):

    if self.response_code == 200:

        return True

    elif self.response_code == 204:

        print('Content Not available, error code: 204')

    return False

def json_file_bulider(self):

    try:

        json_obj = self.response.json()

        with open('weather_data.json', 'w') as file:

            js.dump(json_obj, file, indent = 1, sort_keys = True)

            print("weather_data.json file build successfully")

    except Exception as msg:

        print("json_bulider():", msg)

def best_time_fertilize(self):

    json_obj = self.response.json()

    # print("City:", json_obj['city_name'], "\n")

    prolonged_precip = 0

    prolonged_prob = 0

    heavy_rain_2d = False

    heavy_rain_chance_2d = 0

    precip_2d = 0

    precip_chance_2d = 0

```

```

for i in range(self.days):

    date = json_obj['data'][i]['datetime']

    temp = json_obj['data'][i]['temp']

    rh = json_obj['data'][i]['rh']

    precip = json_obj['data'][i]['precip']

    prob = json_obj['data'][i]['pop']

    w_code = json_obj['data'][i]['weather']['code']

    w_desc = json_obj['data'][i]['weather']['description']

    i_code = json_obj['data'][i]['weather']['icon']

    prolonged_precip += precip

    prolonged_prob += prob

    count_2d = 0

    if i < 2:

        precip_2d += precip

        precip_chance_2d += prob

        if w_code in [202, 233, 502, 521, 522]:

            heavy_rain_2d = True

            heavy_rain_chance_2d += prob

            count_2d += 1

            heavy_rain_chance_2d //= count_2d

di = {

```



```

        "Date":date,

        "Temperature":temp,

        "Relative Humidity":rh,

        "Rainfall":precip,

        "Probability of Precipitation":prob,

        "Weather Description": w_desc

    }

    self.weather_data.append(di)

prolonged_prob //= self.days

precip_chance_2d //= 2

if heavy_rain_2d:

    print("***21, "Warning !!!", "***21)

    print("Heavy Rain Chances within 2 days:", heavy_rain_chance_2d)

    print("Heavy Rainfall puts your fertilizer at risk.")

    print("***21, "Warning !!!", "***21)

    return ('Warning', 'Heavy Rain Alert', 'Heavy Rain Chances within two days
from now is %d%%' % (heavy_rain_chance_2d))

elif prolonged_precip > 12.7 and prolonged_prob >= 50:

    print("***21, "Warning !!!", "***21)

    print("Prolonged Rainfall of greater than 12.7 mm puts your fertilizer at
risk.")

    print("***21, "Warning !!!", "***21)

    return ('Warning', 'Prolonged Rainfall Alert', 'Prolonged Rainfall of greater
than 12.7 mm puts your fertilizer at risk. From now %.2f mm rainfall will receive

```

```

for upcoming seven days, chances %d%%' % (prolonged_precip, prolonged_prob))

    else:

        print("-"*80)

        print("The amount of rain for 2 days, counting today:", precip_2d)

        print("Chances of rain for 2 days, counting today:", precip_chance_2d)

        print()

        return ('Message', 'Precipitation Amount', 'The amount of rain for 2 days,
counting today is %.2f mm and chances is %d%%' % (precip_2d,
precip_chance_2d))

```

NPKEstimatorModule.py:

```

import warnings

import numpy as np

import pandas as pd

from sklearn import metrics

import category_encoders as ce

import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split

from sklearn.ensemble import RandomForestRegressor

warnings.filterwarnings('ignore')

class NPKEstimator:

    def __init__(self, data = 'Nutrient_recommendation.csv', ):

        self.df = pd.read_csv(data, header=None)

        self.X_train = None

        self.X_test = None

```

```

self.y_train = None

self.y_test = None

def renameCol(self):

    self.df.columns = ['Crop', 'Temperature', 'Humidity', 'Rainfall', 'Label_N',
'Label_P', 'Label_K']

    self.df.drop(self.df.index[:1], in

def cropMapper(self):

    # create mapping of crop(string) to int type

    mapping = dict()

    with open("mapped_crops.csv", "w") as fh:

        fh.write("Crops,Key\n")

        for i, crop in enumerate(np.unique(self.df[['Crop']]), 1):

            mapping[crop] = i

            fh.write("%s,%d\n" % (crop, i))

        mapping['NA'] = np.nan

        fh.write("NA,nan")

    # print(mapping)

    ordinal_cols_mapping = [{"col": "Crop", "mapping": mapping}, ]

    encoder = ce.OrdinalEncoder(cols = 'Crop', mapping = ordinal_cols_mapping,
return_df = True)

    return mapping, encoder

def estimator(self, crop, temp, humidity, rainfall, y_label):

    X = self.df.drop(['Label_N', 'Label_P', 'Label_K'], axis=1)

    y = self.df[y_label]

```

```

self.X_train, self.X_test, self.y_train, self.y_test = train_test_split(X, y,
test_size = 0.20, random_state = 42]

mapping, encoder = self.cropMapper()

self.X_train = encoder.fit_transform(self.X_train)

self.X_test = encoder.transform(self.X_test)

regressor = RandomForestRegressor(n_estimators = 50, random_state = 0)

regressor.fit(self.X_train, self.y_train)

# y_pred = regressor.predict(self.X_test)

query = [mapping[crop.strip().lower()], temp, humidity, rainfall]

y_pred = regressor.predict([query])

return y_pred[0]

def accuracyCalculator(self):

    model = RandomForestRegressor(n_jobs=-1)

    estimators = np.arange(10, 200, 10)

    scores = []

    for n in estimators:

        model.set_params(n_estimators=n)

        model.fit(self.X_train, self.y_train)

        scores.append(model.score(self.X_test, self.y_test))

    scores_arr = [round(sc, 3) for sc in scores]

    unique, counts = np.unique(scores_arr, return_counts = True)

    max_count = max(counts)

```

```
accuracy = -1

for uni, count in zip(unique, counts):

    # print(uni, count)

    if count == max_count:

        accuracy = uni

# print("Model accuracy: %.2f" % (accuracy))

return accuracy
```

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