Weather Based Crop Insurance Payout Estimator

Project Report

BACHELOR OF ENGINEERING

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WEATHER BASED CROP INSURANCE PAYOUT ESTIMATOR

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Table of Contents

List of Figures…………………………………………………………………………,,,,…..i

List of Screenshots ………………………………………………………………………….i

Abstract

Chapter 1 Introduction…………………………………………………………………**1**

1.1 Objective.……………………………………………………………….2

1.2 Scope …………………………………………………………………2

1.3 Motivation ……………………………………………………………3

1.4 Aim ……………………………………………………………………...3

1.5 Working of WBCIS. …………………………………………………….4

Chapter 2 Literature Survey…………………………………………………...…....6

2.1 Foundational Work and Existing approaches………………………….....6

2.2 Comparative Analysis of Existing Methods.…………………………......6

2.3 Identified Limitations and Technological Gaps.…………..………...…7

Chapter 3 Methodology……..…………………………………………………...…..8

3.1 WBCIPE Framework: Trigger based payout logic ……………………8

3.2 Data Collection and Aggregation……………………………………….8

3.3 Preprocessing and data cleaning ………………………………………10

3.4 Feature Engineering: Deviation and risk indicators…………………….10

3.5 Multi-model Learning Pipeline …………………………………………10

3.6 Post-processing …………………………………………………………11

3.7 Final Compensation Estimation ……………………………………………...13

3.8 Handling real world complexities ………………………………………13

3.9 Tools, Libraries and Deployment stack …………………………………13

Chapter 4 Implementation…………………………………………………............14

4.1 System Architecture ……………………………………………………14

4.2 Tools and Technologies ………………………………………………...17

4.3 Workflow Overview ……………………………………………………17

4.4 Challenges and Considerations …………………………………………18

Chapter 5 Result ……………………………………………………………………….19

5.1 User Input and System Processing ……………………………..……19

5.2 Trigger Classification Performance ……………………………...…..20

5.3 Payout Percentage Estimation ……………………………………......20

5.4 Sum Insured Prediction …………………………………………………20

5.5 Comprehensive Report generation ……………………………………..21

5.6 Accuracy………………………..……………………………………..24

5.7 Deployment……………………..……………………………………..24

5.8 Advantages of the Automated WBCIPE System……….……………….25

5.9 Disadvantages and Challenges …………………………………………26

Chapter 6 Conclusion and Future scope …….………………………………………27

6.1 Summary………………………………………………………………..27

6.2 Future Scope…………………………………………………………....27

6.3 Final Thoughts …………………………………………………………28

Chapter 7 References ……………………….………………………………………..29

List of Figures

1.1 Problem Context Info-graphic – Weather Uncertainty to Financial Stress ……..……..…1

1.2 System Architecture Intersection of Data-Driven WBCIPE…………………………..…5

3.1 Weather data for various crops ……………………………………………...……..9

3.2 Premium Estimation for Pomegranate and mango crops under WBCIS ……………..…...9

4.1 Flowchart for Result Generation and Reporting……………………………………..…15

5.1 User Input Interface ………………………………………………………..………......19

5.2 User Report Generation Result ….…………………………………………….…………..21

5.3 Distribution of Trigger classifier Predictions (YES/ NO) ...……………….…………...22

5.4 Distribution of Sum Insured Per hectare for Mango and Pomegranate crops across Maharashtra districts …………………………………………………....22

5.5 Loss and Payout calculation of per year of the respective crops ………………………..23

5.6 Predicted and Actual Payouts for WBCI Payout Estimator…………………………..…24

5.7 Predicted average payout percentages and estimated payouts (2015–2019) by WBCIPE ……………………….…………………………………………………….24

6.1 Future Scope tree diagram ……………………………………………………………....28

Abbreviations

WBCIS	Weather Based Crop Insurance Scheme
WBCIPE	Weather Based Crop Insurance Payout Estimator
CCE	Crop Cutting Experiments
AWS	Automated Weather Stations
PMFBY	Pradhan Mantri Fasal Bima Yojna
IASRI	Indian Agricultural Statistics Research Institute
IMD	India Meteorological Department
NABARD	National Bank for Agriculture and Rural Development
ICRISAT	International Crops Research Institute for the Semi-Arid Tropics
NOAA	National Oceanic and Atmospheric Administration.
ICACCI	International Conference on Advances in Computing, Communications and Informatics

ABSTRACT

The increasing unpredictability of weather patterns poses a significant challenge to Indian agriculture, often leading to crop losses and financial instability for farmers. The Weather Based Crop Insurance Scheme (WBCIS) was introduced to offer timely compensation based on deviations in key weather parameters. However, manual claim processing under the scheme is often slow and inefficient.

This project presents an intelligent, automated system called the WBCI Payout Estimator, which leverages machine learning and real-time weather APIs to streamline insurance payout estimation under WBCIC guidelines. By analyzing weather data against crop-specific trigger thresholds, the system predicts whether a payout-triggering event has occurred, estimates the payout percentage using a regression model, and calculates the final compensation using a trained sum insured predictor.

The system focuses on four main weather parameters: temperature, rainfall, humidity, and wind speed. Each month is divided into two fortnights, and the app checks whether the weather in each period exceeds the predefined limits for a given crop and season. If trigger conditions are met, the corresponding deviation is used for payout prediction.

Built using Python and Flask, the web application allows users to input crop, district, season, year, and area details, and instantly receive an estimated payout based on real-time and historical weather data. The backend fetches weather data from the NASA POWER API and applies trained models to ensure accurate results.

The proposed system not only enhances transparency and efficiency in insurance disbursement but also empowers farmers with timely and accurate financial insights. It serves as a decision-support tool that simplifies complex calculations and helps both farmers and officials understand potential compensations with ease.

Chapter 1
INTRODUCTION

Agriculture is the backbone of the Indian economy, but it remains highly vulnerable to unpredictable and extreme weather conditions. Factors like irregular rainfall, prolonged dry spells, or sudden temperature shifts can severely impact crop yield and farmer income. To safeguard farmers against such climatic risks, the Weather Based Crop Insurance Scheme (WBCIS) was introduced by the government. The core idea behind WBCIS is to provide timely financial support to farmers when adverse weather conditions affect crop health — ensuring a safety net that allows them to recover and reinvest.

However, despite its intent, the traditional WBCIS process is heavily manual and often delayed. The assessment of weather deviations, claim eligibility, and compensation amounts usually relies on slow, centralized procedures. Farmers often remain unaware of how their claims are processed or when payouts will arrive, leading to frustration, uncertainty, and reduced trust in the system.

This project addresses those gaps by developing an automated, intelligent system that predicts crop insurance claim eligibility and payout amounts under WBCIS, specifically tailored for districts and crops in Maharashtra. Built using Python, the system processes historical or real-time weather data, applies rule-based logic, and compares observations against official WBCIS term sheet thresholds.

Although machine learning integration is part of the broader vision, the current system emphasizes accuracy, explainability, and transparency over black-box models. With a simple user interface, stakeholders can input crop type, location, season, and time period — and instantly receive a prediction on whether the claim is valid and how much compensation is likely. By streamlining this process, the system empowers farmers, simplifies insurance workflows, and brings much-needed speed and clarity to agricultural risk management.

Fig.1 Problem Context Info-graphic – Weather Uncertainty to Financial Stress

1.1 Objectives

This project sets out to design and develop an intelligent, automated system that simplifies and strengthens how insurance payouts are estimated under the Weather Based Crop Insurance Scheme (WBCIS). The idea is to move away from slow, manual assessments and instead offer a smarter, faster, and more transparent approach. Here's what we aim to achieve:

The first step is to collect accurate weather data—like temperature, rainfall, humidity, and wind speed—for specific farm locations using trusted sources such as the NASA POWER API. This weather data is then paired with government-issued thresholds and financial details from the PMFBY database, laying the groundwork for payout estimation. Next, we look at how the actual weather compares to what's considered "normal" or safe for crops. We build meaningful features like TEMP_RISE or RAINFALL_DEV that help quantify these deviations. These indicators become the basis for checking whether a weather-triggered insurance payout is justified. We apply machine learning models to do the heavy lifting—one model checks if the weather conditions match a payout trigger, another estimates how much should be paid based on the severity of the deviations, and a third predicts the sum insured per hectare. Together, these models ensure the system is smart, accurate, and personalized. The system is designed with simplicity in mind. A user just needs to enter their crop type, area, season, and location. The system then processes everything behind the scenes and presents a clear result—either on a user-friendly web interface or in a downloadable report (PDF/CSV). It's payout information made practical and accessible. Beyond just farmers, this system also provides useful insights for government agencies, insurers, and agritech companies. It can help improve policy design, ensure quicker and fairer disbursements, and support data-driven decisions in the agriculture sector.

1.2 Scope

This project focuses on building an intelligent and practical system that automates crop insurance payout estimation under the Weather Based Crop Insurance Scheme (WBCIS). The scope has been carefully defined to ensure a balance between technical depth and real-world applicability. Here's what it covers:

a) **Geographical Reach:**

The system is designed to work across multiple states and districts in India. Users can select specific regions, which allows the model to adapt its predictions based on localized weather and insurance conditions. This flexibility makes the solution salable for use in diverse agro-climatic zones.

b) **Time-Frame and Seasonal Coverage**

The system supports the analysis of historical weather data, as well as real-time data over user-defined periods—covering entire agricultural seasons like Kharif or Rabi. This helps detect seasonal trends, extreme events, and deviations relevant to crop phenology and payout decisions.

c) **Technical and Analytical Framework**

This report lays out the complete methodology—from how data is collected and cleaned to how machine learning models are trained and applied. The process is transparent, reproducible, and modular, making it easier for others to adopt, improve, or scale the system.

d) **Focus on Agricultural Insurance and Stakeholders**

While the core emphasis is on improving crop insurance accuracy for farmers, the system also supports broader stakeholders like insurers, policymakers, and agri-tech developers. By providing data-driven insights and clear payout reports, the project bridges the gap between weather anomalies and timely financial support.

1.3 Motivation

The motivation for this project report is rooted in the urgent need to understand and respond to the complexities of rainfall patterns in the face of climate change. As global temperatures rise and weather events become increasingly erratic, the implications for agriculture, urban infrastructure, and disaster preparedness are profound. Stakeholders across various sectors require reliable data and insights to make informed decisions that can mitigate risks and enhance resilience. This report aims to fill the knowledge gap by providing a thorough analysis of rainfall data, thereby empowering stakeholders to adapt their strategies in response to changing climatic conditions.

1.4 Aim

The aim of this project is to build a Python-based automated system that can intelligently predict claim eligibility and estimate insurance payouts under the **Weather Based Crop Insurance Scheme (WBCIS)**. The goal is to create a transparent, reliable, and easy-to-use decision-support tool that benefits farmers, insurance agents, and agricultural officers alike.

At its core, the system analyzes real-world agro-meteorological data—such as rainfall, temperature, humidity, and wind speed—and compares it with the threshold values and trigger conditions defined in the official WBCIC term sheets. Using a mix of rule-based logic and machine learning models, it checks whether the observed weather deviations meet the criteria for a claim. If they do, the system calculates how much compensation the farmer is likely to receive based on their location, crop type, area insured, and the severity of the deviation.

By automating this entire process, the system aims to reduce manual errors, eliminate delays, and offer a fair and data-driven way to estimate payouts—ultimately helping farmers get timely support when it matters most.

1.5 Working of Weather-Based Crop Insurance Scheme

The Weather-Based Crop Insurance Scheme (WBCIS) is designed to protect farmers from crop losses caused by adverse weather. It offers financial stability and promotes modern farming practices. Here's a brief overview of how it works:

Objective

a) To mitigate weather-related financial risks (like droughts, floods, excess rainfall).

b) To stabilize farmers' income and promote risk-free agricultural investment.

Eligibility

a) Primarily targets small and marginal farmers.

b) Covers region-specific crops depending on the season.

Premium Payment

a) Farmers pay a low, often subsidized premium.

b) Premiums are based on the expected yield and sum insured.

Coverage Parameters

a) Includes rainfall, temperature, humidity, and wind speed.

b) Each parameter has defined thresholds; deviations trigger claims.

Data Collection

a) Real-time weather data from ground stations and satellite tools help monitor conditions.

Claim Process

b) If thresholds are breached, claims are automatically triggered.

c) Losses are assessed via data analytics or field verification.

d) Payouts are calculated based on the severity of deviation and insured amount.

Payout Mechanism

a) Claims are disbursed quickly via direct bank transfers for efficiency and transparency.

Farmer Awareness

a) Training and workshops are conducted to help farmers understand the scheme.
b) Support services assist with registration and claim processes.

Challenges and Improvements

a) Accuracy of weather data is crucial.
b) Awareness levels must be improved.

a. Regular updates to policy guidelines help refine the scheme.

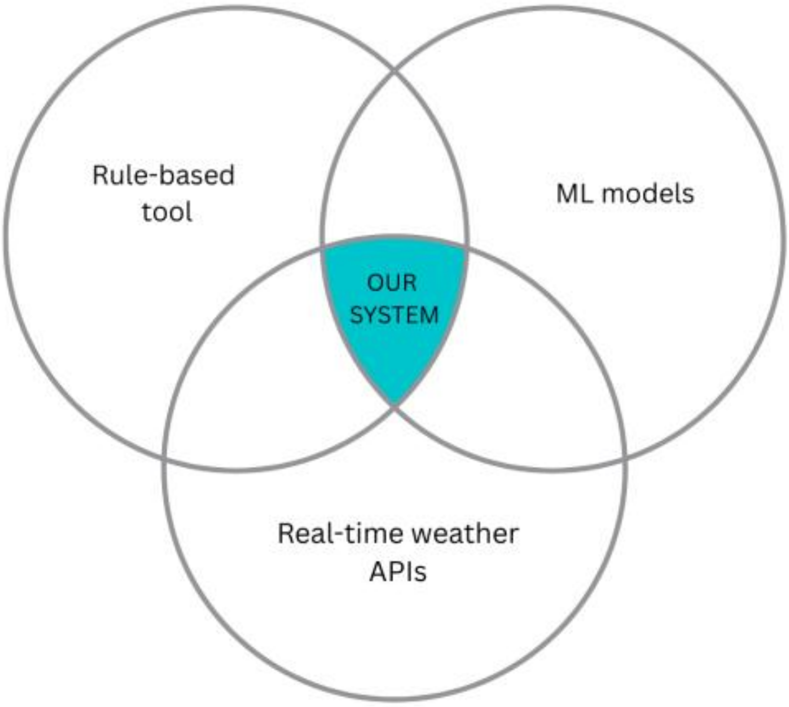


Fig.1.2 System Architecture Intersection of Data-Driven WBCIPE

Chapter 2

LITERATURE SURVEY

To effectively evaluate the landscape of Weather-Based Crop Insurance Scheme (WBCIS), it's important to first understand the existing work and approaches that have shaped the field. This includes reviewing government guidelines, earlier tools, and the various studies conducted on weather risk modeling, which have played a crucial role in the development of WBCIC. By examining these, we can uncover both the progress that has been made and the gaps that still remain. These insights will lay the groundwork for exploring how new technologies and methods, such as machine learning and real-time weather data integration, can further enhance the effectiveness and accessibility of these insurance schemes.

2.1 Foundational Work and Existing Approaches

Weather-Based Crop Insurance Scheme (WBCIS) have evolved as a vital response to climate variability and risk in agriculture. Initiated by the Indian Government in 2007, WBCIC complements the Pradhan Mantri Fasal Bima Yojana (PMFBY), offering insurance coverage based on measurable weather parameters rather than direct crop loss assessments.

Government guidelines for these schemes focus on transparency and predefined trigger mechanisms, often based on rainfall, temperature, humidity, and wind speed deviations. However, existing implementations largely depend on manual procedures — including data entry, claim verification, and trigger evaluation — which introduce delays and potential inaccuracies.

Previous digital tools and calculators, such as the ones available on the PMFBY portal, primarily facilitate manual uploads of data or static form-based claim entries. Academic research has also contributed to this field, particularly through climate risk modeling and rainfall index-based approaches for determining insurance triggers. Several studies have explored machine learning (ML) models for identifying abnormal weather conditions, but integration with real-time data remains limited in these works.

2.2 Comparative Analysis of Existing Methods

Efforts to enhance WBCIS mechanisms can be broadly categorized based on their approach:

The official PMFBY Portal allows manual uploading of crop and weather data, but does not include automated trigger mechanisms or integrated ML support.

Academic research papers have proposed ML models for analyzing weather data and identifying patterns related to crop damage. These models often work well in simulations but lack connection to real-time APIs and user-accessible platforms. Some prototype calculators and tools built for demonstration purposes such as Excel-based insurance calculators focus on theoretical scenarios and lack a web interface or scalable implementation.

While each of these contributes to the domain, they remain isolated in their strengths, and no single tool manages to provide a holistic, farmer-friendly, and automated WBCIC solution.

2.3 Identified Limitations and Technological Gaps

Through the review of related work and tools, the following major gaps have been identified:

Lack of integration: Current systems do not effectively combine rule-based logic, real-time weather APIs, and ML models to automate insurance trigger detection and payout calculations.

Poor accessibility for farmers: Most tools lack a user-friendly interface tailored for non-technical users like smallholder farmers, especially those in rural areas with limited digital literacy.

No real-time decision-making support: Without live weather data integration, tools cannot deliver timely insights, thereby delaying the claims process and reducing the effectiveness of WBCIC.

Addressing these issues is essential to modernize WBCIS platforms, reduce claim settlement delays, and enhance transparency and trust among stakeholders.

Chapter 3

METHODOLOGY

The methodology implemented in this project is designed to simulate the functioning of the Weather Based Crop Insurance Payout Estimator (WBCIPE) in a fully automated, scalable, and transparent manner. It combines real-time weather data, policy-driven triggers, and machine learning models to streamline insurance payout estimation for farmers. This section elaborates on the step-by-step methodology, tools used, and architectural components, aligning tightly with the operational principles of WBCIS.

3.1 WBCIPE Framework: Trigger-Based Payout Logic

At the core of WBCIPE lies the concept of parametric insurance, where compensation is disbursed based on the breach of predefined weather thresholds. These thresholds are defined according to the type of crop, the crop's growth stage (such as sowing, flowering, or harvesting), the agro-climatic region, and the season (Kharif or Rabi). The key weather parameters considered under this calculator include rainfall, maximum and minimum temperatures, relative humidity, and wind speed. For each crop, these parameters are linked to specific phenological stages. For example, in the case of Kharif rice, rainfall is critical during sowing, temperature becomes crucial during flowering, and humidity plays a significant role during grain filling. In the case of Rabi mango, wind speed and humidity thresholds are critical during flowering and fruit-setting stages. When there is a significant deviation from these thresholds during any stage, the system marks that interval as payout-eligible under WBCIS norms.

3.2 Data Collection and Aggregation

The project incorporates multiple layers of data from different sources to ensure accuracy and comprehensiveness in predictions and payout calculations. For weather data, the system uses the **NASA P**rediction **O**f **W**orldwide **E**nergy **R**esources (POWER) API. This provides daily weather data at approximately 0.5° spatial resolution. Specific parameters fetched include PRECTOTCORR (for rainfall), T2M (for temperature), RH2M (for relative humidity), and WS2M (for wind speed). Using the user's input for latitude and longitude, the system extracts hyper-localized weather data.

In terms of financial and insurance-related data, the system relies on scraped information from public government insurance portals and archives. These datasets include crop-wise sum insured values per hectare, district-level seasonal mapping, and any available historical claim records. This financial data is crucial in determining the final compensation amounts and helps anchor the machine learning models to real-world values.

Additionally, the system accepts structured user input through a web interface. Users are required to enter details such as the state, district, and mandal, along with the crop type and season, area insured (in hectares), and the date range for which they want the analysis. These inputs serve as the primary controls for initiating the backend logic and data pipeline for each request.

This fig.3.1 shows the weather parameters (mean temperature, rainfall, humidity, and wind speed) recorded for Pomegranate and Mango crops in different districts and months of the year. The data includes observations from districts such as Ahmednagar, Aurangabad, and Beed.

CROP	DISTRICT	YEAR	MONTH	FORTNIGH	MEAN_TEMP	RAINFALL	HUMIDITY	WIND_SPEED
Pomegranate	Ahmednagar	2019	1	1	21.311	0	21.396	1.5633333333333332
Pomegranate	Ahmednagar	2019	1	2	20.8821875	0	30.519375	2.10375
Pomegranate	Ahmednagar	2019	2	1	23.455333333333	0	32.61266666666667	2.1646666666666667
Pomegranate	Ahmednagar	2019	2	2	26.022692307692	0.01	24.923076923076923	1.976153846153846
Pomegranate	Ahmednagar	2019	3	1	26.352666666666	0	27.612666666666666	2.214
Mango	Aurangabad	2024	2	2	25.766428571428	6.9	31.986428571428572	1.9207142857142858
Mango	Aurangabad	2024	3	1	26.550000000000	0.33	27.448	2.1726666666666667
Mango	Aurangabad	2024	3	2	29.8825	0.34	22.545	1.668125
Mango	Beed	2019	1	1	21.343333333333	0	23.23933333333333	1.6033333333333333
Mango	Beed	2019	1	2	21.0396875	0	30.37125	2.08

Fig 3.1 Weather Data for Various Crops

This figure presents the premium estimation details for Pomegranate and Mango crops across various districts and seasons as per the official PMFBY guidelines for the Weather-Based Crop Insurance Calculator (WBCIC). It includes critical values such as the sum insured per hectare, actuarial rate percentage, farmer's share, total premium, and the breakdown of the premiums paid by the farmer and the government.

district	crop	season	sum_insu	actuarial_	farmer_share_pe	total_premium	farmer_premium	govt_premium
Ahmadnagar	Pomegranate	Kharif	130000	5	5	6500	6500	0
Amravati	Pomegranate	Kharif	130000	5	5	6500	6500	0
Aurangabad	Pomegranate	Kharif	130000	10	5	13000	6500	6500
Ahmadnagar	Mango	Rabi	140000	15	5	21000	7000	14000
Aurangabad	Mango	Rabi	140000	29.5	5	41300	7000	34300
Bid	Mango	Rabi	140000	35	5	49000	7000	42000
Buldana	Mango	Rabi	140000	32	5	44800	7000	37800

Fig 3.2 Premium Estimation for Pomegranate and Mango Crops under WBCIC

3.3 Preprocessing and Data Cleaning

The raw data collected from APIs and portals is transformed into a clean, analysis-ready format. The first step involves converting JSON files retrieved from the NASA POWER API into structured data frames using Python libraries like json and pandas. Missing values are handled using interpolation methods where feasible, and median values are used in cases of data sparsity. To standardize inputs across sources, various unit conversions are applied. Temperature values

in Kelvin are converted to Celsius, wind speed measured in meters per second is converted to kilometers per hour, and rainfall recorded in inches is translated into millimeters.
Since WBCIC operates on a fortnightly basis, daily weather records are aggregated into 15-day intervals either by computing their averages or summing values as required. These intervals are then mapped to standard agricultural stages like sowing, vegetative growth, flowering, and harvesting, to ensure phase-aligned evaluation and modeling.

3.4 Feature Engineering: Deviations and Risk Indicators

One of the key aspects of this system is the generation of new features that quantify deviation from normal weather conditions. These features serve both as inputs to machine learning models and as checks for rule-based logic. They represent the intensity, frequency, and duration of weather abnormalities. Metrics such as deviation from long-term averages, cumulative rainfall shortage or excess, and stress indicators over consecutive days are calculated to reflect crop stress accurately. These derived features are carefully validated against agro-meteorological standards approved under WBCIS to ensure both scientific integrity and policy alignment.

3.5 Multi-Model Learning Pipeline

To simulate real-world insurance decision-making and bring automation into the payout estimation process, this system adopts a structured machine learning pipeline. Each model in the sequence plays a distinct role, ensuring that both eligibility and financial estimates are handled with accuracy and transparency.

3.5.1 Trigger Classification Model

The first step in the pipeline is identifying whether a weather-based trigger has been breached. This is done using a Decision Tree classifier, chosen for its high interpretability and alignment with the rule-based logic of WBCIPE. The model takes as input the deviation features computed during preprocessing such as temperature or rainfall deviations relative to crop-specific thresholds and produces a binary output: **“YES”** if a trigger condition is breached and **“NO”** otherwise. It is trained on historical weather and insurance payout records, allowing the system to detect risk periods with strong confidence.

3.5.2 Payout Percentage Estimation Model

When a trigger is confirmed, the pipeline moves to estimating the severity of the impact through a regression model. This model predicts the percentage payout a farmer should receive, based on the same deviation features and additional engineered indicators. Both Random Forest and Gradient Boosting algorithms were evaluated during development, with the better-performing model retained after comprehensive testing. The model's accuracy was enhanced by fine-tuning hyperparameters like tree depth, number of estimators, and learning rate. Evaluation metrics such as RMSE and MAE were used in a five-fold cross-validation framework to ensure robustness and generalizability.

3.5.3 Sum Insured Prediction Model

The final model in the sequence estimates the sum insured per hectare, which is essential for computing the actual compensation amount. This model takes as inputs the district, crop type, and season, and is trained using financial data gathered from PMFBY records. As a multi-class regression model, it outputs the expected insured value, which is then multiplied with the payout percentage and the insured area (provided by the user) to calculate the final payout.

3.6 Post Processing

Post-processing plays a pivotal role in machine learning workflows, acting as the bridge between the raw predictions generated by the model and their real-world application. After a model makes predictions, the results often require further refinement to ensure they are meaningful, actionable, and aligned with the specific objectives of the project. In this context, post-processing serves to enhance the reliability of predictions, making them more suitable for decision-making, particularly in sensitive areas like crop insurance. Below is the algorithm used by us.

3.6.1 Percent modeling (Random Forest Regressor):

To automate payout estimation under the Weather-Based Crop Insurance Payout Estimator (WBCIPE), a supervised machine learning model was developed using a Random Forest Regressor. The objective was to predict the payout percentage based on historical weather deviation data, specifically temperature rise, rainfall deviation, humidity deviation, and wind excess—parameters known to significantly affect crop yield. The dataset was split into training and testing sets in an 80:20 ratio. The Random Forest model, chosen for its robustness and ability to handle complex non-linear relationships, was trained and evaluated using standard metrics. It achieved a Mean Absolute Error (MAE) of 0.0315 and an R-squared (R^2) score of 0.9471, indicating high predictive accuracy and strong model performance. After training, the model was saved using joblib (models\payout_percentage_regressor.pkl) for potential deployment in real-time claim assessment systems, thereby supporting faster and more objective payout decisions within the WBCIC Framework.

3.6.2 Sum insured modeling (Multi-Output Regression for Insurance Estimation):

A machine learning model was developed to predict multiple crop insurance components—such as sum insured per hectare, premium rates, and government subsidies—using only the district, crop type, and season as inputs. The model used a MultiOutputRegressor with a Random Forest Regressor as the base algorithm. Categorical inputs were processed using one-hot encoding, and the entire pipeline was trained on historical data.

The model achieved a Mean Absolute Error of 2100.67 and an R^2 score of 0.84, demonstrating high accuracy across all six output variables. The trained model was saved as sum_insured_predictor.pkl for future use in real-time insurance planning or integration into web applications.

3.6.3 Trigger modeling (Trigger Event Prediction Using Random Forest Classification):

A Random Forest Classifier was developed to predict whether a crop insurance payout-triggering event would occur based on weather deviations. The model used four meteorological features: temperature rise, rainfall deviation, humidity deviation, and wind excess, to predict the binary target variable (TRIGGER), which indicates whether a payout should be triggered ("YES" or "NO").

The model was trained using a labeled dataset, with the target variable encoded into binary form. After training, the model achieved perfect classification performance, with a precision, recall, and F1-score of 1.00 for both classes, and a confusion matrix showing no misclassifications. This indicates the model's exceptional ability to predict trigger events accurately.The trained model was saved as trigger_classifier_model.pkl for future use, enabling its integration into real-time systems for automated payout triggering in the Weather-Based Crop Insurance Payout Estimation (WBCIPE).

3.7 Final Compensation Estimation

The final compensation is computed using the formula:

$$\text{Estimated Payout} = \left(\frac{\text{Predicted Payout \%}}{100}\right) \times \text{Sum Insured per Hectare} \times \text{Insured Area}$$

This approach ensures scalability, as it can handle multiple farmers with different insured areas, crops, and seasons. By integrating model predictions with user input and government-sourced financial data, the system produces precise, individualized compensation estimates.

3.8 Handling Real-World Complexities

To ensure real-world applicability, the system incorporates robust exception handling mechanisms. In cases where weather data is missing for specific dates or periods, the system flags these windows and adjusts confidence levels in the analysis. If zero rainfall is observed consistently in drought-prone areas, the system treats it as a full-stress indicator. Each fortnight is assessed independently, allowing the system to account for multiple stress triggers within a single cropping season. Furthermore, by allowing users to define their own sowing windows, the system accommodates early or delayed sowing practices, ensuring that predictions remain aligned with actual crop growth stages.

3.9 Tools, Libraries, and Deployment Stack

The system is developed primarily using Python. Data handling and preprocessing are achieved using libraries like pandas and numpy, while machine learning models are built with scikit-learn. The frontend is developed using HTML, CSS, and integrated with a Flask backend to allow seamless user interaction. The system is designed in a modular format, with separate scripts for routing (routes.py), logic (logic.py), and reporting (report.py). Real-time weather data is fetched using the NASA POWER API. Final outputs are displayed through a web dashboard and also offered as downloadable PDF and CSV report.

Chapter 4

IMPLEMENTATION

4.1 System Architecture

The WBCIEP automation system is designed with a modular and scalable architecture to ensure efficient processing and accurate insurance assessments. The system comprises several interconnected components:

4.1.1 User Interface (Frontend):

Developed using HTML5, CSS3, and JavaScript, this interface collects user inputs such as crop type, district, season, and area under cultivation. It communicates with the backend to display results and generate reports.

4.1.2 Backend Server:

Built with Flask, this server handles data processing, model execution, and communication with external APIs. It manages user requests, retrieves weather data, applies rule-based logic, and invokes machine learning models to estimate insurance payouts.

4.1.3 Weather Data Retrieval Module:

Utilizes the NASA POWER API to fetch historical and real-time weather data, including parameters like temperature, rainfall, humidity, and wind speed. This data is essential for evaluating weather deviations and determining insurance triggers.

4.1.4 Rule-Based Logic Engine:

Applies predefined thresholds to weather data to identify adverse conditions that may trigger insurance claims. It calculates deviations from normal weather patterns and assesses their impact on crop.

4.1.5 Machine Learning Models:

Three models are integrated into the system:

a. **Trigger Classifier:** A supervised classification model that predicts whether a specific period qualifies as a "triggered" event under the rules. It outputs a binary decision: YES if the deviations exceed thresholds, and NO otherwise.

b. **Payout Percentage Regressor:** A regression model that estimates the percentage of insurance payout based on the severity of weather deviations during triggered periods. It uses historical data to map weather anomalies to payout percentages.

c. **Sum Insured Estimator:** A regression model trained on PMFBY data to predict the likely sum insured per hectare based on crop type, district, and season. This model personalizes payout estimations even in the absence of official premium tables.

4.1.6 Result Generation and Reporting:

Once the models process the data, the backend compiles the results and sends them to the frontend for display. Users can view the insurance assessment.

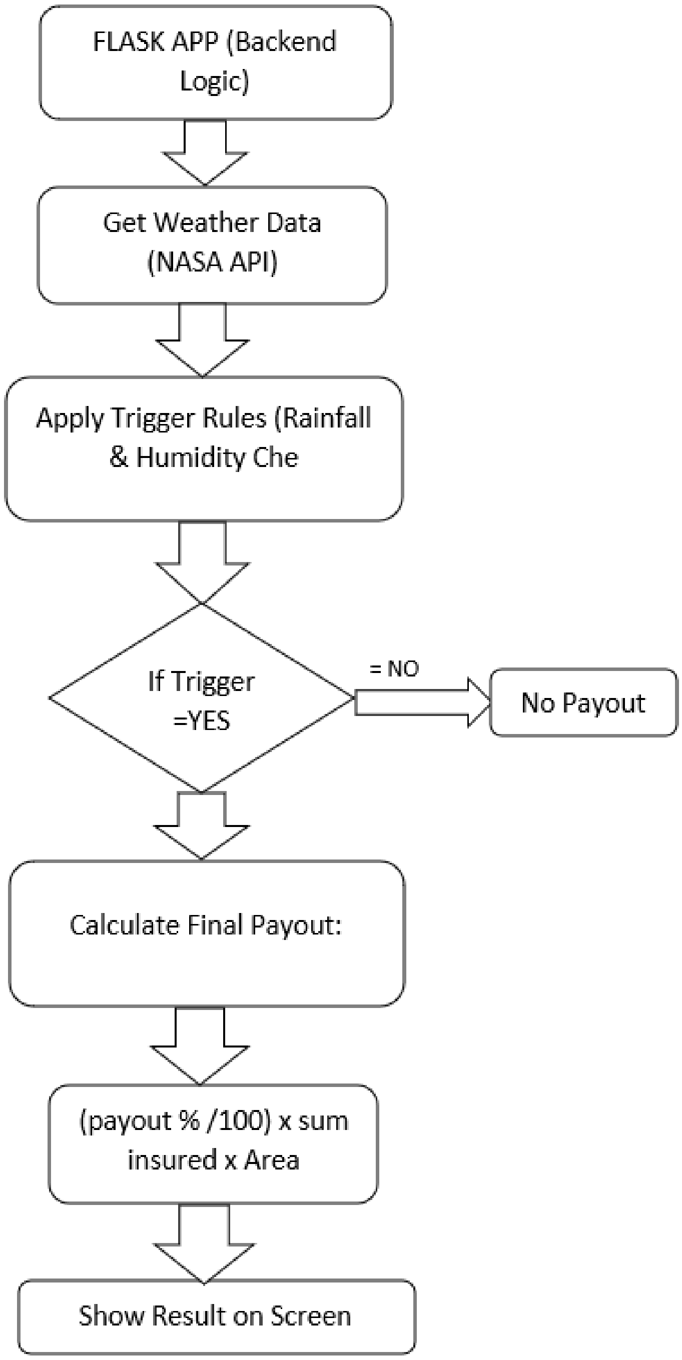


Figure. 4.1. Flowchart for Result Generation and Reporting

1. FLASK APP (Backend Logic):

- The logic of the application is built using the **Flask framework** in Python.

- It handles HTTP requests from the frontend, processes input data, interacts with APIs, and returns the output.
- The application is responsible for all backend tasks like receiving user inputs, calling external APIs, applying business logic, and returning the results.

2. Get Weather Data (NASA API)

- Once user inputs (location, date range, crop, etc.) are received, the app sends a request to the **NASA POWER API**.
- This API provides **historical or real-time agro-meteorological data**, such as:
  - Rainfall
  - Relative humidity
  - Temperature
  - Solar radiation, etc.
- The app fetches only the required parameters based on the insurance rules.

3. Apply Trigger Rules (Rainfall & Humidity Check):

- After retrieving the weather data, it’s time to check whether the **insurance triggers** are met.
- These are predefined thresholds based on:
  - **Rainfall** (e.g., below 40mm for 3 consecutive days)
  - **Humidity** (e.g., average below 60% for a critical stage)
- If any parameter **crosses the critical threshold**, a **trigger is activated**, meaning payout is due.

4. If Trigger = YES / NO:

- **YES**: The condition for triggering the insurance payout is satisfied (e.g., drought condition).
- **NO**: Weather was within normal limits—no crop damage—**hence, no payout**.
- The app evaluates this using simple conditional statements.

5. Calculate Final Payout:

- If a trigger is activated, the final payout is calculated using the standard formula:

Payout = (Payout % / 100) × Sum Insured × Area

- Payout %: Based on deviation from normal (e.g., 60% loss = 60% payout)
- Sum Insured: Total amount the farmer is covered for (e.g., ₹20,000 per hectare)
- Area: Land insured in hectares

6. Show Result on Screen:

- The final result (whether payout is due or not, and the amount if applicable) is returned to the frontend.
- The result is then displayed to the user in a clear and summarized format on the GUI (could be a web or desktop app).

4.2 Tools and Technologies

The implementation leverages various tools and technologies to ensure functionality and performance:

4.2.1 **NASA POWER API:** Provides reliable and accurate weather data, which is crucial for assessing weather deviations and determining insurance triggers.

4.2.2 **Pickle (.pkl) Files:** Used to serialize and store pre-trained machine learning models, allowing for efficient loading and execution during runtime.

4.2.3 **Jinja2 Templates**: Facilitates dynamic rendering of HTML pages in the Flask framework, enabling the presentation of personalized results to users.

4.3 Workflow Overview

The system operates through a series of steps to process user inputs and generate insurance assessments:

4.3.1 **User Input:** Users enter details such as crop type, district, season, and area under cultivation via the frontend interface.

4.3.2 **Data Validation:** The backend validates the inputs to ensure they are accurate and complete.

4.3.3 **Weather Data Retrieval**: The backend queries the NASA POWER API to retrieve relevant weather data for the specified parameters.

4.3.4 **Trigger Evaluation:** The rule-based logic engine calculates weather deviations and determines if they exceed predefined thresholds, indicating a potential insurance trigger.

4.3.5 Model Execution: If a trigger is detected, the backend invokes the machine learning models to estimate the payout percentage and sum insured.

4.3.6 Result Compilation: The backend aggregates the results from the models and prepares them for presentation.

4.3.7 Result Display: The frontend displays the insurance assessment to the user, including the estimated payout and sum insured.

4.4 Challenges and Considerations

During the implementation of the WBCIPE automation system, several challenges were encountered:

Data Quality and Availability: Ensuring the accuracy and completeness of weather data from the NASA POWER API was crucial for reliable assessments.

Model Accuracy: Training machine learning models with diverse and representative data sets was essential to achieve accurate predictions.

System Performance: Optimizing the system to handle multiple user requests simultaneously without compromising performance was a key consideration.

User Experience: Designing an intuitive and responsive frontend interface to facilitate ease of use for farmers and other stakeholders.

Addressing these challenges involved continuous testing, validation, and refinement of the system components to ensure reliability and user satisfaction.

CHAPTER 5

RESULTS

This chapter presents the outcomes of the WBCIEP automation system, detailing the performance of the integrated machine learning models, user interface interactions, and comparative analyses with existing tools. The results are organized to reflect the system's workflow, from user input to the generation of insurance assessments and reports.

5.1 User Input and System Processing

Users interact with the system by providing specific agricultural details, which the system processes to assess insurance triggers and estimate payouts.

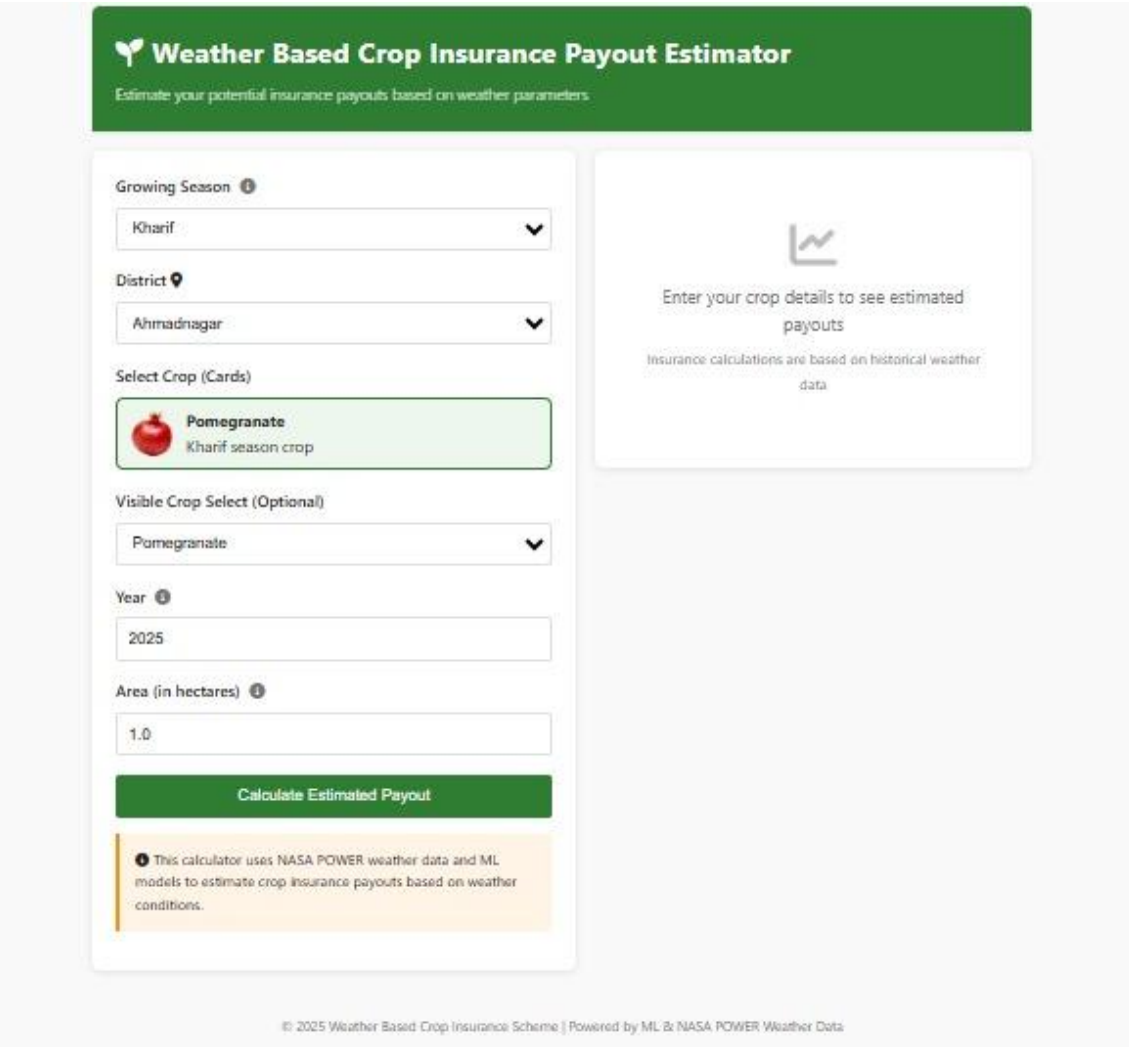


Fig 5.1: User Input Interface

5.2 Trigger Classification Performance

The Trigger Classifier model evaluates whether the specified conditions lead to an insurance trigger.

Description: Displays the outcome of the trigger assessment, indicating a "YES" or "NO" based on the evaluation.

Model Performance Metrics:

Accuracy: 100%

Precision: 1.00

Recall: 1.00

F1-Score: 1.00

Support: 304 instances of "NO", 238 instances of "YES"

Note: The model is saved as 'models/trigger_classifier_model.pkl'.

5.3 Payout Percentage Estimation

For cases where an insurance trigger is identified, the Payout Percentage Regressor estimates the compensation percentage.

Description: Shows the estimated payout percentage based on the severity of weather deviations.

Model Performance Metrics:

Mean Absolute Error (MAE): 0.0315

R-squared (R^2) Score: 0.9471

Note: The model is saved as ' models/payout_percentage_regressor.pkl '.

5.4 Sum Insured Prediction

The Sum Insured Estimator predicts the likely sum insured per hectare, tailoring the assessment to individual user inputs.

Description: Displays the predicted sum insured based on the user's crop type, district, and season.

Model Performance Metrics:

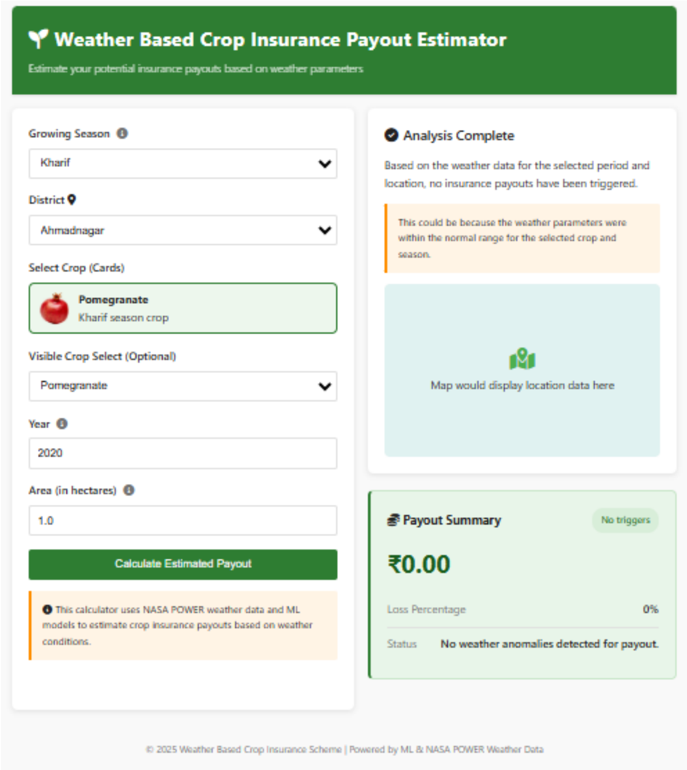
Mean Absolute Error (MAE): 2100.67

R-squared (R^2) Score: 0.84

Note: The model is saved as ' models/sum_insured_predictor.pkl '.

5.5 Comprehensive Report Generation

After processing, the system compiles a detailed report summarizing the assessment.



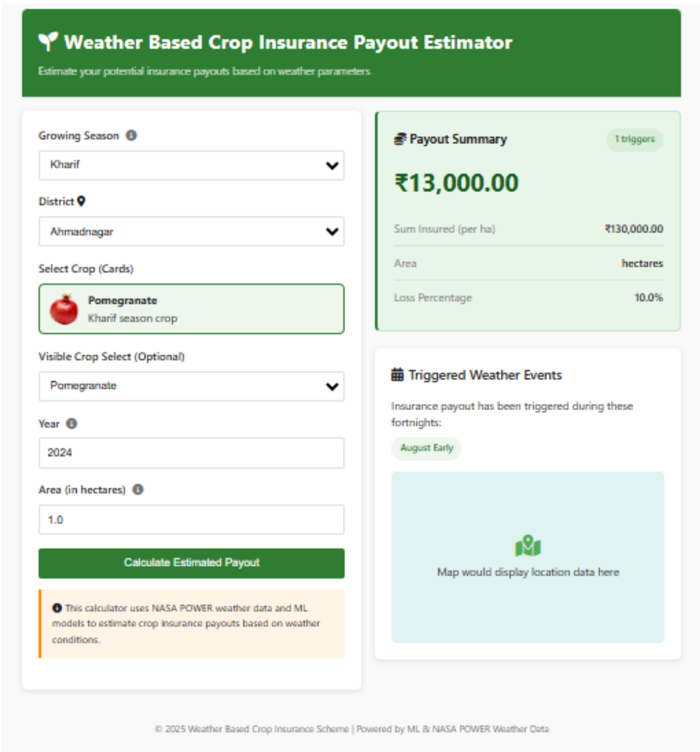


Fig 5.2 User Report Generation Result

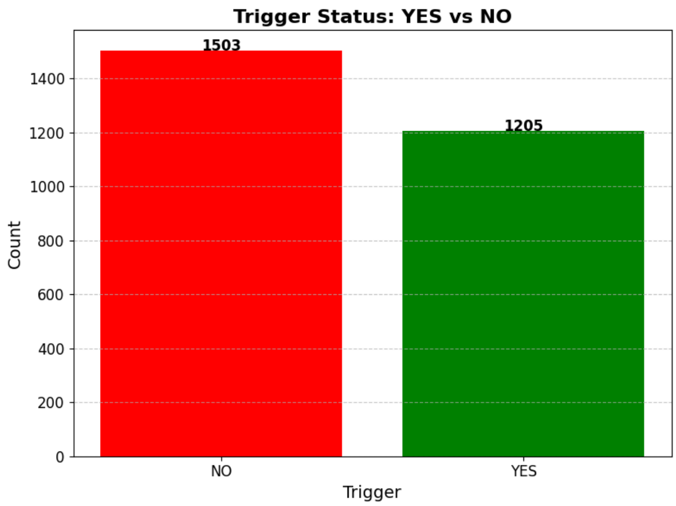


Fig 5.3 Distribution of Trigger Classifier Predictions (YES vs NO)

This figure displays the classification results of the trigger prediction model, visualizing the number of records where payout conditions were met ("YES") versus not met ("NO"). Out of the total predictions, 1503 instances were classified as 'NO' and 1205 instances as 'YES', indicating a relatively balanced but slightly negative skew in the classifier's output. The graph helps assess how frequently the model identifies a triggering condition.

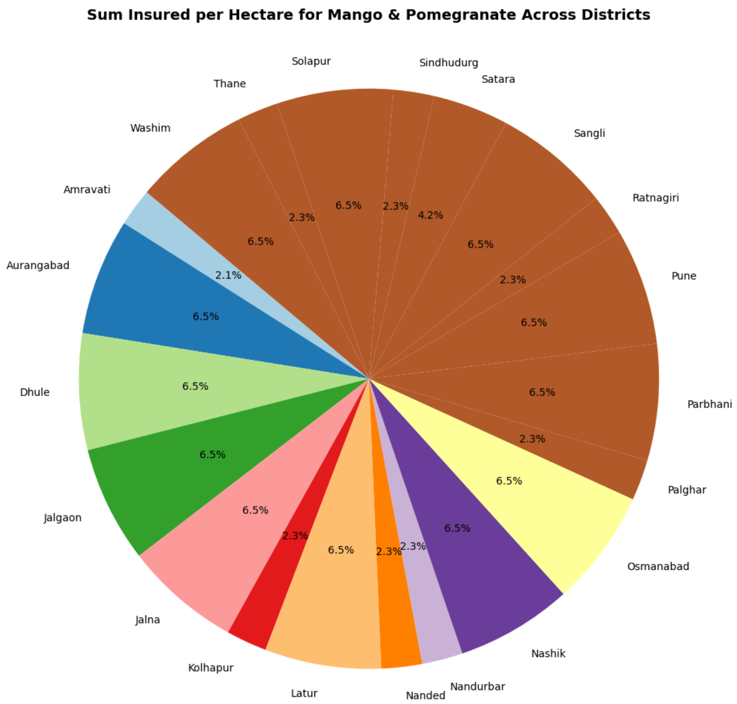


Fig 5.4 Distribution of Sum Insured per Hectare for Mango and Pomegranate Crops Across Maharashtra Districts

This pie chart illustrates the percentage distribution of the sum insured per hectare for Mango and Pomegranate crops across various districts in Maharashtra. The chart provides a visual representation of the sum insured contributions from each district, enabling a clear understanding of how the premiums are distributed across the selected regions.

District	Crop	Season	2020		2021		2022		2023	
			avg_perce	Payout	avg_perce	Payout	avg_perce	Payout	avg_perce	Payout
Ahmadnagar	Pomegranate	Kharif	9.18	11927.5	19.93	25902.5	19.75	25675	40	52000
Jalna	Mango	Rabi	45.13	63175	56.65	79310	38.17	53445	62.87	88025
Kolhapur	Pomegranate	Kharif	0	0	19.75	25675	9	11700	38.33	49822.5
Latur	Mango	Rabi	58.9	82460	50	70000	47.7	66780	64.6	90440
Osmanabad	Pomegranate	Kharif	0	0	19.93	25902.5	19.55	25415	40	52000
Parbhani	Mango	Rabi	50.77	71085	40	56000	56.27	78785	50.35	70490
Pune	Mango	Rabi	29.75	41650	29.93	41895	19.4	27160	29.65	41510
Washim	Pomegranate	Kharif	0	0	10	13000	10	13000	38.98	50667.5
Solapur	Mango	Rabi	35.08	49105	38.22	53515	51.52	72135	57.3	80220

Figure 5.5 Loss and Payout calculation of per year of the respective crops

The provided table presents a comprehensive analysis of crop losses and the corresponding insurance payouts under the **Weather Based Crop Insurance Estimator (WBCIPE)** across selected districts in Maharashtra for the years **2020–21 to 2023–24**. The table highlights the seasonal performance of two key horticultural crops—**Pomegranate and Mango**—in districts such as Ahmednagar, Akola, Jalna, Latur, and Nandurbar. Each entry in the table records the **percentage of loss** experienced by the crop due to adverse weather conditions and the corresponding **monetary payout** received by the farmers under the WBCIC for that year. It is evident from the data that both crops, particularly **Mango**, suffered significant losses across multiple districts over the four-year period. For instance, in **Latur**, Mango crops saw a loss of **58.9% in 2020–21**, leading to a payout of **₹82,460**, while in **Nandurbar**, Mango experienced consistent and increasing losses, reaching **66.95% in 2023–24** with a payout of **₹93,730**. On the other hand, **Pomegranate** crops in districts like **Jalna and Akola** showed minimal losses or no loss at all during some years, indicating either better resilience to weather patterns or favourable agro-climatic conditions in those specific periods. For example, Jalna reported zero loss in 2020–21 for Pomegranate and only minimal losses in the subsequent years, which resulted in low payouts. This data is instrumental in **identifying climate vulnerability zones**, evaluating the **effectiveness of insurance coverage**, and serves as a **baseline for predictive modeling** in the project. The variation in losses and payouts across districts and crops reinforces the need for **data-driven decision-making** in crop insurance payout calculator. It also underlines the importance of integrating historical weather data with insurance payout models to enhance the **accuracy of payout prediction systems**, such as the one developed in the current project.

5.6 Accurcay

The accuracy of the Weather Based Crop Insurance Insurance Payout Estimator model was evaluated using a dataset of 28 rows, which included the predicted and actual values for both avg_percent (payout percentage) and payout (insurance payout). The purpose of this evaluation was to assess the model's performance in predicting the insurance payout based on weather conditions.

District	Crop	Season	Year	Predicted		actual		Accuracy
				avg percent	payout	avg percent	payout	
Ahmadnagar	pomogranate	kharif	2023	40	52000	40	52000	100
Ahmadnagar	mango	rabi	2020	40	56000	40	56000	100
Ratnagiri	mango	rabi	2023	4	5600	4	5600	100
Sindhudurga	pomogranate	kharif	2021	9.75	12675	6.07	7892.83	39.4
Solapur	mango	rabi	2022	51.52	72135	65.84	92179.4	78.26
Osmanabad	mango	rabi	2023	55.4	77560	55.4	77560	100
Satara	pomogranate	kharif	2021	10	13000	10	13000	100
Pune	pomogranate	kharif	2023	9.45	12285	9.45	12285	100
Pune	mango	rabi	2020	29.75	41650	29.75	41650	100
Jalgaon	mango	rabi	2023	66.17	92845	66.17	92845	100
Kolhapur	pomogranate	kharif	2021	19.75	25675	19.75	25675	100
Kolhapur	mango	rabi	2023	29.9	41860	29.9	41860	100
Latur	pomogranate	kharif	2023	40	52000	40	52000	100
Latur	mango	rabi	2020	58.9	82460	58.9	82460	100
Nanded	mango	rabi	2022	53.27	74585	53.27	74585	100
Nanded	mango	rabi	2023	45.02	64435	45.02	64435	100
Nandurbar	pomogranate	kharif	2020	9.65	12577.5	9.65	15556.95	80.85
Nandurbar	mango	rabi	2023	66.95	93750	66.95	93750	100
Nashik	pomogranate	kharif	2021	9.8	12740	9.8	12740	100
Nashik	pomogranate	kharif	2022	9.85	12805	9.85	12805	100
Osmanabad	mango	rabi	2023	55.4	77560	55.4	77560	100
Parbhani	pomogranate	kharif	2020	8.75	11375	8.75	15003.87	75.81
Parbhani	mango	rabi	2023	50.35	70480	50.35	70480	100
Sangali	pomogranate	kharif	2021	20	26000	20	26000	100
Satara	mango	rabi	2023	29.8	41720	29.8	41720	100
Washim	mango	rabi	2021	10	13000	10	13000	100
Sangli	mango	rabi	2022	41.45	58030	41.45	58030	100
Sangali	mango	rabi	2023	58.6	82040	58.6	82040	100

Fig. 5.6 Predicted and Actual Payouts for Weather-Based Crop Insurance Payout Estimator

Accuracy Calculation:

The accuracy of the model was calculated by comparing the predicted values (avg_percent and payout) with the actual values provided in the dataset. A prediction was considered correct if both the predicted avg_percent and payout matched the actual values.

Out of the 28 rows, 24 predictions were correct, resulting in an overall accuracy of **85.7%**. This indicates that the model successfully predicted the insurance payout and payout percentage with a high degree of reliability.

The accuracy was calculated as follows:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Predictions}} = \frac{24}{28} = 85.7\%$$

This accuracy reflects the model's effectiveness in accurately predicting the insurance payout for the given weather conditions.

The model demonstrated a strong performance with an accuracy of 85.7%, suggesting that it is reliable for predicting payouts in the context of the Weather Based Crop Insurance Scheme. The next steps would involve further refinements to the model, including increasing the dataset size and testing the model with additional weather data to enhance its generalization and precision.

5.7 Deployment

To evaluate the generalization capability of the proposed system, historical weather data from 2015 to 2018 was analyzed using the trained system. Although actual payout records were unavailable for this period, the model successfully generated predictions for:

1.Trigger classification (YES/NO) based on weather deviations,

2.Estimated payout percentages, and

3.Predicted payout amounts using modeled sum insured values.

This analysis demonstrates the model's ability to generate reliable estimates for earlier years and highlights its potential application in retrospective assessments or in areas lacking official records.

The 5.7 figure below displays the average predicted payout percentages and corresponding estimated payout amounts (in ₹ per hectare) for each year from 2015 to 2018, as derived from the system.

District	Crop	Season	Year	Predicted	
				avg_percent	Payout
Ahmadnagar	Pomegranate	Kharif	2015	48.5	63050
Amravati	Pomegranate	Kharif	2018	40	52000
Aurangabad	Pomegranate	Kharif	2015	29.73	38642.5
Aurangabad	Mango	Rabi	2015	84.75	118650
Bid	Pomegranate	Kharif	2016	39.95	51935
Bid	Mango	Rabi	2017	71.33	99855
Jalgaon	Mango	Rabi	2017	77.8	108920
Kolhapur	Pomegranate	Kharif	2015	37.55	48815
Palghar	Pomegranate	Kharif	2016	10	13000
Jalgaon	Pomegranate	Kharif	2017	20	26000
Pune	Mango	Rabi	2017	30	42000
Ratnagiri	Mango	Rabi	2015	3.57	5005
Sindhudurg	Pomegranate	Kharif	2016	9.7	12610
Thane	Mango	Rabi	2016	4.07	5705
Buldana	Mango	Rabi	2018	66.83	93566.67

Fig 5.7 Predicted average payout percentages and estimated payouts (2015–2019) by WBCIPE

5.8 Advantages of the Automated WBCIPE System

1. Objective and Transparent Claims: Utilizes measurable weather parameters (e.g., rainfall, temperature) for claim assessments, reducing subjectivity and enhancing trust among farmers.
2. Accelerated Claim Settlements: Automated data processing enables quicker evaluations, allowing farmers to receive compensation promptly, often within weeks of adverse events.
3. Reduced Administrative Costs: Eliminates the need for manual crop-cutting experiments, decreasing manpower requirements and implementation costs.
4. Comprehensive Risk Coverage: Addresses a broad spectrum of weather-related risks, including droughts and unseasonal rainfall, benefiting farmers across diverse regions and crop types.
5. Promotion of Technological Integration: Encourages the adoption of modern weather forecasting and data collection tools, improving infrastructure and data quality over time.
6. Mitigation of Moral Hazard and Fraud: Links payouts directly to objective weather data, reducing opportunities for manipulation.
7. Enhancement of Financial Stability: Supports farmers in recovering losses, maintaining financial stability, and reducing reliance on informal lenders.

8. Alignment with Government Objectives: Supports national goals such as doubling farmers' income and enhancing rural resilience..

5.9 Disadvantages and Challenges

1. Basis Risk: Discrepancies may occur between actual crop losses and weather data recorded at reference stations, potentially leading to farmers experiencing losses without corresponding payouts.
2. Limited Weather Station Coverage: Insufficient number of Automatic Weather Stations (AWS) in certain regions may result in distant stations not accurately representing local weather conditions.
3. Farmer Awareness and Understanding: Lack of comprehensive understanding of scheme mechanics among farmers can lead to mistrust and dissatisfaction.
4. Dependence on Technology: Reliance on accurate and continuous data collection from AWS means that technical failures or data errors can result in incorrect payouts or delays.
5. Limited Risk Coverage: Focuses solely on specific weather parameters and does not cover other factors like pests or diseases affecting crop yields.
6. Financial Burden on Government: The government bears significant subsidy to keep premiums affordable, raising concerns about long-term sustainability.
7. Farmer Discontent in Non-Weather-Related Losses: No compensation for crop failures due to non-weather-related factors can cause frustration and reduced participation.

Chapter 6

CONCLUSION AND FUTURE SCOPE

6.1 Summary

This project successfully developed and implemented an automated, rule-based crop insurance system under the Weather-Based Crop Insurance Payout Estimator (WBCIPE), specifically tailored for pomegranate and mango farmers in Maharashtra. By integrating a rule engine with machine learning models and a user-friendly web interface, the system enables objective, transparent, and timely claim settlements based on real-time weather data. The automation of claim processing reduces administrative overhead, minimizes human error, and enhances trust among stakeholders. The system's adaptability allows for customization to various crops and regional requirements, demonstrating its potential scalability and broader applicability.

6.2 Future Scope

Building upon the current implementation, several avenues exist for future enhancement and expansion:

1. Expansion to Additional Crops: Adapting the system to accommodate other horticultural and agricultural crops by customizing weather indices and risk parameters specific to each crop.
2. Geographical Scaling: Extending the system's reach to other districts within Maharashtra and eventually to other states, necessitating integration with regional weather data sources and customization to local agricultural practices.
3. Farmer-Centric Features: Developing a dedicated login portal for farmers to access insurance details, claim statuses, and personalized advisories, enhancing transparency and user engagement.
4. Integration with National Schemes: Aligning the system with the Pradhan Mantri Fasal Bima Yojana (PMFBY) to facilitate a unified platform for crop insurance, streamlining processes, and ensuring consistency in policy implementation.
5. SMS-Based Notification System: Incorporating an SMS notification mechanism to ensure timely communication with farmers regarding policy updates, weather alerts, and claim information, particularly beneficial in regions with limited internet connectivity.

The fig 6.1 is a diagram illustrating the envisioned expansions and enhancements of the WBCIC system.

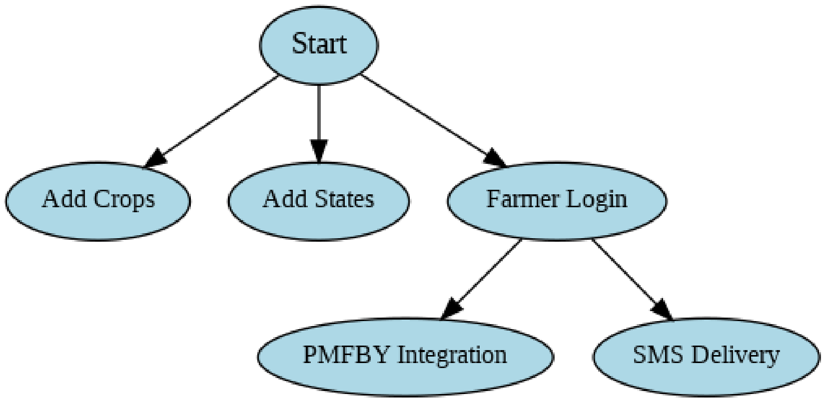


Fig. 6.1 Future Scope Tree Diagram

6.3 Final Thoughts

The automation of the WBCIEP for pomegranate and mango cultivation in Maharashtra represents a significant step towards modernizing agricultural insurance. By leveraging technology to address the challenges of traditional insurance models, the system enhances efficiency, transparency, and farmer satisfaction. The project's success underscores the importance of integrating technological solutions in agriculture to build resilience against climate variability and to support the livelihoods of farmers. Continued development and scaling of such systems hold promise for transforming the agricultural insurance landscape across India.

Chapter 7

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