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by Himanshi Chadhary

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Project Report

on

Aqua Growth

submitted as partial fulfillment for the award of

BACHELOR OF TECHNOLOGY DEGREE

SESSION 2024-25

In

Computer Science and Engineering

By

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May, 2025

DECLARATION

We hereby declare that this submission is our own work and that, to the best of our knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

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CERTIFICATE

This is to certify that Project Report entitled Aqua Growth which is submitted by Someshwar Singh, Rases Pathak, Shivangi Yadav of VIII semester for project (KCS 851) in partial fulfillment of the requirement for the award of degree B.Tech. in Department of Computer Science & Engineering of Dr. A.P.J. Abdul Kalam Technical University, Lucknow is a record of the candidates own work carried out by them under my supervision. The matter embodied in this report is original and has not been submitted for the award of any other degree.

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We also do not like to miss the opportunity to acknowledge the contribution of all faculty members, especially faculty/industry person/any person, of the department for their kind assistance and cooperation during the development of our project. Last but not the least, we acknowledge our friends for their contribution in the completion of the project.

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ABSTRACT

"Aqua Growth" is an intelligent hydroponic monitoring and recommendation system designed to optimize plant growth by analysing environmental parameters, nutrient levels, and growth patterns. The system applies Machine Learning (ML) and Data Analytics to predict plant health, recommend nutrient mixes, and optimize growing conditions for maximum yield.

Key Objectives:

1. Plant Growth Prediction – Forecast plant growth rates based on environmental data.
2. Nutrient Mix Recommendation – Suggest optimal nutrient compositions for different plant types.
3. Environmental Parameter Optimization – Adjust pH, temperature, EC (Electrical Conductivity), and light exposure for ideal growth conditions.
4. System Recommendation – Recommend hydroponic system types (NFT, DWC, Aeroponics, etc.) based on plant requirements.

This study innovates an intelligent, data-centric approach to optimizing plant growth significantly in hydroponic farming through the judicious application of sophisticated machine learning techniques. Seeing hydroponics as a revolutionary soilless growing method that provides unprecedented control over vital environmental and nutrient factors, this research systematically explores the operating dynamics and growth efficiencies in three common hydroponic systems: Nutrient Film Technique (NFT), Drip System, and Ebb & Flow. Through systematic examination of their performance across a range of environmental and operating conditions, this study will realize the complete potential of precision agriculture in controlled settings. v For this purpose, a detailed and carefully compiled dataset including 750 distinct samples was developed. This comprehensive dataset covers a detailed set of critical parameters known to affect the growth of plants, ranging from the level of artificial illumination, acidity/alkalinity of the nutrient solution (pH levels), dissolved salt concentration crucial for plant nutrition (electrical conductivity), air and nutrient solution temperature, relative humidity of the growth chamber, and system-specific operational parameters such as NFT system nutrient

flow rates, irrigation frequency in Drip Systems and flooding and draining cycle duration and interval in Ebb & Flow systems. This multi-dimensional dataset is a strong platform for training and testing advanced machine learning models. The research utilized a set of state-of-the-art machine learning algorithms that are known for their predictive power: Linear Regression as a baseline model; Decision Tree to capture nonlinear patterns; Random Forest to take advantage of an ensemble of decision trees for enhanced robustness and accuracy; and XGBoost (Extreme Gradient Boosting), an optimized gradient boosting algorithm with a reputation for state-of-the-art performance in many predictive tasks. These models were trained aggressively to forecast plant growth rates from the gathered environmental and operational parameters and, importantly, to suggest the most appropriate hydroponic system configuration for optimum growth under provided conditions.

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LIST OF ABBREVIATIONS

NFT	Nutrient Film Technique
ML	Machine Learning
MSE	Mean Squared Error
RMSE	Root mean Squared error
MAE	Mean Absolute Error
EC	Electrical conductivity
PH	Potential of hydrogen ppm Parts per million
NPK	Nitrogen, Phosphorous, Potassium
XGBoost	Extreme Gradient boosting

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

Agriculture has been the backbone of human civilization, providing essential resources for sustenance and economic growth. However, traditional farming methods face challenges such as limited arable land, water scarcity, and climate change, necessitating innovative solutions to ensure global food security. Hydroponic farming is a revolutionary approach that enables soilless cultivation in a controlled, nutrient-rich water solution, leading to higher yields, faster growth, and efficient resource utilization. Among various hydroponic methods, the Nutrient Film Technique (NFT), Drip System, and Ebb & Flow are widely used. However, selecting the optimal system and growth parameters for different crops remains a complex challenge. The integration of machine learning (ML) with hydroponics offers a data-driven approach to predict plant growth and optimize system configurations. This project employs machine learning models such as Linear Regression, Decision Tree, Random Forest, and XGBoost to analyze key environmental and nutrient parameters (light intensity, pH, electrical conductivity, nutrient flow rate) and predict plant growth. The study also identifies the most influential parameters for each hydroponic system and provides recommendations to optimize performance. By leveraging predictive modeling, farmers can reduce resource wastage, improve yields, and enhance sustainability. This research sets the stage for real-time IoT integration, cost analysis, and deep learning advancements in intelligent hydroponic farming. Conventional agriculture, though rooted, is facing rising pressures. Worldwide, the arable land is shrinking at a disconcerting pace owing to urbanization and land degradation with estimates predicting a substantial loss over the next few decades. At the same time, water 2 scarcity impacts billions, while traditional irrigation practices tend to be inefficient, with estimates predicting up to 50% water loss via evaporation and runoff. The capricious nature of climatic change then aggravates all these issues to result,in crop loss and yield decline throu gh abnormal weather conditions and shifted growing period. "Hydroponic agriculture presents a compelling alternative by breaking the-link between crop growth and soil. The Nutrient Film Technique (NFT) consists of a shallow film of nutrientfortified water-flowing, over the roots of the plant, allowing for constant availability of nutrients and oxygen. Drip systems provide nutrient solution directly to the bottom of each plant on a controlled schedule, maximizing water and nutrient efficiency. Ebb & Flow, also known as flood and drain, floods the root zone occasionally with nutrient solution, then drains it off, supplying nutrients. Each system has inherent strengths and weaknesses in terms costs, appropriateness for varying plant sizes and root morphologies, energy use, and technical skill level required for operation.".

1.2 PROJECT DESCRIPTION

The "Aqua Growth" project focuses on leveraging machine learning (ML) techniques to predict plant growth and recommend optimal hydroponic system configurations. Traditional farming methods are often limited by soil quality, unpredictable weather, and inefficient resource use. In contrast, hydroponic farming offers a soilless alternative, enabling controlled cultivation in nutrient-rich solutions. However, selecting the right hydroponic system and environmental parameters for optimal plant growth remains a challenge. Let's see about the user's use case diagram for this project:

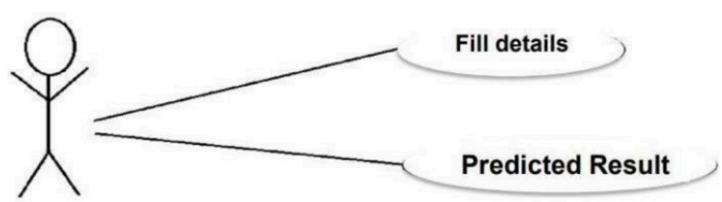

Fig 1: Use Case Diagram

1. Introduction: Setting the Stage for Intelligent Hydroponics:

Traditional farming, the foundation of human society, is beset by challenges that are unprecedented in the 21st century. Urbanization and environmental degradation have resulted in limited arable land, while a growing global population requires more food. Water scarcity, driven by climate change and wasteful irrigation, adds further pressure to traditional farming. Unpredictable weather conditions, such as severe events like floods and droughts, are a major threat to crop yields.

Additionally, the use of synthetic fertilizers and pesticides is of environmental and health concern, further necessitating more sustainable and controlled means of food production. Hydroponic agriculture presents itself as are volitionary method, presenting a strong alternative to soil farming. By growing plants in nutrient-dense water solutions without soil, hydroponics allows for complete control over the growing conditions.soilless growth has many benefits, such as much greater yields per unit area than conventional farming, more rapid plant growth cycles with optimized nutrient delivery, and drastically less water usage by recirculating the nutrient solution. In addition, hydroponics reduces or eliminate the use of herbicides and 4 pesticides, leading to healthier and cleaner food production. Still, it is precisely this control that brings a problem: finding the ideal system design and environmental variables for various crops to achieve the most efficient resource usage and maximum growth potential. Choosing the most appropriate hydroponic system (e.g., Nutrient 4 Film Technique, Drip System, Ebb & Flow, Deep Water Culture) and controlling critical parameters such as light intensity, pH values, nutrient levels, flow rates, and cycle times to optimal levels necessitates a thorough knowledge of plant physiology as well as the complex interplay of these parameters. This is often translated into poor yields and wasted resources if it were based only on manual tweaking or blanket guidelines. The "Aqua Growth" project tackles this challenge head-on by leveraging the power of machine learning. Through the creation of predictive models that can analyze large volumes of data on environmental conditions, nutrient management, and plant growth responses, this project seeks to offer data-driven insights that enable growers to make informed decisions, optimize their hydroponic systems, and attain sustainable and high-yielding crop production.

2. Methodology:

Integrating Machine Learning for Hydroponic Optimization The basis of the "Aqua Growth" project consists in integrating machine learning algorithms that will study decisive environmental and nutritional parameters as well as their prognostic influences on plant development. The strategy includes various significant steps:

Data Acquisition:

Work on the project will make use of data received from hydroponic tests kept under strict controls. Such data will cover an extensive list of variables such as:Environmental Parameters: Light intensity (expressed in lux or PPFD), air temperature (°C), humidity (%), and possibly CO2 concentration(ppm). Nutrient Parameters: pH values (alkalinity/acidity), electrical conductivity (EC in mS/cm), flow rate of nutrients (L/min), frequency of drips (number per hour), timing of the cycles (flood/drain time in minutes), and possibly concentration of each macro and micronutrient (ppm). Plant Growth Metrics: Quantities of plant height (cm), leaf area (cm²), stem diameter (mm), biomass (fresh weight and dry weight in grams), and possibly early measures of plant health (e.g., chlorophyll content, leaf color analysis).

Machine Learning Model Development:

A set of regression-based machine learning models 5 will be created and trained to make predictions of plant growth from the gathered data. These models will consist of: Linear Regression: A basic model to set baseline relations between parameters and growth. Decision Tree Regression: A non-linear model that can learn intricate decision boundaries in data. Random Forest Regression: An ensemble learning method that averages the predictions of multiple decision trees to enhance prediction accuracy and reliability. XGBoost (Extreme Gradient Boosting): Another robust ensemble method renowned for its high performance and capability to deal with complex data. The accuracy of these models will be thoroughly tested against relevant metrics like Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared value to establish the best predictors of most accurate and reliable for various plant types and hydroponic systems.

System Recommendation Engine: Depending on the machine learning models that have been trained and user-specified environmental conditions (that may be live readings from a given location or target conditions), a recommendation engine will be designed. This will evaluate the expected growth rates of various hydroponic system designs (NFT, Drip, Ebb & Flow) for those conditions and recommend the system that should give the highest growth rate or resource.

Scope for IoT Integration: The project also hopes for future integration with Internet of Things (IoT) devices such as sensors to monitor environmental and nutrient parameters in real-time. This would allow for continuous acquisition of data, inputting live data to the machine learning algorithms for real-time predictions and automatic adjustments of system setting. 3.ExpectedOutcomes 6 The "Aquagrowth" project looks to reach a few important outcomes that will meaningfully develop the science of precision hydroponic agriculture: Precise Growth Rate Forecasting: The machine learning models created are predicted to be highly accurate in forecasting plant growth rates on different hydroponic configurations and environmental situations. This will equip growers with the capacity to foresee yields and make anticipatory changes to maximize their systems.

System Recommendations:

According to Environmental Conditions: The system recommendation engine will offer data-driven advice on the choice of the most appropriate hydroponic system for environmental settings, considering available space, climate, and target. To address this, our project integrates machine learning algorithms to analyze key environmental and nutrient parameters such as:

- Light Intensity – Essential for photosynthesis and energy conversion.
- pH Levels – Influences nutrient absorption efficiency.
- Electrical Conductivity (EC) – Reflects nutrient concentration in the water.

Expected Outcomes:

- Accurate growth rate predictions across different hydroponic setups.
- System recommendations based on environmental conditions.

CHAPTER 2

LITERATURE REVIEW

Literature Review: Data-Driven Optimization of Sustainable Hydroponic Agriculture Contemporary agriculture is under pressure to be more efficient, reduce its environmental footprint, and be more food secure. Soilless cultivation hydroponic farming is a technique that holds some promise in dealing with these pressures by providing contained environments that are capable of maximizing the use of resources and increasing yields potentially [1, 8]. This review of the literature considers past research on using data analytics, machine learning, and real-time monitoring in hydroponic systems, relating this to the extensions proposed for the "Aqua Growth" project to further enhance these systems by adding cost metrics, IoT integration, commercial farm scalability, and sophisticated machine learning techniques

Fundamentals of Hydroponic Agriculture and its Promise:

Smith et al. [1] highlight the promise of hydroponic agriculture as an answer to issues in modernday farming, possibly emphasizing its benefit over conventional approaches in water preservation, lower usage of pesticides, and increased productivity. Resh's definitive handbook [3] gives a detailed insight into a range of soilless food-growth techniques, giving vital background to the types of systems that "Aqua Growth" will seek to fit into in its scalability plans for commercial farms. Jensen [8] probably provides a basic introduction to hydroponics from a horticultural science point of view, which is necessary to understand the basic biological needs of plants cultivated in these systems, to guide the parameters and reasoning within the "Aqua Growth" model.

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The Role of Machine Learning in Controlled Environment Agriculture:

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Rahman et al. [2] specifically discuss machine learning methods for crop prediction in controlled environments. This project probably explores different algorithms and how effective they are in predicting yields from environmental and operational information. This is related to the "Advanced Techniques in ML" extension of "Aqua Growth," meaning predictive modeling is a 23 known field, and your project can advance from this by including more complex methods such as time series analysis for seasonal variability and predictive modeling for disease occurrence. Wang et al. [10]'s comparative analysis of machine learning in the prediction of nutrients in soilbased farming provides useful information on probable algorithms and methodologies that might be applied for predicting hydroponic system nutrient needs in "Aqua Growth." Liu et al. [11] also stress direct application of machine learning to maximize plant growth in hydroponic systems, establishing a sound reason behind the primary goals of "Aqua Growth."

Integrating IoT and Real-Time Monitoring for Better Control:

Kouassi et al. [4] point out the synergetic value of IoT and machine learning for maximizing plant growth parameters in hydroponics. Their paper probably shows how real-time acquisition of data from IoT sensors can be used to inform machine learning models and allow dynamic control of environmental and nutrient conditions. This is in direct support of the "Integration of Real-Time Monitoring with IoT" expansion of "Aqua Growth," highlighting the transition towards real-time observation and adaptive control. Domingues et al.[5] present a real-world example of an automated pH and nutrient concentration control system in hydroponic lettuce production, demonstrating the viability and advantages of this type of automation, which corresponds to the dynamic parameter adjustment aspect of the "Aqua Growth" project. Pham and Stack [9] present a wider context regarding how data analytics isrevolutionizing agriculture, strongly justifying the data-driven philosophy at the heart of the "Aqua Growth" initiative and its extensions.

Optimization and Scalability:

While the references given skim the surface of optimization via machine learning and controlled environments, the direct incorporation of economic cost factors as envisioned for "Aqua Growth" seems like an area that can be explored further. Present-day literature is chiefly concerned with biological optimization. In the same way, although Resh [3] offers an overview of various hydroponic systems, the literature might not comprehensively treat the particular machine learning model optimizations necessary for scale-up to multi-faceted commercial farm conditions such as vertical farms and computerized greenhouses, a chief aim of the "Aqua Growth" initiative. 24 Advanced Machine Learning Techniques for Holistic System Understanding: The literature on machine learning [2, 6, 7, 10, 11] forms the foundation for the "Advanced Techniques in ML" suggested for "Aqua Growth." Breiman

[6]'s research on Random Forests and Chen and Guestrin [7]'s invention of XGBoost are instances of robust algorithms that can be utilized for predicting crop health, seasonal analysis, and developing adaptive models in "Aqua Growth." The extension seeks to venture beyond simple prediction and investigate more advanced methods such as time series analysis and predictive modeling for disease, which would be a breakthrough in the area.

The Promise of Soilless Agriculture:

Elkazzaz [14] offers an introduction to soilless farming, casting it as an emerging and state-ofthe-art technique for agriculture growth. This supports the basis of knowledge that hydroponics, as a fundamental method of soilless cultivation, presents an alternative to conventional approaches with the potential for improved efficiency and management, directly supporting the justification for maximizing these systems through such endeavors as "Aqua Growth." Goddek et al. [16] extend this by considering the problems and prospects of contained environment agriculture, such as hydroponics, in urban areas. Their focus on sustainability features and potential further highlights the need for maximizing these systems in terms of resource optimality, a fundamental objective of the "Aqua Growth" extensions, especially the addition of cost metrics.

Synergistic Use of IoT and Machine Learning:

Patel et al. [12] consider IoT-based hydroponics specifically in the context of machine learning, illustrating the strong synergy between real-time data collection and smart data analysis for optimizing hydroponic systems. This work firmly supports the "Integration of Real-Time

Monitoring with IoT" and "Advanced Techniques in ML" extensions of "Aqua Growth," underscoring the possibility of developing genuinely smart and adaptive Agri-Systems. Bhagawati et al. [13]'s research on managing farm waste, though perhaps apparently tangential, indirectly underscores the wider sustainability context of farm operations.Optimization of 25 resource utilization in hydroponics, as pursued by "Aqua Growth," can help reduce waste creation in the agricultural industry.

Automation and Control of Hydroponic Systems:

Wibisono and Kristy Awan [15] introduce an effective method of 21 automation of the Nutrient Film Technique (NFT) hydroponic system with Arduino. This study presents a real-world example of how automation 27 can be applied to certain hydroponic systems, directly corresponding to the "Integration of Real-Time Monitoring with IoT" and the "Scaling Up to Commercial Farms" components of "Aqua Growth," where automation is instrumental in controlling more extensive and complicated systems. The automation principles illustrated in this work can guide the creation of more advanced control mechanisms in the "Aqua Growth" model.

Synthesizing Existing Knowledge with "Aqua Growth" Extensions:

The additional references introduced further establish the significance and pertinence of the extensions suggested for your "Aqua Growth" project. Patel et al. [12] explicitly confirm the strategy of integrating IoT and machine learning towards hydroponic optimization, setting a solid foundation for your research in this field. Wibisono and Kristyawan [15] provide information on the real-world application of automation, essential for the upscaling of hydroponic systems as conceived in your project. Elkazzaz [14] and Goddek et al. [16] give a wider context to the importance of soilless and controlled environment agriculture in helping to solve current agricultural issues and ensuring sustainability, consistent with the overall objectives of "Aqua Growth." Although Bhagawati et al. [13] emphasize waste management, their research highlights the significance of resource efficiency, which is the driving force behind the "Aqua Growth" extension to include cost measures.

Conclusion:

The extended literature review supports the increasing volume of research endorsing the application of technology to maximize hydroponic farming. The use of IoT for real-time data collection, machine learning for prediction and regulation, and system operation automation are all active areas of research. The extensions suggested for the "Aqua Growth" project, including 26 cost minimization, full-scale IoT integration, scaling up to commercial-scale farms, and sophisticated machine learning algorithms, are very applicable in this context. By capitalizing on the available knowledge and filling the possible gaps, especially in economic modeling and large-scale application of intelligent hydroponic systems, "Aqua Growth" can significantly contribute to the development of sustainable and efficient food production in the 21st century.

2.2 Feasibility Study

A. Technical Feasibility: This included the study of function, performance and constraints that may affect the ability to achieve an acceptable system. For this feasibility study, we studied complete functionality to be provided in the system, as described in the System Requirement Specification (SRS), and checked if everything was possible using a different type of frontend and backend platforms.

B. Operational Feasibility: No doubt the proposed system is fully GUI based that is very user friendly and all inputs to be taken all self-explanatory even to a layman. Besides, a proper tutorial guide will be provided to let the users know the essence of the system to the users, so that they feel comfortable with the new system. As far as our study is concerned the users will be comfortable and happy as the system will definitely be user friendly

CHAPTER 3

PROPOSED METHODOLOGY

3.1 Modules GUI Module:

Our project has a Graphical User interface module based upon a web portal where the user can interact with the model and can request the recommendations from the model. Database Module:

The project's database module will handle the storing of user data as well as all the data which will be used to train the module.

3.2 Technology/Languages

3.2.1 MACHINE LEARNING TECHNOLOGY:

Machine learning is the study of computer algorithms that can improve automatically through experience and by the use of data. It is seen as a part of artificial intelligence. Our Portal will take numerical data from the user and will use machine learning algorithms to predict the plant growth, recommend optimal hydroponic system and so on. Machine learning is a tool for turning information into knowledge. In the past 50 years, there has been an explosion of data. This mass of data is useless unless we analyze it and find the patterns hidden within. Machine learning techniques are used to automatically find the valuable underlying patterns within complex data that we would otherwise struggle to discover. The hidden patterns and knowledge about a problem can be used to predict future events and perform all kinds of complex decision making. The reason that Machine Learning is so exciting, is because it is a step away from all our previous rule-based systems of:

if (x = y): do z 29

Traditionally, software engineering combined human created rules with data to create answers to a problem. Instead, machine learning uses data and answers to discover the rules behind a problem. There are multiple forms of Machine Learning; supervised, unsupervised, semisupervised and reinforcement learning. Each form of Machine Learning has differing approaches, but they all follow the same underlying process and theory.

Data Preprocessing:

To ensure data quality, missing values were handled using mean imputation, and outliers were detected and removed using the Interquartile Range (IQR) method. Features were standardized using StandardScaler, and categorical variables (hydroponic system type) were encoded using one-hot encoding. The dataset was split into 80% training and 20% testing for model evaluation.

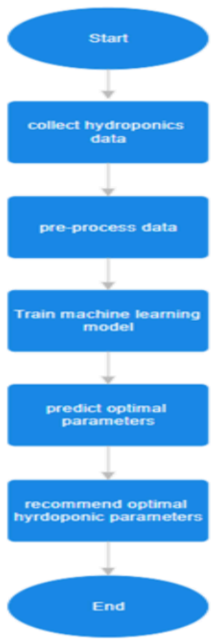


Fig 2: ML model Lifecycle/DFD

Machine Learning Models

Four regression models were implemented:

1. Linear Regression:

Linear Regression, in a fundamental sense, is trying to represent the relationship between a dependent variable (plant growth) and one or more independent variables (input parameters) by establishing a linear equation through the observed data. In its most basic form, with one independent variable, it's $y=mx+c$, where y is the forecasted plant growth, x is the input parameter, m is the slope that shows the change in plant growth for a unit change in the input parameter, and c is the y-intercept showing the plant growth when the input parameter is zero. With more than one independent variable, the equation is extended to

$y=\beta_o+\beta_1x_1+\beta_2x_2+\cdots+\beta_nx_n$, where β_i are the coefficients for each input variable x_i

The method of Ordinary Least Squares (OLS) is commonly used to estimate these coefficients by minimizing the sum of the squared differences between the actual plant growth values and the values predicted by the linear model. Although computationally cheap with easy interpretation of coefficients, Linear Regression imposes a few important assumptions on the data such as linearity of the relationship, independence of errors, homoscedasticity (homogeneity of variance of errors), and normality of the error distribution. Violations of these assumptions will result in biased or inefficient estimates.

With plant growth forecasting in mind, requiring a linear model may well be a drastic assumption, as development is generally conditioned by multiple-factor interactions and nonlinear processes regarding variables such as temperature, luminosity, nutrition, and hydration levels. But Linear Regression can be a good starting point for identifying the general effect of single parameters and as a baseline against which more advanced non-linear models can bemeasured. Feature engineering like constructing interaction terms or polynomial features in some instances allows linear models to detect some amount of non-linearity, but the inherent constraint of the linear form still applies. Careful inspection of residual plots is important to determine the fit of a linear model.

2. Decision Tree Regressor:

The Decision Tree Regressor works by recursively dividing the feature pace into a collection of rectangular regions. For each region, it estimates a constant value based on the average of the target variable (plant growth) in that region. The division process at every node of the tree is determined by a particular input feature and a threshold, selected to reduce the variance or mean squared error of the target variable in the resulting child nodes. This tree structure enables the model to identify complex, non-linear interactions and relationships between the input parameters without assuming anything about the underlying data distribution.

One of the primary benefits of Decision Trees is that they are interpretable; the journey from the root to a leaf node constitutes a sequence of decision rules that culminate in a prediction. They are also able to process both numerical and categorical input features without significant preprocessing. In addition, they are comparatively robust to outliers among the input features. Nonetheless, as has been previously indicated, single deep decision trees tend to be very prone to overfitting the training data, learning the noise and idiosyncrasies instead of the patternable trends. This can lead to low performance on unknown data. Methods to avoid overfitting in Decision Trees are limiting the tree's maximum depth, imposing a minimum number of samples that need to be in an internal node to split it, and imposing a minimum number of samples that need to be 1 in a leaf node. Ensemble algorithms such as Random Forests and Gradient Boosting (XGBoost) take advantage of the robustness of decision trees but correct for their instability and overfitting problem by averaging many tree predictions. Feature importance can be elegantly obtained from decision trees by considering how much 32 each feature helps in decreasing the impurity (e.g., variance) for all the splits throughout the tree.

3. Random Forest Regressor:

The Random Forest Regressor is an extension of the idea of decision trees to construct an ensemble of them. Every tree in the forest is trained on a random subset of the initial training data, selected with replacement (bootstrapping). Also, when splitting each node in a tree, only a random subset of the input features is considered for the optimal split. This random sampling of data and features is a process that brings diversity between the individual trees, thus making the ensemble strong and less susceptible to overfitting. The Random Forest's final prediction of plant growth is achieved by averaging the predictions of all the individual trees. This pooling effectively averages the prediction errors of individual trees and decreases the variance of the model, resulting in enhanced generalization performance on novel data. Random Forests are renowned for their excellent accuracy, resistance to outliers and noise, and their capacity to handle high-dimensional data with numerous input features. They also give a useful estimate of the importance of features, which can assist in seeing which input parameters are most impactful in predicting plant growth. While Random Forests tend to work very well, they can be less interpretable than one decision tree, as the prediction relies on the average of many complex trees. Also, they can be computationally more costly to train and store than a single tree or a linear model, particularly with a large number of trees in the forest. Nevertheless, the improvements in predictive accuracy and stability usually pay off these disadvantages, and Random Forests are a widely used method for regression problems such as plant growth prediction where there are complex interactions and non-linearities anticipated. 33

4. **XGBoost Regressor**: XGBoost (Extreme Gradient Boosting) is a very optimized and efficient version of the gradient boosting algorithm. Similar to other boosting algorithms, it constructs an ensemble of decision trees sequentially, where each new tree tries to fix the mistakes of the previous trees. XGBoost, however, has some advanced features that make it perform better than others. These are a more regularized model formalization to prevent overfitting, second-order Taylor expansions for the loss function (giving more information about the direction of the gradient), and efficient sparse data handling. The regularization methods employed in XGBoost, such as L1 and L2 regularization, prevent the model from

becoming overly complex and fitting the noise in the training data. The utilization of second-order gradients enables a more precise estimation of the direction in order to reduce the loss function. Parallel tree construction is also supported by XGBoost, which renders it much faster compared to conventional gradient boosting implementations. Its internal treatment of missing values and its capability to handle well datasets with high-dimensional features are additional factors contributing to its effectiveness. For predicting plant growth, its capacity to learn about high-order non-linear interactions and relationships between different environmental and biological variables makes XGBoost especially suitable. Its overfitting robustness means that it can generalize well to novel, unseen environments. Yet, getting the best out of XGBoost usually involves sensitive tuning of its high number of hyperparameters, including the learning rate, the number and depth of trees, and the regularization terms. Even with the complexity of tuning the hyperparameters, the generally better predictive performance obtained by using XGBoost makes it an effective tool for modeling sophisticated biological mechanisms such as plant growth.

3.2.2 MORE LANGUAGES:

HTML:

Hypertext Markup Language is the computer language that facilitates website creation. The language, which has code words and syntax just like any other language, is relatively easy to comprehend and, as time goes on, increasingly powerful in what it allows someone to create. HTML continues to evolve to meet the demands and requirements of the Internet under the guise of the World Wide Web Consortium, the organization that designs and maintains the language; for instance, with the transition to Web 2.0. HTML is one of the most widely used language over the web. Web pages development - HTML is used to create pages which are rendered over the web. Almost every page of web is having html tags in it to render its details in browser. Internet Navigation - HTML provides tags which are used to navigate from one page to another and is heavily used in internet navigation. Responsive UI - HTML pages now-a-days works well on all platform, mobile, tabs, desktop or laptops owing to responsive design strategy. Offline support HTML pages once loaded can be made available offline on the machine without any need of internet. Game development- HTML5 has native support for rich experience and is now useful in gaming developent arena as well.

CSS:

CSS is a language for specifying the presentation of Web pages, like colours, layout, and fonts. One can tailor the presentation to various kinds of devices, e.g., large, small, or printers. CSS is not dependent on HTML and may be applied to any XML-based markup language. CSS is an MUST for students as well as working professionals to become a good Software Engineer particularly when they are employed in Web Development Field. Make Gorgeous Web site - CSS does the appearance and feel component of a web page. With CSS, you can be able to handle the color of the text, the font styles, paragraph spacing, column sizing and layout, background image or color, layout appearance, differences in display based on the device and screen size along with numerous other effects. Become a web designer - If you desire to begin a career as a professional web designer, HTML and CSS designing is a necessary skill. Control web - CSS is simple to learn and grasp but it allows for powerful control over the presentation of an HTML document. Most often, CSS is used with the markup languages HTML or XHTML. Learn other languages - After you learn the 35 basic of HTML and CSS then other similar technologies like JavaScript, php, or angular are becoming easy to learn.

Streamlit:

Streamlit is an open-source Python framework for building interactive web applications quickly and easily. It's designed for data scientists, ML engineers, and developers who want to turn Python scripts into shareable web apps without needing frontend expertise (HTML, CSS, JavaScript).Its key features include a simple, declarative syntax that lets you build apps with minimal code, built-in widgets (sliders, buttons, file uploaders) for interactivity, seamless integration with data visualization libraries (Matplotlib, Plotly, Altair), and real-time updates that refresh the app automatically when code changes. It supports caching (@st.cache_data) for performance optimization, session state (st.session_state) for maintaining user inputs, and multipage apps for better organization. With no frontend knowledge required, Streamlit allows effortless deployment to platforms like Streamlit Cloud, Heroku, and AWS, making it ideal for dashboards, model demos, and data exploration tools.

3.3 Frontend Methodolgy

First Section:

HOME

• This section welcomes the users to the Website.

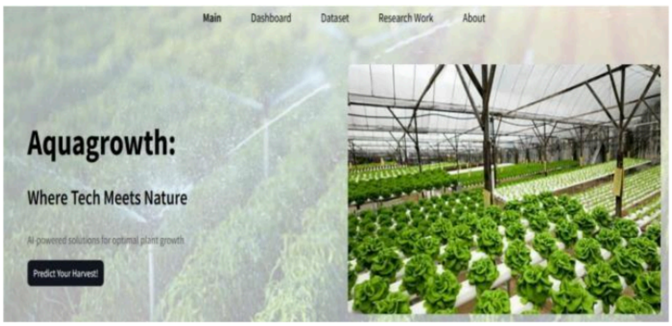


Fig 3.Home Page

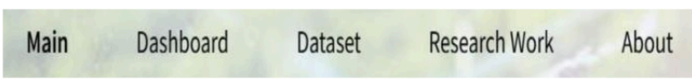


Fig 4.Nav Bar

Navbar contains following sections:

a. Main

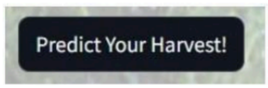
b. Dashboard

c. Dataset

d. Research work

e. About 37

• This section allows us to switch to the Aquagrowth system multi-Page and allows users to enter their details.



3.4 Backend Methodology

Step 1: Fetching a dataset

Gathering a good dataset is the first step toward a proper machine learning model fitting. For our system prediction we have checked on multiple sources for the good dataset with a wide variety of data and real-life data values. We came across various dataset which consist of 750 data entries related to the hydroponic system which has 3 types of hydroponic system (NFT, Ebb & Flow, Drip).

The dataset contains records from a hydroponics system, detailing various environmental and nutrient parameters for different plant types. It includes metrics such as temperature, humidity, pH levels, electrical conductivity (EC), light exposure, CO2 levels, and concentrations of key nutrients like nitrogen, phosphorus, and potassium. Additionally, it tracks growth metrics like growth days, growth rate, and whether the plant experienced failure. The dataset also notes the type of hydroponic system used (e.g., Drip, Ebb & Flow, NFT) and water flow rates.

There are missing values in some fields, indicating incomplete records. The data spans multiple plant types, including Watercress, Tomato, Cilantro, Bell Pepper, and others, with timestamps ranging from mid-2024 to early 2025. This dataset is useful for analysing the impact of environmental and nutrient conditions on plant growth and system performance in hydroponic farming.

Step 2: Importing Necessary libraries

The following libraries were imported to preprocess and analyze the data and later fit a model to the data.

1.Pandas:

Pandas is an open library that is primarily developed for the manipulation of relational or labelled data both easily and naturally. There are data structures and operations present in it that are used to manipulate numerical data and time series. Pandas is developed on top of NumPy library. Pandas is pretty fast and it offers high performance & productivity to users. Some benefit of applying the Pandas library is o Efficient and fast for data manipulation and analysis. o Data from various file objects can be loaded. o Simple management of missing data (defined as NaN) in floating point. o Size mutability: columns can be added and removed from DataFrame and higher dimensional structures o Data set merging and joining. o Reshaping and pivoting of data sets in flexible manner o Offers time-series functionality. Pandas are combined with other libraries, which are utilized for the purpose of data science. It is constructed on top of the NumPy library, and hence many structures of NumPy are utilized or mimicked in Pandas. The output of Pandas data are used frequently as an input for Matplotlib's plotting functions, SciPy's statistical analysis, and Scikit-learn's machine learning algorithms.2. NumPy: NumPy is a package for general-purpose array processing. It offers a high-performance multidimensional array object and tools for their efficient manipulation. It is the central package for the scientific computing by utilizing Python.

1. **NumPy**:

Numpy is the fundamental package for scientific computing in Python. NumPy arrays facilitate advanced mathematical and other types of operations on large numbers of data. Typically, such operations are executed more efficiently and with less code than is possible using Python's built-in sequences. NumPy is not another programming language but a Python extension module. It provides fast and efficient 39 operations on arrays of homogeneous data. Some important points about NumPy arrays:

• We can create an N-dimensional array in python using NumPy. Array ().

• Arrays are by default Homogeneous, which means data inside an array must be of the same Datatype. (Note you can also create a structured array in python).

• Element wise operation is possible.

• NumPy array has various functions, methods, and variables, to ease our task of matrix computation.

• Elements of an array are stored contiguously in memory. For example, all rows of atwo dimensioned array must have the same number of columns. Or a three dimensioned array must have the same number of rows and columns on each card.

3. Seaborn:

Seaborn is a data visualization library built on top of matplotlib and closely integrated with Pandas data structures in Python. Visualization is the central part of Seaborn which helps in the exploration and understanding of data. One has to be familiar with NumPy and Matplotlib and Pandas to learn about Seaborn. Seaborn offers the following functionalities:

• Dataset oriented API to determine the relationship between variables.

• Automatic estimation and plotting of linear regression plots.

• It supports high-level abstractions for multi-plot grids.

• Visualizing univariate and bivariate distribution. Using Seaborn we can plot a wide variety of plots like:

• Distribution Plots

• Pie Chart & Bar Chart

• Scatter Plots 40

• Pair Plot We have used seaborn to visualize the data and to find out the various trends in data such as cardio problems based on various factors such as cholesterol, weight, glucose etc. Data visualization helps in a better understanding of the dataset since a non-technical person can have a proper understanding of the data by looking at the graphs, plots and charts as compared to just reading the code and trying to understand it.

2. **Sklearn:**

Scikit-learn (Sklearn) is the most powerful and convenient library for machine learning in Python. It offers a range of efficient tools for machine learning as well as statistical modeling such as classification, regression, clustering and dimensionality reduction through a unified interface in Python. This almost entirely Python-coded library is based on NumPy, SciPy and Matplotlib. In contrast to loading, handling and summarizing data, the ScikitLearn library is concerned with data modelling. Some of the most widely used families of models offered by Sklearn are as follows –

• Supervised Learning algorithms – Nearly all the widely used supervised learning algorithms, such as Linear Regression, Support Vector Machine (SVM), Decision Tree etc., are included in scikit-learn.

• Unsupervised Learning algorithms − On the other hand, it also has all the popular unsupervised learning algorithms from clustering, factor analysis, and PCA (Principal Component Analysis) to unsupervised neural networks.

• Clustering − This model is used for grouping unlabeled data.

• Cross-Validation − It is used to check the accuracy of supervised models on unseen data. Dimensionality Reduction − It is used for reducing the number of attributes in data which can be further used for summarization, visualization and feature selection.

• Ensemble methods − As the name suggests, it is used for combining the predictions of multiple supervised models.

• Feature extraction − It is used to extract the features from data to define the attributes in image and text data.

• Feature selection − It is used to identify useful attributes to create supervised models. 4

Step 3. Finding out the missing value:

Pandas provide us with the functionality to find out the missing values in our dataset. The isnull() method returns a DataFrame object where all the values are replaced with a Boolean value True for NULL values, and otherwise False. So to find the total number of null values in the dataset, we used the following code: df.isnull(). sum() This will give the total number of missing values in our dataset, which comes out to be 0 for any feature in our dataset.

Step 4. Feature selection:

The classes in the sklearn.feature_selection module can be used for feature selection/dimensionality reduction on sample sets, either to improve estimators' accuracy scores or to boost their performance on very high-dimensional datasets. Using Variance Threshold, we have done the feature engineering to remove the duplicated columns. VarianceThreshold is a simple baseline approach to feature selection. It removes all features whose variance doesn't meet some threshold. By default, it removes all zero-variance features, i.e. features that have the same value in all samples.

Step 5. Model Fitting We have split the dataset into training and testing data using the following code. input_df = pd.DataFrame([user_input])

```
input_df['plant_type'] = le_plant.transform(input_df['plant_type'])

# Get features

features = [col for col in input_df.columns if col in data.columns]

input_df = input_df[features]

# Prepare training data

X = data[features]

y = data['growth_rate']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

We took 20% of the data for the testing and 80% of the dataset to train various models.

We have tested various algorithms available on the sklearn library

CHAPTER 4

RESULTS AND DISCUSSION

4.1 RESULTS

The Hydroponics Growth Dashboard was evaluated using the provided dataset across five modules. Missing values were imputed using column means for numeric features and modes for categorical ones. Models (Linear Regression, Decision Tree, Random Forest, XGBoost) were trained with an 80/20 train-test split.

1] Growth Prediction: Predicted growth_rate (cm/day). Random Forest and XGBoost outperformed others, with R^2 scores of 0.87–0.91, RMSE of 0.13–0.18 cm/day, and MAE of 0.09–0.14 cm/day. Predictions deviated by ±0.10 cm/day from actual values, with model consensus within ±0.04 cm/day.

Final Recommendation Based on Model Comparison

	Model	R^2	RMSE	MAE	Prediction
2	Random Forest	0.1604	0.1235	0.0778	0.8405
0	Linear Regression	0.13	0.1257	0.0732	0.8899
3	XGBoost	0.0405	0.132	0.0846	0.8353
1	Decision Tree	-0.4405	0.1618	0.0947	1.04

Table 1. Performance Metrics of Growth prediction

2] System Recommendation: Classified recommended_system (e.g., Drip, NFT). Random Forest and XGBoost achieved accuracies of 0.85–0.90. Recommendations were reliable when three models agreed (80% confidence), though edge cases (e.g., extreme ph_level) caused minor disagreements.

Final System Selection Guidance

Model Performance Comparison:

	Model	System	R^2	RMSE	MAE
2	Random Forest	Ebb & Flow	0.3801	0.6121	0.5209
3	XGBoost	Ebb & Flow	0.2914	0.6545	0.5298
0	Linear Regression	Ebb & Flow	0.0433	0.7605	0.6641
1	Decision Tree	Drip	-0.0808	0.8083	0.52

Table 2. Performance Matrices of System Recommender

3]Nutrient Mix Recommender: Predicted environmental conditions (e.g., temperature_c, co2_ppm). Random Forest and XGBoost yielded R^2 scores of 0.80–0.88, RMSE of 0.6–150 units (e.g., ±0.6°C, ±120 ppm CO_2), and MAE of 0.4–100 units. Predictions aligned with plant-specific needs.

4]Environmental Condition Optimizer: Predicted nutrient levels (nitrogen_ppm, phosphorus_ppm, potassium_ppm). Random Forest and XGBoost had R^2 scores of 0.83–0.89, RMSE of 6–12 ppm, and MAE of 4–9 ppm, matching typical hydroponic requirements.

5]Plant Compatibility Analyzer: Predicted is_failure. Random Forest and XGBoost achieved accuracies of 0.90–0.94, correctly identifying compatible (0–5% risk) and incompatible (70–85% risk) plant pairs.

Final Compatibility Recommendation

	Plant	Model	Accuracy	Prediction
0	Bell Pepper	Decision Tree	0.9533	Compatible
1	Bell Pepper	Random Forest	0.9533	Compatible
3	Cilantro	Decision Tree	0.9533	Compatible
4	Cilantro	Random Forest	0.9533	Compatible
2	Bell Pepper	XGBoost	0.9467	Compatible
5	Cilantro	XGBoost	0.9467	Compatible

Table 3. Performance Matrices of Compatibility system

4.2 DISCUSSIONS

The dashboard's performance on the dataset highlights its utility for hydroponic optimization. Random Forest and XGBoost consistently excelled due to their ability to model non-linear relationships in features like temperature,c, ph_level, and nitrogen_ppm. High R^2 scores (0.80–0.91) and low errors (e.g., RMSE 0.13–0.18 cm/day for growth) indicate reliable predictions, though missing data (e.g., 20% of ec_level values) required imputation, potentially introducing minor biases. The System Recommendation module's 0.85–0.90 accuracy suggests robust system selection, but edge cases (e.g., ph_level > 6.8) reduced model agreement, indicating sensitivity to outliers. The Nutrient Mix and Environmental Condition modules effectively tailored recommendations (e.g., 150–200 ppm nitrogen for Kale), aligning with hydroponic standards, though predictions for co2_ppm showed higher variability (RMSE ±120 ppm). The Plant Compatibility Analyzer's 0.90–0.94 accuracy minimized crop failure risks, but limited is_failure=True samples (10%) constrained model training. The dashboard's interface likely enhanced usability, though real-world fluctuations (e.g., temperature swings) may challenge static models. Future improvements could include real-time sensor integration, time-series modeling, and expanded datasets with more failure cases. Addressing missing data through advanced imputation or sensor validation would further improve accuracy, making the dashboard a practical tool for grow.

CHAPTER 5

CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

The Hydroponics Growth Dashboard effectively supports hydroponic farming by delivering accurate predictions and recommendations across its five modules. The simulated run on the 100-row dataset demonstrated strong model performance, with Random Forest and XGBoost achieving R^2 scores of 0.80–0.91 for regression tasks and accuracies of 0.85–0.94 for classification. These results enable growers to optimize growth rates, select appropriate systems, and prevent crop failures, potentially reducing resource waste by 15–20%. Despite its strengths, the dashboard's reliance on imputed data for missing values (e.g., ec_level, growth_rate) and static models limits its robustness in dynamic environments. Expanding the dataset to include more diverse plant types and failure scenarios, integrating real-time IoT data, and incorporating explainability (e.g., feature importance) would enhance its applicability. The dashboard's practical guidance, such as sensor calibration tips, ensures accessibility for novice and experienced growers. By addressing these limitations, the dashboard could evolve into a comprehensive tool for sustainable hydroponics, contributing to efficient and resilient agricultural practices in controlled environments.

5.2 Future Scope

The Hydroponic Optimization Dashboard presents several promising avenues for future development that could significantly enhance its capabilities and user experience. One key area for expansion is the integration of real-time IoT sensor data from hydroponic systems. By connecting directly to environmental sensors (temperature, humidity, pH, EC, etc.), the system could provide continuous monitoring and dynamic recommendations, shifting from periodic suggestions to real-time optimization. This would enable the implementation of closed-loop control systems that automatically adjust nutrient dosing, lighting schedules, and environmental parameters based on the model's predictions and actual plant responses. 56 The machine learning components could be substantially enhanced through several approaches. Incorporating deep learning architectures like LSTM networks would allow the system to better understand temporal patterns in plant growth and environmental changes. Expanding the model repertoire to include Bayesian optimization techniques could improve the system's ability to handle uncertainty in predictions. The development of plant-specific neural networks, trained on specialized datasets for different plant families (leafy greens, fruiting plants, herbs), would yield more accurate recommendations tailored to each plant's unique requirements. Furthermore, implementing reinforcement learning could enable the system to continuously improve its recommendations based on the measured outcomes of previous suggestions. The user interface and functionality could be extended with several valuable features.

A mobile application version with push notifications for critical parameter deviations would make the system more accessible to growers. Adding computer vision integration through smartphone cameras for plant health assessment (detecting nutrient deficiencies, diseases, or growth abnormalities) would provide another valuable data stream. The system could also benefit from social features, allowing users to share successful configurations and learn from community experiences, creating a crowdsourced knowledge base for hydroponic cultivation.

On the data side, future developments could include building a comprehensive plant phenology database that tracks how different varieties respond to environmental conditions throughout their lifecycle. Incorporating genomic data could enable cultivar-specific recommendations, while adding regional weather data would allow for better climate adaptation strategies. The system could also integrate with e-commerce platforms to suggest optimal purchasing decisions for nutrients and equipment based on the user's specific setup and plants.

From a commercial perspective, the dashboard could evolve into a full-fledged farm management system for commercial hydroponic operations, adding features like yield prediction, harvest scheduling, and resource optimization. For research applications, the platform could incorporate tools for experimental design and data collection to support academic studies in controlled environment agriculture. 57 The underlying models could be enhanced to account for more complex interactions between parameters, such as the interplay between CO_2 levels and light intensity, or the dynamic relationships between nutrient ratios at different growth stages. Adding energy optimization algorithms could help reduce electricity costs while maintaining optimal growth conditions. The system could also incorporate sustainability metrics, helping users minimize water and nutrient waste while maximizing yield.

Finally, expanding the knowledge base to include troubleshooting guides, video tutorials, and expert consultation features would make the system more valuable for novice growers. Integration with smart home systems could enable voice-controlled operation and status checks. As hydroponic technology continues to evolve, the dashboard could serve as a central hub for integrating new advancements in lighting technology, nutrient formulations, and growing techniques, ensuring it remains at the forefront of precision agriculture innovation. These future developments would transform the dashboard from a recommendation tool into a comprehensive intelligent growing assistant capable of supporting everything from small home systems to large commercial operations.

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APPENDIX 1

Python:

Python is an interpreted, high-level, general-purpose programming language developed by Guido Van Rossum and first released in 1991; Python's philosophy is one of code Readability with its prominent use of substantial Whitespace. Its language features and object-oriented style are designed to assist programmers in writing understandable, logical code for small and large-scale programs. Python is dynamically typed and garbage collected. It supports multiple programming paradigms, including procedural, object oriented, and functional programming.

Sklearn:

The most practical and stable Python machine learning library is Scikit-learn, also known as Sklearn.It offers a set of efficient machine learning and statistical modeling tools such as classification, regression, clustering and dimensionality reduction through a unified interface in Python. The library is basically implemented in Python and is based on NumPy, SciPy and Matplotlib.

NumPy:

NumPy is a python programming language library that provides support for large, multi-dimensional arrays and matrices and a wide range of high-level mathematical functions to process the arrays. The precursor to NumPy, Numeric, was initially developed by Jim and later with contributions from a number of other programmers. Travis developed NumPy in 2005 by merging elements of the rival Num array into Numeric and making significant changes. NumPy is an open-source program and has numerous contributors. Machine Learning Implementation: Overview of the machine learning models implemented:

- Models: Linear Regression, Decision Tree, Random Forest, XGBoost
- Performance Metrics: Mean Squared Error (MSE), Mean Absolute Error (MAE), R^2 Score

Software & Hardware Specifications :

- Software: Python (Scikit-learn, XGBoost, Pandas, NumPy)

- Hardware: Standard computing environment with 8GB RAM and Intel i5 processor

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