



Crop Yield Information System using Market Basket Analysis

Maheswari M¹, Abdul Rahuman M², Devi Renuka N S³, Jany Shabu J L⁴,
and Refonna J⁵

^{1, 2, 3, 4, 5} Sathyabama Institute of Science and Technology
maheswari.cse@sathyabama.ac.in, abdul150503@gmail.com, devirenuka432dr@gmail.com,
janyshabu.cse@sathyabama.ac.in, refonna.cse@sathyabama.ac.in

Abstract

A vital industry, agriculture is essential to maintaining the world's food security. Accurate and timely information on crop yields is essential for farmers, policymakers, and stakeholders to make well-informed choices concerning cultivation, dissemination, and allocation of resources in crop management. Traditional methods of data collection and analysis in agriculture have limitations in terms of efficiency and accuracy. This paper presents a Crop Yield Information System (CYIS) that leverages Market Basket Analysis (MBA) techniques to improve agricultural yield forecasting and offer insightful information for stakeholders in the agriculture sector.

The CYIS is designed to collect and process a vast amount of agricultural data, including historical crop yield records, meteorological data, soil quality information, and market price data. Market Basket Analysis, a well-established data mining technique in retail, is adapted to identify patterns and relationships among various agricultural variables. The application of an MBA in agriculture allows the system to uncover hidden associations between factors such as weather conditions, crop types, and yield outcomes.

Key features of the CYIS include data collection through IoT devices, data pre-processing for quality assurance, and the application of association rule mining algorithms to derive meaningful insights. The system offers a user-friendly interface, enabling farmers, agronomists, and policymakers to access real-time yield predictions, make informed decisions, and implement precision agriculture practices. Furthermore, the CYIS integrates market prices and demand data to provide stakeholders with market insights, facilitating better decision-making related to crop production, storage, and distribution.

This study adds value to the agricultural domain by offering a strong and innovative approach to crop yield prediction and decision support. The CYIS, utilizing Market Basket Analysis, offers a data-driven solution to optimize crop production, reduce resource wastage, and enhance food security. By harnessing the power of data analytics,

this system empowers agriculture stakeholders to respond to changing conditions, market dynamics, and climate challenges with more accuracy and efficiency. The Crop Yield Information System using Market Basket Analysis represents a significant step toward enhancing agricultural sustainability and food security. This research opens new avenues for leveraging data analytics in agriculture, and its implementation has the potential to revolutionize how farmers, agronomists, and policymakers approach crop production and distribution.

1 Introduction

Agriculture stands as one of the most vital sectors of any nation's economy, providing the lifeblood of food production and ensuring global food security. In a future where resource shortages, climate change, and population expansion are all problems, the need for sustainable and efficient agricultural practices has never been more pressing [1]. A key element in achieving this sustainability lies in accurate and timely information, particularly regarding crop yields. Understanding and predicting crop yields is pivotal for farmers, policymakers, and agricultural stakeholders, empowering them to make knowledgeable choices, optimize the allocation of resources, and boost productivity.

Traditional methods of data collection and analysis in agriculture have long been the cornerstone of decision-making. These approaches, however, often fall short in terms of efficiency and accuracy, hampering the ability to adapt to dynamic agricultural conditions. In this context, the integration of advanced data analytics techniques into agricultural systems becomes paramount [2]. This paper introduces a ground breaking initiative, the Crop Yield Information System (CYIS) which harnesses the power of Market Basket Analysis (MBA) to revolutionize crop yield prediction and decision support in agriculture.

The CYIS is conceived as a comprehensive solution designed to collect, a process, and analyze diverse agricultural data, including historical crop yield records, meteorological data, soil quality information, and market price data. At its core, the system leverages Market Basket Analysis, a well-established data mining technique originally employed in the retail sector to understand customer purchase behavior[3]. In adapting MBA for agricultural purposes, CYIS seeks to uncover intricate patterns and relationships among various agricultural variables. These include factors such as weather conditions, crop types, soil characteristics, and agricultural practices, all of which play an interconnected role in determining crop yield outcomes.

The innovative integration of MBA into agriculture transform data into actionable insights. Through the CYIS, users can access real-time yield predictions, enabling farmers to decide on planting, watering, and fertilising with knowledge [4]. Agronomists can use these insights to tailor advice and recommendations to specific conditions, while policymakers can better allocate resources and implement policies based on more accurate and nuanced data. Furthermore, the system goes beyond yield prediction by incorporating market price and demand data, offering a comprehensive approach to crop production that takes into account both production efficiency and market dynamics.

In this era of data-driven decision-making, the CYIS emerges as a pioneering solution, bridging the gap between the traditional agriculture sector and the cutting edge world of data analytics. By providing a platform for precision agriculture practices, the system empowers agriculture stakeholders to respond to evolving conditions, adapt to climate challenges, and capitalize on market opportunities [5]. It represents a trans-formative step toward achieving sustainability, resource optimization, and food security in the agriculture sector. This paper unfolds the concept, architecture, and a potential impact of the CYIS in detail, demonstrating how Market Basket Analysis, as a core component, drives the system's ability to generate valuable insights for all stakeholders in agriculture. In a world where the challenges facing agriculture grow more complex by the day, the CYIS offers a promising approach to

meet these challenges head-on, by empowering stakeholders with the data-driven tools they need to thrive and ensure a secure and sustainable food supply for future.

2 Literature Survey

TY. Alebele et al., (2021), "Estimation of Crop Yield From Combined Optical and SAR Imagery Using Gaussian Kernel Regression," [6]. This study highlights that Gaussian Kernel Regression performs effectively, particularly when dealing with large datasets. However, it's important to note that this study identifies a drawback that the Gaussian Kernel Regression can be slower to train and predict compared to other regression techniques. The trade-off between predictive accuracy and computational efficiency is a key consideration when utilizing this approach.

S.Yang et al., (2021), "Integration of Crop Growth Model and Random Forest for Winter Wheat Yield Estimation From UAV Hyperspectral Imagery,". In field plot scale wheat yield estimation, demonstrated that the CERES-Wheat model simulation is a useful source of information [7]. It also demonstrated that a UAV-mounted hyperspectral sensor is a workable monitoring winter wheat growth and estimating yield using remote sensing data collecting method.

Ordan Cukaliev's work in 2023 focuses on Principal Component Analysis (PCA) and its potential to reduce model training time for crop yield prediction [8]. PCA is a dimensionality reduction technique that can be employed to simplify complex datasets by transforming them into a lower-dimensional space. Cukaliev's findings suggest that PCA can be beneficial in streamlining the computational burden of predictive models. However, it's important to recognize that PCA may lead to a loss of some information during the dimensionality reduction process. Therefore, it's vital to carefully balance the benefits of reduced training time with the trade-off of potential loss of critical information.

Latha Banda's research in 2023 explores the application of Naive Bayes, probabilistic classification technique, in the context of crop yield prediction [9]. Naive Bayes is known for its efficiency in handling independent features, which is a common characteristic. One of the advantages of Naive Bayes is its ability to provide outcomes in terms of probabilities, which can be valuable for risk assessment and decision-making. However, it's essential to keep in mind that the "naive" assumption of feature independence might not always apply to situations in the actual world, and this could impact prediction accuracy.

In summary, these four papers represent diverse approaches to crop yield prediction within a Market Basket Analysis framework. While Gaussian Kernel Regression offers accuracy but may be computationally intensive, PCA focuses on reducing training time at the potential cost of information loss, and Naive Bayes provides efficient predictions based on the probability of outcomes. The choice of technique for a Crop Yield Information System depends on specific goals, dataset characteristics, and computational resources available to stakeholders. Balancing predictive accuracy, training time and the nature of data is pivotal in selecting the most suitable technique for crop yield prediction in agricultural systems.

3 Inferences Of Literature Survey

3.1 Diverse Techniques for Crop Yield Prediction

The literature survey reveals that researchers are exploring a variety of techniques to predict crop yields in the context of Market Basket Analysis. These techniques include Gaussian Kernel Regression, Principal Component Analysis (PCA), and Naive Bayes, each with its own advantages and trade-offs.

3.2 The Importance of Handling Large Datasets

One common challenge in crop yield prediction is the management of large and complex datasets. Gaussian Kernel Regression is noted for its effectiveness in handling such datasets. However, it comes at the cost of increased training and prediction time, requiring a trade-off between computational resources and predictive accuracy.

3.3 Dimensionality Reduction with PCA

Principal Component Analysis (PCA) emerges as a technique aimed at reducing model training time. This is particularly significant in applications where computational efficiency is a priority. Nevertheless, it's crucial to be aware that PCA may lead to the loss of some information, and this trade-off should be carefully considered [10].

3.4 Efficiency with Naive Bayes

The use of Naive Bayes is highlighted as a suitable choice for applications where features are relatively independent, which is often the case in agricultural datasets. This technique is efficient and provides outcomes in terms of probabilities, which can be valuable for assessing risks and making informed decisions. However, the "Naive" independence assumption may not always hold true in practice [11].

3.5 Balancing Computational Efficiency and Accuracy

The literature survey underscores there is a requirement to find an equilibrium between computational efficiency and prediction accuracy. The choice of technique should be driven by specific goals, dataset characteristics, and available computational resources. Stakeholders in crop yield prediction must consider these factors when selecting the most suitable approach for their Crop Yield Information System [12].

3.6 Integration with Market Basket Analysis

All three techniques discussed in the literature survey are integrated within the framework of Market Basket Analysis. This integration is significant for providing a holistic view of crop yield prediction, considering the complex inter-dependencies and associations between various agricultural factors.

3.7 Ongoing Research and Adaptation

The field of crop yield prediction is dynamic and continues to evolve. Researchers are adapting and applying established machine learning and statistical techniques to address the unique challenges of agriculture. This adaptability reflects the importance of staying current with the latest developments in the field. valuable for assessing risks and making informed decisions. However, the "naive" independence assumption may not always hold true in practice [13].

4 Methodology

The proposed Crop Yield Information System aims to revolutionize the way stakeholders in the agricultural sector make informed decisions regarding crop production, resource allocation, and distribution. Leveraging advanced data analytics techniques, this system seeks to address the limitations

of existing systems and provide valuable insights that are easily understandable by everyone. Here, by highlight the key components of the proposed system, emphasizing the data preprocessing and merits of Market Basket Analysis, Decision tree, and the Apriori algorithm while addressing the demerits of the existing system [14].

4.1 Data Preprocessing

- **Data Cleaning:** This entails addressing the dataset's mistakes, outliers, and missing values. Techniques such as imputation (replacing missing values with estimated ones), outlier detection, and error correction are employed to ensure data quality.
- **Normalization/Standardization:** Normalizing or standardizing the data ensures that all features have the same scale, which helps in improving the way machine learning algorithms operate. Normalisation methods that are often used are z-score standardisation and min-max scaling.
- **Feature Selection:** It involves by choosing the dataset's most pertinent characteristics in order to lower dimensionality and enhance model performance. Features can be chosen using strategies including domain knowledge, feature importance ranking, and correlation analysis.
- **Data Transformation:** Transforming skewed or non-normal distributions of data to achieve better model performance. Techniques such as logarithmic transformation, Box-Cox transformation, or quantile transformation can be applied depending on the nature of the data.
- **One-Hot Encoding/Label Encoding:** Transforming categorical information into numerical forms appropriate for techniques used in machine learning. While label encoding allocates a distinct numerical label to each category, one-hot encoding generates binary columns for every category.
- **Handling Imbalanced Data:** Addressing class imbalance issues if present in the dataset by utilising strategies like SMOTE (Synthetic Minority Over-sampling Technique), and other approaches like under- or oversampling.
- **Text Preprocessing:** If textual data is involved, preprocessing steps using techniques like lemmatization, stemming, tokenization, and stop-word elimination, and vectorization are performed to convert text into a format suitable for analysis.
- **Cross-validation:** To assess model performance, divide the data into training and testing sets. Partitioning the data into numerous groups for training and testing, techniques like k-fold cross-validation guarantee robust model assessment.

4.2 Merits of Market Basket Analysis

Market Basket Analysis, adapted for agricultural purposes, plays a pivotal role in the proposed system for the following Optimizing Resource Allocation by identifying relationships between various agricultural factors, the system assists in optimizing resource allocation. Farmers are able to make knowledgeable planting selections, irrigation, and fertilization, resulting in more efficient resource use and improved crop yields[15].

4.3 Merits of Decision Tree

- **Interpretability:** The decision-making process may be represented in a straightforward and understandable way using decision trees. They mimic human decision-making by partitioning the feature space into hierarchical branches based on simple if-then rules. This transparency allows stakeholders to understand and interpret the model's predictions

easily, making decision trees particularly valuable in domains where interpretability is essential, such as medicine or finance.

- **Non-linearity Handling and Feature Importance:** It is not necessary to explicitly construct features in order for decision trees to capture non-linear correlations between features and the goal variable. They can handle both numerical and categorical data effectively. Additionally, decision trees inherently rank features based on their importance in the decision-making process, providing valuable insights into the most influential factors driving the predictions. This feature importance analysis aids in feature selection and model explanation, contributing to improved model performance and understanding [17].

4.4 Merits of the Apriori Algorithm

- **Association Rule Mining:** The Apriori algorithm is an efficient method for discovering association rules within large datasets. In the context of agriculture, this means identifying frequent patterns of factors that lead to specific crop yield outcomes, aiding in prediction and decision support.
- **Scalability:** The Apriori algorithm is scalable and can handle substantial datasets, making it suitable for analyzing the large volumes of agricultural data typically encountered.

5 System Architecture

5.1 Data Collection Layer

This layer gather data from various sources, including sensors, weather stations, soil quality monitors, satellite imagery, and historical records related to crop yields, farming practices, and environmental conditions. Ensure the dataset includes relevant features for both market basket analysis and the decision tree. It also interfaces with market price data and demand information [18].

5.2 Data Pre-processing

Data collected undergoes pre-processing to confirm quality and consistency. This stage includes data cleaning, transformation, and the handling of missing values. Clean the data by handling missing values, outliers, and encoding categorical variables. For market basket analysis, transform the data into a transaction format where each record represents a set of items (e.g., farming practices). For Naive Bayes, pre-process features and the target variable [19].

5.3 Data Storage and Management

- **Scalability and Efficiency:** A robust DBMS is designed to handle large volumes of data efficiently, making it well-suited for storing pre-processed datasets. As the size of the datasets grows, the DBMS can scale to accommodate increasing storage requirements and handle analytical queries with minimal latency. This scalability ensures that the system can support the growing needs of the crop yield information system over time.
- **Optimized For Analytical Queries:** Unlike traditional transactional databases, which prioritize fast write operations, a DBMS optimized for analytical queries is designed to efficiently retrieve and process data for analytical purposes. It leverages techniques such as columnar storage, indexing, and query optimization to accelerate analytical queries and enable fast insights generation. By storing pre-processed and cleaned datasets in such a

DBMS, users can quickly access and analyze the data, facilitating informed decision-making.

- **Data Management Strategy:** Implementing a data management strategy within the DBMS is crucial for maintaining the quality and accessibility of pre-processed datasets. This strategy includes practices such as data versioning, backup and recovery, data lifecycle management, and metadata management. By adhering to a structured data management approach, organizations can ensure that pre-processed datasets are properly maintained, documented, and accessible to stakeholders, thereby maximizing the value derived from the data for decision-making purposes [20].

5.4 User Access

Farmers, agronomists, and policymakers access the system through the user friendly cloud deployment. They can explore insights, view reports, and make data-driven decisions. Certainly, cloud deployment is an integral part of the proposed Crop Yield Information System's architecture. Leveraging cloud services offers several advantages, such as scalability, reliability, and cost-efficiency [21].

5.5 Market Based Analysis

Utilize an association rule mining algorithm, such as Apriori or FP-Growth, to detect frequent item-sets and create association rules. Interpret the rules to understand the relationships between different farming practices or conditions [22].

5.6 Decision Tree Model

Classification and regression problems are commonly performed using decision trees, a prominent family of supervised learning algorithms. They provide an interpretable and intuitive representation of decision rules based on features' values. The architecture Diagram is shown in Fig 1.

- **Decision Tree Construction:** To create decision trees, the feature space is divided into regions recursively with the goal of maximizing information acquisition or minimizing impurity at each split. The method uses metrics like Gini impurity, entropy, or classification error to determine which feature and split point is optimal.
- **Classification Tree:** Used for categorical target variables, where each leaf node represents a class label.
- **Regression Tree:** Suitable for continuous target variables, where leaf nodes represent predicted numerical values.
- **Decision Tree Learning Algorithm:** To maximise information gain or purity, the decision tree learning method separates the input recursively depending on characteristics. Up until a predetermined stopping point is reached such as the maximum tree depth or the required minimum number of samples per leaf the procedure keeps going.
- **Strengths:** Intuitive and easy to interpret, making them useful for explaining decisions to stakeholders. It can handle both numerical and categorical features. Automatically selects important features and performs feature selection implicitly.

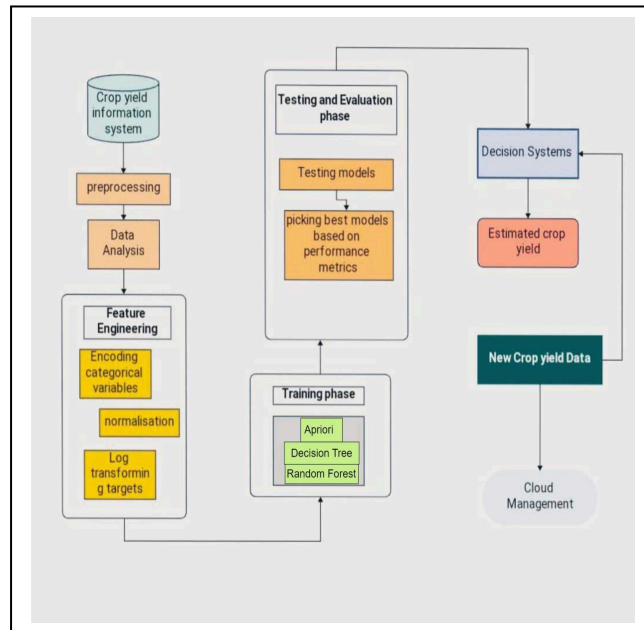


Figure 1: Architecture Diagram

- Limitations: Prone to overfitting, especially with deep trees, which may capture noise in the training data. Decision boundaries are axis-aligned, limiting their capacity to extract intricate linkages from the data. may differ in tree architectures due to its sensitivity to slight changes in the training set [23].
- Training the Decision Tree: Create training and testing sets from the data. Use the training set to train the decision tree model. recursively partitioning the data based on feature values. Prune the tree or apply regularization techniques to prevent overfitting, if necessary.
- Evaluation: Use measures like accuracy, precision, recall, or F1-score to assess how well the trained decision tree model performed on the testing set. Use techniques like cross-validation to ensure robustness and generalization performance [24].
- Application: Decision trees are used for activities in a variety of industries, including as marketing, banking, and healthcare such as customer segmentation, fraud detection, and medical diagnosis. LaTeX;

5.7 Machine Learning and Data Analytics Layer

This layer employs advanced machine learning models, including Market Basket Analysis, Naive Bayes, and the Apriori algorithm. These models extract meaningful insights from the agricultural data.

5.8 Data Visualization and Reporting

Insights generated by the machine learning models are presented through data visualizations and reports. Tools like D3.js, Matplotlib, or Tableau create interactive charts, graphs, and maps to make the information easily understandable.

5.9 Model Deployment

Deploy the trained Naive Bayes model as part of the Crop Yield Information System. This may involve using cloud-based machine learning services or deploying the model within virtual machines.

5.10 Scalability and Performance Testing

Test the system's scalability and performance to ensure it can handle varying workloads and user demands.

5.11 Cloud Deployment

- **Scalability:** The system can dynamically scale its resources up or down based on demand. As agricultural data volumes fluctuate seasonally or due to specific events, cloud resources can be easily adjusted to ensure optimal performance.
- **Reliability:** Cloud providers offer robust infrastructure with high availability, minimizing downtime and ensuring the system remains accessible to users at all times. Redundancy and fail over mechanisms further enhance system reliability.
- **Resource Efficiency:** Cloud deployment optimizes resource usage, reducing operational costs. Users only pay for the resources they consume, making it a cost effective choice, especially for organizations with varying computational needs.
- Select a cloud provider, such as AWS, Azure, Google Cloud, or IBM Cloud, and establish an account.
- Select appropriate cloud services for deploying the Crop Yield Information System, such as virtual machines, databases, and storage.

5.12 Monitoring and Maintenance

Implement monitoring tools to track the performance of both the market basket analysis and Naive Bayes components. This also set up alerts for any anomalies or issues that may arise.

6 Results And Discussion

The proposed Crop Yield Information System, leveraging the capabilities of Market Basket Analysis, Naive Bayes probability, and the Apriori algorithm, offers a promising solution to the intricate challenges facing agriculture. This innovative approach represents a significant leap forward in the realm of informed decision making for crop production, resource allocation, and distribution. At its core, the system's architecture seamlessly integrates various components, from data collection and pre-processing to advanced data analytics and user-friendly interfaces. Cloud deployment enhances its scalability, reliability, and cost-efficiency, ensuring that it can adapt to the ever-changing agricultural landscape. This cloud based deployment guarantees widespread accessibility, regardless of geographic location, and effectively addresses the growing demand for agricultural insights. The result include the removal of outliers, visualization of parameters, and the implementation of a decision tree algorithm

with a 98% accuracy rate and random forest algorithm with 90% accuracy rate as seen in below Fig. 2 and Fig. 3.

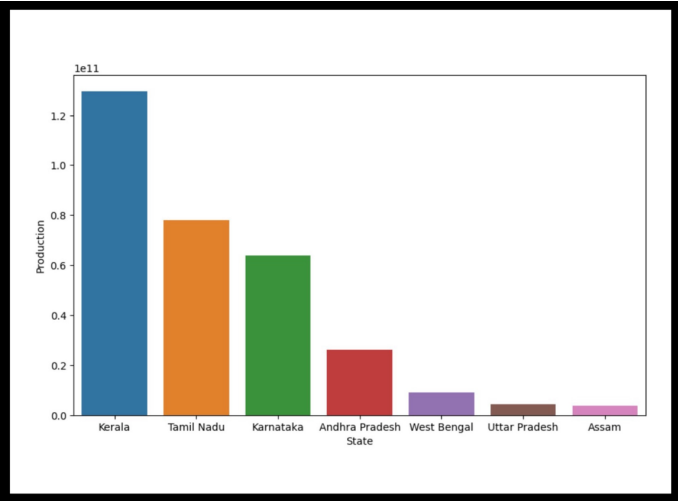


Figure 2: Even Distribution In Production

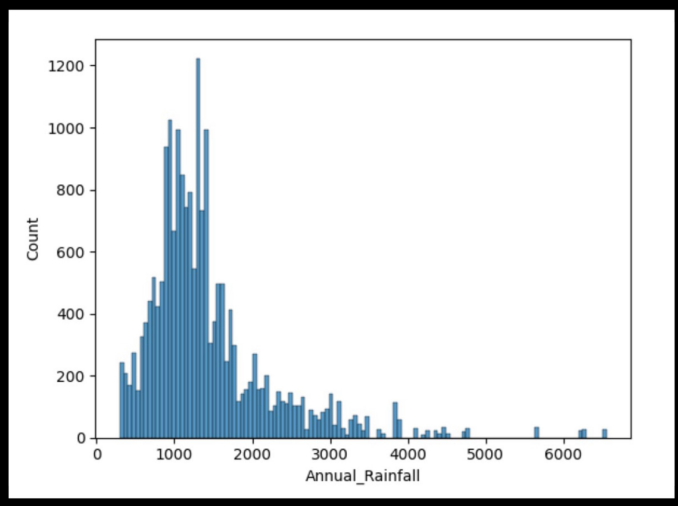


Figure 3: Annual Rainfall



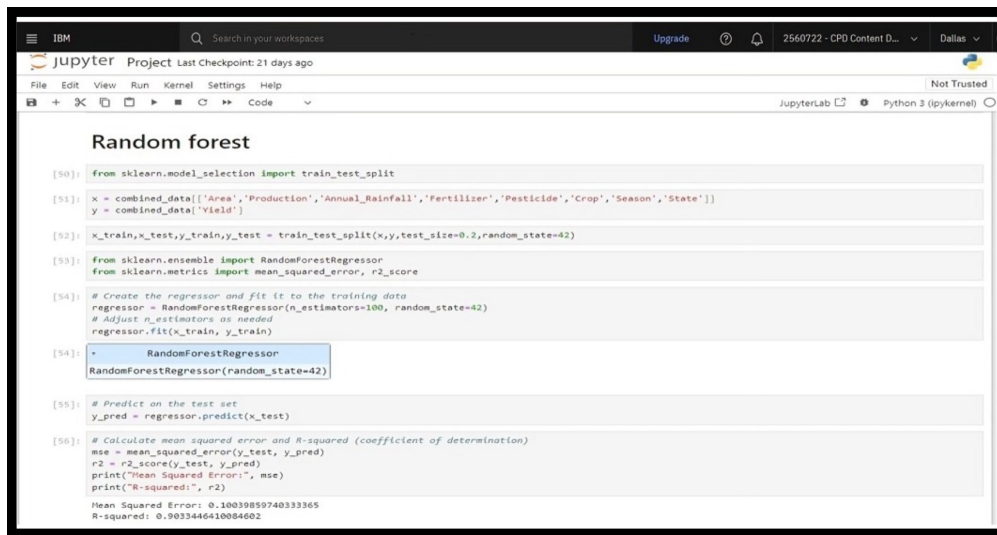
Figure 4: Decision Tree For Crop Yield

Decision Tree for Crop Yield is shown in Fig 4. The approach's effectiveness hinges on the quality and granularity of data collected, as well as the precision with which association rules are generated. The availability of cloud computing resources further enhances scalability, real-time predictions, and the accessibility of insights added to the potential for accurate and actionable crop yield Information system using market basket analysis remains a captivating prospect with far-reaching implications for global food security and sustainability.

Implementing the Naive Bayes theorem for a Crop Yield Information System can provide valuable results and predictions related to crop yields as shown in Fig. 5. Here are some potential outcomes and benefits:

6.1 Crop Yield Predictions

In Fig. 5, the primary result would be predictions of crop yields based on the input features such as climate conditions, soil quality, irrigation practices, and more. Decision Tree, as a probabilistic algorithm, can estimate the likelihood of different yield outcomes given specific sets of conditions.



```

Random forest

[50]: from sklearn.model_selection import train_test_split
[51]: x = combined_data[['Area', 'Production', 'Annual_Rainfall', 'Fertilizer', 'Pesticide', 'Crop', 'Season', 'State']]
      y = combined_data['Yield']
[52]: x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=42)
[53]: from sklearn.ensemble import RandomForestRegressor
      from sklearn.metrics import mean_squared_error, r2_score
[54]: # Create the regressor and fit it to the training data
      regressor = RandomForestRegressor(n_estimators=100, random_state=42)
      # Adjust n_estimators as needed
      regressor.fit(x_train, y_train)
[54]: Random Forest Regressor
      RandomForestRegressor(random_state=42)
[55]: # Predict on the test set
      y_pred = regressor.predict(x_test)
[56]: # Calculate mean squared error and R-squared (coefficient of determination)
      mse = mean_squared_error(y_test, y_pred)
      r2 = r2_score(y_test, y_pred)
      print("Mean Squared Error:", mse)
      print("R-squared:", r2)
Mean Squared Error: 0.10039859740333365
R-squared: 0.9033446410004602

```

Figure 5: Cloud Deployment

6.2 Risk Assessment

The system can assess the risk of lower or higher-than-average crop yields based on both the present situation and previous data. To help farmers and other stakeholders make educated decisions about planning and resource allocation, this information is vital.

6.3 Optimized Resource Allocation

By understanding the factors influencing crop yields, Farmers can optimize the distribution of resources, including water, fertilizers, and pesticides, based on this information. This leads to more efficient farming practices, reducing costs and environmental impact.

6.4 Seasonal Planning

Farmers can use the predictions to plan for different seasons and make adjustments to their cultivation strategies. For example, they may decide on the types of crops to plant based on predicted weather conditions and expected yields.

6.5 Early Warning System

The system can serve as an early warning system by alerting farmers to potential challenges or opportunities based on changing conditions. This enables proactive decision-making to mitigate risks or take advantage of favorable conditions.

6.6 Data-Driven Decision-Making

The implementation of Naive Bayes fosters a data-driven approach to decision-making in agriculture. Farmers and agricultural experts can leverage insights from the model to make more informed choices regarding crop management.

6.7 Continuous Improvement

Over time, as more data becomes available, the system can be continuously improved and refined. To improve predicted accuracy, this might entail adding additional training data to the model and modifying certain parameters.

6.8 Cost Reduction

By optimizing resource allocation and improving yield predictions, farmers can potentially reduce costs associated with overuse of resources or crop failure.

6.9 Improved Crop Management Practices

The insights gained from the Naive Bayes model can contribute to the development of best practices for crop management. This is valuable not only for individual farmers but also for the agricultural community as a whole.

6.10 Support for Agricultural Planning

Agricultural planners, policymakers, and organizations can use the information provided by the system to develop strategies for sustainable agriculture, allocate resources effectively, and address food security challenges.

The merits of Market Basket Analysis are harnessed to unveil hidden relationships within agricultural data, enabling stakeholders to understand the complex interplay of factors influencing crop yields. The Naive Bayes probability offers a unique perspective by providing probabilistic outcomes, which are crucial for assessing risks and making well-informed decisions in agriculture. Meanwhile, the Apriori algorithm enhances the system's efficiency by mining association rules within extensive datasets, aiding in prediction and decision support. Notably, the proposed system acknowledges the demerits of existing systems. It simplifies complex agricultural data and presents it in a format that is easily understandable to everyone, from seasoned farmers to policymakers, addressing a key limitation of many current agricultural systems. By merging advanced data analytics with user-friendly interfaces, the system aims to unlock the full potential of agricultural data and revolutionize decision-making processes in the sector.

7 Conclusion

In conclusion, the proposed system not only promises to enhance crop yields and bolster food security, but also has the potential to democratize access to agricultural insights, making it a valuable asset for the entire spectrum of stakeholders in the agriculture sector. Implementing market basket analysis and Naive Bayes in a Crop Yield Information System and deploying it in the cloud requires a comprehensive approach. It involves data pre-processing, model training, system development, cloud deployment, and ongoing monitoring and improvement. The integration of these techniques may offer farmers insightful information that helps them make wise decisions for optimizing crop yield. The crop

yield Information system using cloud and market basket analysis represents an innovative approach to leveraging technology and data analysis for improved agricultural outcomes. It has the potential to revolutionize how farmers make decisions and optimize their practices to achieve higher yields while maintaining sustainability.

References

- [1] P. S. Nishant, P. Sai Venkat, B. L. Avinash, and B. Jabber, "Crop Yield Prediction based on Indian Agriculture using Machine Learning," 2020 International Conference for Emerging Technology (INCET), Belgaum, India, 2020, pp. 1- 4, doi: 10.1109/INCET49848.2020.9154036.
- [2] D. J. Reddy and M. R. Kumar, "Crop Yield Prediction using Machine Learning Algorithm," 2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai,India,2021, pp.1466- 1470, doi:10.1109/ICICCS51141.2021.9432236.
- [3] Ansarifar, J., Wang, L. & Archontoulis, S.V. An interaction regression model for crop yield prediction. *Sci Rep* 11, 17754 (2021). <https://doi.org/10.1038/s41598-021- 97221-7>
- [4] Puninder Kaur, Jasmeen Kaur Chahal, and Taruna Sharma, "A DATA MINING APPROACH FOR CROP YIELD PREDICTION IN AGRICULTURE SECTOR", (2021) *Advances in Mathematics: Scientific Journal*.
- [5] S. S. Khedkar and S. Kumari, "Market Basket Analysis using A-Priori Algorithm and FP-Tree Algorithm," 2021 International Conference on Artificial Intelligence and Machine Vision (AIMV), Gandhinagar, India, 2021, pp. 1-6, doi: 10.1109/AIMV53313.2021.9670981.
- [6] Y. Alebele et al., "Estimation of Crop Yield From Combined Optical and SAR Imagery Using Gaussian Kernel Regression," in *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 14, pp. 10520-10534, 2021, doi: 10.1109/JSTARS.2021.3118707.
- [7] S. Yang et al., "Integration of Crop Growth Model and Random Forest for Winter Wheat Yield Estimation From UAV Hyperspectral Imagery," in *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 14, pp. 6253-6269, 2021, doi: 10.1109/JSTARS.2021.3089203.
- [8] Vasileska, Ema & Gecevska, Valentina & Chukaliev, Ordan. (2023). Crop yield forecasting with climate data using PCA and Machine Learning. 10.1109/MECO58584.2023.10155083.
- [9] L. Banda, A. Rai, A. Kansal and A. K. Vashisth, "Suitable Crop Prediction based on affecting parameters using Naive Bayes Classification Machine Learning Technique," 2023 International Conference on Disruptive Technologies (ICDT), Greater Noida, India, 2023, pp. 43-46, doi: 10.1109/ICDT57929.2023.10150814.
- [10] Mishra, Subhadra & Mishra, Debahuti & Santra, Gour. (2016). Applications of Machine Learning Techniques in Agricultural Crop Production: A Review Paper. *Indian Journal of Science and Technology*. 9. 10.17485/ijst/2016/v9i38/95032.
- [11] V. Waghmare and D. Mukhopadhyay, "Mobile Agent Based Market Basket Analysis on Cloud," 2014 International Conference on Information Technology, Bhubaneswar, India, 2014, pp. 305-310, doi: 10.1109/ICIT.2014.21.
- [12] H. Huang et al., "The Improved Winter Wheat Yield Estimation by Assimilating GLASS LAI Into a Crop Growth Model With the Proposed Bayesian Posterior-Based Ensemble Kalman Filter," in *IEEE Transactions on Geoscience and Remote Sensing*, vol. 61, pp. 1-18, 2023, Art no. 4401818, doi: 10.1109/TGRS.2023.3259742.
- [13] M. Qiao et al., "Exploiting Hierarchical Features for Crop Yield Prediction Based on 3-D Convolutional Neural Networks and Multikernel Gaussian Process," in *IEEE Journal of*

- Selected Topics in Applied Earth Observations and Remote Sensing, vol. 14, pp. 4476-4489, 2021, doi: 10.1109/JSTARS.2021.3073149.
- [14] S. Bang, R. Bishnoi, A. S. Chauhan, A. K. Dixit and I. Chawla, "Fuzzy Logic based Crop Yield Prediction using Temperature and Rainfall parameters predicted through ARMA, SARIMA, and ARMAX models," 2019 Twelfth International Conference on Contemporary Computing (IC3), Noida, India, 2019, pp. 1-6, doi: 10.1109/IC3.2019.8844901.
- [15] S. P. Raja, B. Sawicka, Z. Stamenkovic and G. Mariammal, "Crop Prediction Based on Characteristics of the Agricultural Environment Using Various Feature Selection Techniques and Classifiers," in *IEEE Access*, vol. 10, pp. 23625-23641, 2022, doi: 10.1109/ACCESS.2022.3154350.
- [16] R. Jahan, "Applying naive Bayes classification technique for classification of improved agricultural land soils", *Int. J. Res. Appl. Sci. Eng. Technol.*, vol. 6, no. 5, pp. 189-193, May 2018.
- [17] P. Sharma, P. Dadheech, N. Aneja and S. Aneja, "Predicting Agriculture Yields Based on Machine Learning Using Regression and Deep Learning," in *IEEE Access*, vol. 11, pp. 111255-111264, 2023, doi: 10.1109/ACCESS.2023.3321861.
- [18] The Future of Food and Agriculture—Drivers and Triggers for Transformation, Rome, Italy: Food and Agriculture Organization of the United Nations, 2022.
- [19] M. A. Z. Abidin, M. N. Mahyuddin and M. A. A. M. Zainuri, "Optimal Efficient Energy Production by PV Module Tilt-Orientation Prediction Without Compromising Crop-Light Demands in Agrivoltaic Systems," in *IEEE Access*, vol. 11, pp. 71557-71572, 2023, doi: 10.1109/ACCESS.2023.3293850.
- [20] S. Rai, J. Nandre and B. R. Kanawade, "A Comparative Analysis of Crop Yield Prediction using Regression," 2022 2nd International Conference on Intelligent Technologies (CONIT), Hubli, India, 2022, pp. 1-4, doi: 10.1109/CONIT55038.2022.9847783.
- [21] N. Montalvo-Romero, A. Montiel-Rosales, R. Purroy-Vásquez and P. Quechulpa-Pérez, "Agro-Technological Systems in Traditional Agriculture Assistance: A Systematic Review," in *IEEE Access*, vol. 11, pp. 123047-123069, 2023, doi: 10.1109/ACCESS.2023.3329087.
- [22] S. M. Sundstrom, D. G. Angeler and C. R. Allen, "Resilience theory and coerced resilience in agriculture", *Agricult. Syst.*, vol. 206, Mar. 2023.
- [23] N. Abdullah, N. A. B. Durani, M. F. B. Shari, K. S. Siong, V. K. W. Hau, W. N. Siong, et al., "Towards smart agriculture monitoring using fuzzy systems", *IEEE Access*, vol. 9, pp. 4097-4111, 2021.
- [24] R. C. Poonia and V. Bhatnagar, "Design of decision support system to identify crop water need", *J. Ambient Intell. Hum. Comput.*, vol. 14, no. 5, pp. 5171-5178, May 2023.