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Crop Yield Prediction Using Big Data Techniques

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PROJect REPORT MIning Of Massive DaTA SPRIng 2024 Crop Yield Prediction Using Big Data Techniques Manal Rizwan1, Muhammad Ibrahim2, and Aisha Muhammad Nawaz3 1Department

9of Computer Science, National University of Computer and Emerging Sciences, Lahore

May 6, 2024 Abstract The increasing concern

38of Crop Yield prediction has encouraged the use of

technical means to predict crop yield in advance. With the massive data, using Big Data Techniques has become a necessity. Our project focuses on taking advantage of PySpark and using methods like Linear Regression, Gradient Boosted,

28K-Means Clustering, and Random Forest Regressor to solve the problem of

crop yield prediction. After pre-processing the data and applying the models, we fine tuned the models and managed to obtain an amazing accuracy of 99 percent with Gradient Boosted. We then combined our models and deployed the PySpark code to Cluster on Google DataProc. Overall, we managed to obtain a decent accuracy but improvements such as increasing the number of features can be made to increase performance.

201 Introduction Agriculture, which has been the foundation of civilizations

since antiquity, has changed into an industry where traditional methods and cutting-edge technology now coexist. The modern agri- cultural environment is defined by a symbiotic relationship between tradition and innovation, with data-driven insights guiding every choice toward sustainability and efficiency. This change, driven by the combination of agricultural knowledge and data science, has ushered in a new era of productivity. Leading this movement is PySpark, a powerful framework for data processing known for its ability to handle large datasets with ease. Our project demonstrates the revolutionary poten- tial of this combination by first properly preprocessing the Crop Yield dataset and then applying carefully chosen PySpark's methods such as

33 **Linear Regression, Gradient Boosted Trees, K-Means Clustering, and Random Forest**

Regressor to predict agricultural yield with amazing accuracy and efficiency. After this, we deployed our PySpark code to a cluster on Google DataProc. We hope that this project will further agricultural analytics and add to the conversation on resource management and sustainable food production. 2 Problem

Background With the many moving parts of agricultural production, forecasting crop yield is still a difficult task full with unknowns. A wide range of interrelated factors, such as insect pressures, market dynamics, soil health, and climate variability, affect crop productivity. Conventional approaches to yield estimation are frequently insufficient, requiring more effective and scalable alternatives. Crop yield forecasting is made more difficult by the intrinsic complexity of agricultural production, the increasing unpredictability of weather patterns, and the growing need for sustainable farming methods. Particularly in light of

16 **climate change**, which **is increasing the frequency and severity of extreme weather occurrences**

, there are substantial concerns. These variations can throw off planting plans, have an impact on crop development and growth, and intensify pest and disease challenges already present. Yield prediction is further complicated by the important roles that market dynamics and customer preferences play in determining crop pricing and agricultural practices. Therefore, there is a pressing need for sophisticated analytical tools and methodologies that can handle these complex issues and offer useful information for raising resilience and production in agriculture. 3 Literature Review 3.1 BIG DATA ANALYTICS IN AGRICULTURE [1]

17 **The research paper discusses the** application **of Big Data** Analytics in agriculture, **and how** structured **and**

unstructured data can help farmers to have insights. This not only will allow them to make informed decisions but it will also reduce losses due to unforeseen disasters. It outlines various techniques such as predictive analysis, recommendation systems, and data mining, along with specific applications like intelligent crop recommendation systems and precision agriculture using MapReduce. Moreover, the paper also discusses different machine learning approaches including Grey wolf optimization

1 **and K-means clustering** are explored **for crop**

prediction, while Smart Farming

1 **services like** the **Internet of Things** and **Cloud Computing** are **detailed. The**

paper also delves into

1crop analysis using data mining techniques

and proposes a Spark-based system for distributed data analytics in agriculture. It also mentions some of

1the problems faced in big data analysis

while also addressing future scopes including product traceability and genetic engineering. Lastly, a comparison table is also provided that suggests MapReduce for weather

1data and K-Means Clustering for crop and vegetation data

analysis. 3.2

1CROP PREDICTION ON THE REGION BELTS OF INDIA: A NAIVE BAYES MapReduce PRECISION AGRICULTURAL MODEL [2

] This research paper suggests a data-driven utilized by big data analytics to optimize crop selection for agriculture in the city of Telangana, India. It starts off by analyzing the agricultural system in Telangana while also collecting relevant data from various sources. During this time, the development of a recommendation system based on the Naive Bayes classifier to suggest suitable crops like rice, cotton, maize, and chillies, was still ongoing. Moreover, after building upon previous research in precision agriculture, the paper introduces a methodology to predict crop suitability across various zones in Telangana. The methodology also takes into account other factors

10such as soil types, temperature, rainfall, and atmospheric pressure. The

results from this methodology are then used to advise the optimal timing for sowing and harvesting crops. Lastly, the paper analyses

27the effectiveness of the proposed approach, with the goal of

improving agricultural productivity in Telangana through future enhancements. 3.3 PREDICTION OF

21CROP YIELD USING BIG DATA [3] The paper explores the use of

big data analytics

36for crop yield prediction and food security in

China. It emphasises the need for early and exact crop projections to ensure food security. The paper presents a strategy that uses MapReduce and closest neighbour analysis to accurately predict crop yield. The results show that the proposed strategy is excellent at predicting crop production with minimum deviation. The paper continues by pushing for additional research to improve data collection and computing efficiency, putting emphasis on the approach's scalability across diverse geographical contexts. 3.4

1ENVIRONMENT CHANGE PREDICTION TO ADAPT CLIMATE- SMART AGRICULTURE USING BIG DATA ANALYTICS [4] The

paper

25focuses on using Big Data Analytics to forecast

weather patterns and assist farmers in making informed agricultural decisions, which will solve global

1food insecurity aggravated by climate change. The

authors use the Hadoop framework to collect

19data from a variety of sources, including social media, sensors, and

weather forecasts, with an emphasis on precipitation, temper- ature, and cloud cover in Karnataka. They use Hive for data processing, taking use of its SQL capabilities to manage massive datasets stored on HDFS. MapReduce is used for data analysis, which improves query response times. The work uses Apache Mahout to create prediction functions using k-means clustering and logistic regression techniques, then evaluates accuracy and visualises the findings using Flot. The authors plan to improve the model for generating alerts on disasters in the future, showing its potential for solving important global concerns using advanced data analytics approaches. 3.5

1CROP YIELD PREDICTION USING AGRO ALGORITHM IN HADOOP [5] The paper

provides a new approach that uses the

1Agro Algorithm to predict crop production and select suitable crops

, therefore improving farmers' profitability and supporting the agricultural sector. It combines soil, and crop disease datasets to make more precise predictions. The authors analyse existing crop prediction systems and their limitations, emphasising the importance of variables such as soil pH and seed selection. Implementation on the Hadoop platform allows for the processing of massive datasets, while normalisation and classification improve prediction accuracy. They present an architecture for data collecting, analysis,

and prediction that addresses technical gaps and limited data availability. The model predicts soil quality and recommended crops using varied datasets, allowing farmers to make informed decisions. The paper shows that this technique improves agricultural output and production standards while providing enormous value to farmers by directing crop choices depending on weather and soil conditions. Future research intends to classify illnesses comprehensively, hence improving crop quality. 3.6

1**SURVEY ON WEATHER PREDICTION USING BIG DATA** AN-ALYTICS [6]

] The paper mentions several weather prediction systems and their effects, emphasising the importance of precise forecasts in minimising damage and improving agricultural planning. It describes the collecting and analysis of weather information using big data analytics, focusing on problems such as dataset size and parameter changes. Different prediction approaches, such as MapReduce and Linear Regression, are reviewed, with comparative analysis demonstrating their efficacy in weather forecasting. Overall, the paper recommends for the use of MapReduce for efficient processing of big weather datasets and proposes using K-means clustering to improve agricultural predictions, with the goal of increasing resilience and optimising farming techniques. 3.7

23**A SURVEY ON DATA MINING FOR CROP YIELD**

PREDICTION [7] The paper examines

35**various data mining strategies for crop yield prediction**

, showing their importance in dealing with the complex dynamics of agricultural systems. It emphasises the need of accurate yield forecasting for farmers and agricultural organisations, as well as the importance of new technology in increasing production efficiency. This paper examines the use of

12**techniques such as K-Means, K-Nearest Neighbour, Artificial Neural Networks, and Support Vector Machines in agricultural data**

analysis using a thorough literature review. It explores the problems and opportunities of data mining in agriculture, demonstrating its ability to extract significant insights from vast datasets. The paper supports the integration

37**of data mining techniques in agricultural decision-making**

processes by presenting a methodology

15**for crop yield prediction and emphasising the role of**

inputs such as weather and soil conditions, ultimately leading to increased productivity and sustainability in agriculture. 3.8

18 **PREDICTIVE ABILITY OF MACHINE LEARNING METHODS FOR MASSIVE CROP YIELD PREDICTION** [8] **The**

paper

11 **compares the predictive accuracy of machine learning and linear regression algorithms for crop yield prediction across ten crop datasets**

, emphasising the necessity of precise yield estimation for agricultural planning. Several machine learning approaches, including

8 **multiple linear regression, M5-Prime regression trees, perceptron multilayer neural networks, support vector regression, and k-nearest neighbour, were**

tested on

34 **real data from an irrigation zone in Mexico**

. Four different accuracy metrics were used: root mean square error (RMSE),

6 **root relative square error (RRSE), normalised mean absolute error (MAE), and correlation factor (R). The results show that M5-Prime and k-nearest**

neighbour algorithms consistently outperform others, with the lowest average errors across metrics. This shows their applicability

24 **for large-scale crop yield prediction in agricultural planning**

. M5-Prime stands out for its excellent ability in producing models with low errors, indicating its usefulness as a tool for predicting agricultural yields. 3.9

2 **MACHINE LEARNING FOR LARGE SCALE CROP YIELD FORE- CASTING** [9] **This**

paper offers

2a **machine learning baseline for large-scale crop yield forecasting, with the**

goal of addressing previous approach constraints, particularly transferability and scalability. By merging agronomic concepts with machine learning approaches, the study creates a workflow that prioritises correctness, modularity, and reusability.

15**Crop growth and development** principles guide **the** creation of

features, which rely on

29**data from a variety of sources such as**

2**crop simulation outputs, weather, remote sensing, and soil. The**

workflow is modular and can be easily converted to different crops and nations with small setup modifications, allowing for repeatable tests and outcomes. Case studies including five crops from three countries show encouraging results, with early season estimates equivalent to operational forecasting systems in several crops and regions. The paper identifies areas for further improvement, such as incorporating other data sources and refining predictive features, with the ultimate goal of promoting

2**the use of machine learning in large-scale crop** output **forecasting**

. 3.10

14**WB-CPI: WEATHER BASED CROP PREDICTION IN INDIA USING BIG DATA ANALYTICS** [10] The **paper**

addresses the critical topic of crop yield

30**prediction in India using big data analytics and**

innovative approaches. Recognising agriculture's critical significance in India's economy, as well as the problems faced by unexpected weather conditions, the paper points out the use of modern predictive technologies. The authors take a multi-step strategy, using data from several places on temperature, rainfall, soil, seed, and crop yield. They preprocess the data, use

32**the MapReduce framework for analysis**, then use **k-means clustering**

to extract insights. They also create a recommender system that suggests crops depending on the analysed data. They use bar graphs, scatter plots, and a graphical user interface to visualise and explain the correlations between many elements that influence crop yield. The paper emphasises the importance of big

data analytics in revolutionising agricultural practices while also proposing scalable crop prediction tools. By combining meteorological and agricultural data, the authors hope to deliver useful information for farmers, resulting in increased agricultural output . 4 Dataset Information The dataset comprises agricultural data spanning from 1997 to 2020, encompassing multiple crops cultivated across various states in India. It includes essential features for

5crop yield prediction, such as **crop types, crop years, cropping seasons**

(e.g., Kharif, Rabi, Whole Year), states, cultivated area,

5production quantities, annual rainfall, fertilizer usage, pesticide usage, and calculated yields. Each entry in the

dataset provides specific information about the crop, including its name, the year of cultivation, the cropping season, the state where it was cultivated, the total land area under cultivation, the quantity of crop production, the annual rainfall received, the amount of fertilizer used, the amount of pesticide used, and the calculated yield (production per unit area). It contains 19,689 entries and 20 columns, providing comprehensive agricultural data for analysis and modeling. 5 Data Preprocessing Before applying big data techniques on the dataset, the data was preprocessed and cleaned. The preprocessing steps were carried out in python. 5.1 Label Encoding Three columns in the dataset were of object type. These were Crop, Season and State. The aforementioned columns were encoded to type int using the LabelEncoder of sklearn. 5.2 Outlier Detection and Removal Upon visualization of the box plots of columns, it was observed that there were a considerable amount of outliers in the data. To amend this, winsorization was applied with an upper limit of 0.8 and a lower limit of 0.1. The box plots visualising the dataset before and after Winsorization are shown below. Figure 1: Box Plots Before Winsorization Figure 2: Box Plots After Winsorization 5.3 Standardization Standardization was applied on the data using the StandardScaler of sklearn. As the range of values of the columns differed largely, this step was necessary so that the model didn't develop a bias towards columns having larger values. Due to this step, the distribution of data improved. The histograms visualising the dataset before and after standardization are shown below. Figure 3: Histograms Before Standardization Figure 4: Histograms After Standardization 6 Methodology Several big data techniques were applied on the dataset using PySpark's machine learning library. These include Linear Regression, Gradient Boosted Trees, K-Means Clustering, and Random Forest Regressor. After the individual assessments, we combined the best performing models of all the techniques and deployed the PySpark code to a cluster on Google DataProc. The detailed methodology followed and results obtained from each technique is explained below. 6.1

22Linear Regression Multiple linear regression was applied on the dataset as the

first technique. Three models were developed. For model 1, 70

26percent of the data was used for the training

phase while the rest was used for the testing phase. Model 2 had a split of 80-20 whereas the third model had a split of 90-10. Model 1 outperformed the other models with a R2 score of 0.43, Root Mean Squared Error of 0.77, and Mean Absolute Error of 0.62. In addition to these evaluation metrics, Accuracy with a 1.5 tolerance was also calculated. The Accuracy of the best model was 95 percent.

6.1.1 Scatter Plot The scatter plot of the best performing model is displayed below. As can be seen from the plot, the model only captures about 42 percent of the variability of the data. Figure 5: Scatter Plot of Predicted vs Actual Yield

6.1.2 Residual Plot The shape of the plot suggests that a non-linear relationship exists between the independent and dependent variables. This explains the poor R2 score of the model. Figure 6: Residual Plot

6.1.3 Frequency

3 **Distribution of Residuals** The data distribution of the residuals

is right-skewed. This suggests that the model is overestimating the target variable. Figure 7: Frequency Distribution of Residuals

6.2 Gradient Boosted Trees Three models of Gradient Boosted Trees were developed. The best performing model had a train-test split of 90-10. It had a R2 score

7 of 0.85, **Root Mean Squared Error of 0.39**, and Mean **Absolute Error of**

0.26. The model's Accuracy with a 1.5 tolerance level was 99 percent.

6.2.1 Scatter Plot The scatter plot of the best performing model of Gradient Boosted Trees is displayed below. As can be seen from the plot, the model seems a fairly good fit. Figure 8: Scatter Plot of Predicted vs Actual Yield

6.2.2 Residual Plot As the points in the plot are randomly scattered around the horizontal line, with no clear pattern, it indicates that the model's predictions were unbiased and have

3 **constant variance across the range of predicted values**

. Figure 9: Residual Plot

6.2.3 Frequency

3 **Distribution of Residuals** The data distribution of the residuals

is fairly normal. This suggests that on average, the model was making predictions that were fairly accurate. Figure 10: Frequency Distribution of Residuals

6.3 Random Forest Regressor To find the best results of predicting yield through different methods in PySpark, we also explored the Random Forest Regressor technique. A model was built with number of trees set to 3, feature subset strategy set to auto, impurity set to variance, and max bins set to 32. This model was later fine tuned to obtain an amazing accuracy (with a 1.5 tolerance level) of 94.5 percent, R2 score

7 of 0.51, **Root Mean Squared Error of 0**

.711,

13**Mean Absolute Percentage Error of 59.13, Mean Absolute Error of 0.533, Mean Squared Error of 0**

.528. This model used a 80-20 split for training and testing datasets, with a maximum depth of trees set to 10. The Scatter, Residual, and Frequency Distribution of Residuals plots of the best performing model of Random Forest Regressor is visible in figure 14, 15 and 16 respectively. Among the other models of Random Forest Regressor we experimented with, we obtained an accuracy (with a 1.5 tolerance level) of 92 percent and an R2 Score of 0.33 with model 1 which used a

470- 30 split for training and testing datasets, **with**

maximum depth of trees set to 6. With model 2 we obtained an accuracy (with a 1.5 tolerance level) of 93.5 percent and an R2 Score of 0.45 with the same

470-30 split for training and testing datasets but **with**

maximum depth of trees set to 8. With model 3 we obtained an accuracy (with a 1.5 tolerance level) of 94.2 percent and an R2 Score of 0.48 with

470-30 split for training and testing datasets, **with**

maximum depth of trees set to 9. This trend suggests that increasing the depth of trees increases the accuracy and R2 score values but this was observed only up to maximum depth of trees set to 10.

6.3.1 Scatter Plot

The scatter plot of the best performing model of Random Forest Regressor is shown in Figure 14. As visible, the model captures roughly 51 percent of the variability of the data.

Figure 11: Scatter Plot of Predicted vs Actual Yield

6.3.2 Residual Plot

The residual plot of the best performing model of Random Forest Regressor is shown in Figure 15. The plot's shape implies a non-linear association between the independent and dependent variables, which likely contributes to the model's average R2 score as it may struggle to capture the complex relationship accurately.

Figure 12: Residual Plot

6.3.3 Frequency Distribution of Residuals

The frequency distribution of residuals plot of the best performing model of Random Forest Regressor is shown in Figure 16. The data distribution of the residuals seems normally distributed, suggesting a symmetrical pattern around zero, implying the model's predictions exhibit minimal bias and effectively capture the variability in the data.

Figure 13: Frequency Distribution of Residuals

6.4 K-Means Clustering

Before applying clustering, correlation of Yield with other independent variables was calculated. This was done to select the top three variables which had the highest correlation with Yield. As there were around 10 variables, this step was necessary. Yield, Production and Season were picked as their correlation with the yield column was 1, 0.41, 0.31 respectively which was more than that of remaining columns. K-means clustering was run on the dataset for three values of k. The optimal value of k turned out to be 5. The Silhouette Score was around 0.7, the Within-Cluster Sum of Squares Error was 17459.67, and the Between-Cluster Sum of Squares Error was 161.64.

Figure 14: K-Means Clustering for K=5

6.4.1 Results of Clustering

The image below shows the cluster centroids for k=5.

Figure 15: Cluster Centroids

- Cluster 1 has an average yield of 1.35 and average production of 1.64. The most frequent season in this cluster is 4 which is actually the 'Whole Year' season.
- Cluster 2 has an average yield of -0.51 and average production of -0.59. The most frequent season in this cluster is 1 which is actually the 'Kharif' season.

Cluster 3 has an average yield of 1.42 and average production of -0.42. The most frequent season in this cluster is 3 which is actually the 'Summer' season. • Cluster 4 has an average yield of 0.41 and average production of 1.54. The most frequent season in this cluster is 1 which is actually the 'Kharif' season. • Cluster 5 has an average yield of -0.63 and average production of -0.54. The most frequent season in this cluster is 4 which is actually the 'Whole Year' season.

6.5 Google DataProc Deployment After individually assessing each of the techniques and fine-tuning the models, we combined them and deployed the PySpark code to a cluster on Google DataProc. The successful results of running the job are visible in Figure 17.

Figure 16: Deploying PySpark Code to Cluster on Google DataProc

7 Contributions In this project we used a mixture of techniques and evaluated each one using different measures to ensure that each model's performance can be judged. Linear Regression, Gradient Boosted, and Random Forest Regressor code was written by ourselves using built in libraries. The K-Means clustering was implemented with the help of github codes. Three of the techniques were implemented by each member individually except K-Means Clustering was discussed and implemented together to ensure proper understanding.

8 Improvements and Future Work There are a number of directions that future study and development in the field of agricultural production prediction can go. First, model performance can be enhanced by adding more agricultural variables to the feature engineering process, such as soil parameters, weather forecasts, and satellite imagery. Furthermore, investigating ensemble learning methodologies to merge forecasts from many machine learning models may result in improved prediction precision. Lastly, further insights can be gained by performing temporal and spatial studies to identify seasonal trends, cyclic patterns, and geographic factors impacting crop yield variability.

Conclusion In conclusion, our research demonstrates

31the potential of PySpark and machine learning techniques in

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