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Regional Prediction of Crop Yield Success Rate in the Philippines using Geographic Trend Analysis Algorithm

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Abstract: - Agriculture holds an important role in the economy of the Philippines by ensuring the food security of domestic products. It involves about 40 % of Filipino workers and it contributes an average of 20 percent to the Gross Domestic Product. Crop prediction in the Philippine's agriculture is a big problem. At the present time, farmers are having a difficult time in choosing the right crops due to unnatural climate changes, soil type, rainfall, and other environmental factors. These can affect the economic life of farmers and can make them less familiar in forecasting future crops. This project aims to guide the farmers for sowing the reasonable crops by using geographic trend analysis algorithm. The findings from this study demonstrate the potential of the Geographic Trend Analysis Algorithm as a powerful tool for regional crop yield prediction. The success rate of each region will always equate to 100% in context with the set optimal yield prediction where the crop with highest percentage appears to be the dominant one. Irrigated palay (rice) demonstrates a greater rate of success across diverse Philippine regions when contrasted with rainfed or non-irrigated palay, as well as white and yellow corn. Additionally, the methodology employed by the researchers sets the groundwork for upcoming investigations in the domain of agricultural data analytics and geographic information science. This paves the way for a data-centered and sustainable strategy toward crop production in the Philippines.

Keywords: Agriculture, Crop Yield Success, Filipino farmers. Geographic Trend Analysis, Gross Domestic Product.

I. Introduction

This the historical role of the agricultural industry in the Philippine economy has been noteworthy, playing a crucial role in the advancement of rural areas, assurance of food availability, and provision of employment opportunities. Despite being a foundational component of the Philippine economy, it's worth noting that the survival of local farmers facing challenges such as unchanging agricultural productivity, strong competition from more affordable food imports, and the intermittent impact of droughts and floods, which have severely affected crops and sources of income, has largely relied on the financial support from overseas migrant workers' remittances [1].

While the portion of agriculture's contribution to the economy has experienced a gradual decrease, shifting from 20% between 2000 and 2001 to 18% in the period from 2007 to 2009, its significance within the Philippine economy remains substantial. Despite these changes, the agricultural sector maintains a vital role, particularly in rural regions where the majority of Filipinos reside. It remains a primary economic catalyst in these areas. With roughly 36% of the overall employed workforce engaged in the agricultural sector, it remains a significant source of employment (ADB, 2011) [2].

Understanding the requirements for optimal growth of crops holds significant importance in achieving success in farming endeavors. Possessing accurate knowledge about these specific crops can lead to amplified crop yields and improved profit margins. For those engaged in cultivating grains, a multitude of decisions arises when selecting the appropriate crop for cultivation. Farmers must meticulously assess factors like seed expenses, fertilizers, herbicides, planting procedures, and harvesting outlays, which are then weighed against a seed balance sheet. It's also crucial to factor in crop rotation, as planting the same crop consecutively could lead to challenges involving diseases, nutrient deficiencies, and pests [3]. Only after considering these aspects can the chosen crop variety be sowed, its progress monitored, and insights gathered for the subsequent year's planting strategy.

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Furthermore, these experienced farmers traditionally relied on their own knowledge and historical data to predict crop yields and make pivotal cultivation decisions based on these forecasts. Nonetheless, recent advancements, including the integration of crop model simulation and machine learning, have emerged as more precise tools for yield prediction. These innovations enable the comprehensive analysis of vast datasets through high-performance computing [4]–[7]. In various investigations [8], [9], [10], machine learning algorithms exhibit greater potential compared to conventional statistical methods. Machine learning, a facet of artificial intelligence, empowers computers to learn without explicit programming. These techniques excel in deciphering intricate agricultural systems, whether linear or non-linear, by delivering notable predictive capabilities [11].

The objective of this study is to provide Filipino farmers with a tool that enables them to identify the optimal crop choice based on historical data. The intended datasets for this purpose involve regional crop yields. These yield statistics per region will be sourced from the Philippine Statistics Authority (PSA) database. The outcomes derived from the analysis, employing the K-Nearest Neighbors algorithm available in the PHP-Machine Learning Library, will facilitate the identification of the most economically viable region within the Philippines for cultivating a specific crop at a designated yield level.

II. Method

The K-nearest neighbor algorithm (k-NN), a non-parametric statistical method, is utilized for tasks involving both classification and regression. In this method, the input comprises the k closest instances from a provided dataset. Whether k-NN is used for classification or regression purposes, the resulting consequences can be elucidated as follows:

In the context of k-NN classification, the outcome pertains to the belongingness of an item to a specific class. The categorization is determined by a consensus vote from the nearby instances, resulting in the item being assigned to the class that prevails among its k closest neighbors. In this context, k signifies a positive integer, often small in value. When k is set to 1, the object is straightforwardly assigned to the class of its closest neighbor.

In the case of k-NN regression, the result corresponds to the property value linked to the object. This value is derived by computing the average of property values originating from the k closest neighbors.

Data Collection

To ensure accurate and relevant results in the process of determining the most suitable crop for a specific region in the Philippines, the researchers gathered fundamental data necessary for producing the findings. This vital data includes regional crop yields obtained from the Philippine Statistics Authority (PSA). The PSA dataset encompasses various crop types, such as irrigated palay, rainfed palay, white corn, and yellow corn. Information concerning the crop harvest volumes is reported on a quarterly frequency.

Data Cleaning

Formulating the X data essential for the k-NN algorithm necessitates the construction of a framework that merges the crop's name with the associated quarter of its yearly harvest, exemplified by "Yellow Corn – Q2". Concurrently, the Y data is chosen to portray the quarterly crop harvest quantities spanning the entirety of the years 2019 through 2020.

Prior to incorporating the crop data, symbolized as the cells within the algorithm, a preliminary step involves categorizing these cells into regions using historical data. This initial classification serves the purpose of streamlining processing demands and minimizing potential inaccuracies. Once the cells have been assigned to their respective regions, the X and Y data are then integrated into the algorithm through the utilization of PHP's inherent k-NN library. The value of k in the k-NN approach is adjustable according to user preference, although it defaults to 3 for the purpose of mitigating erroneous outcomes. For determining the nearest neighbors, the researchers employed the Euclidean Distance as the chosen measurement metric.

This metric is frequently selected due to its prevalence as the default measurement for the K-Nearest Neighbor Algorithm integrated into the PHP-Machine Learning module. In the realm of Euclidean space, it signifies the actual straight-line distance between two points.

Classification Accuracy

The precision primarily relies on the X and Y data. Yet, the k-NN algorithm embedded within the chosen module is projected to offer an accuracy ranging from 70% to 85%, contingent on factors such as the size of the sample and computational capabilities. As a measure, the accuracy of the results was tested with the default filter of the system, Estimated best crop type and planting quarter per region.

For example, the actual data from the PSA database for Region I for the Irrigated Palay crop are shown below:

Table I. PSA Database for Region 1

Quarter	2019	2020	Average
Q1	328,555.00	330,328.85	329,441.93
Q2	158,805.00	163,467.00	161,136.00
Q3	157,190.00	161,482.00	159,336.00
Q4	705,162.00	729,834.00	717,498.00

Based on the raw data, it can be quickly estimated that Quarter 4 is the best time to plant Irrigated Palay in Region I, which can be seen in the default mode of the system.

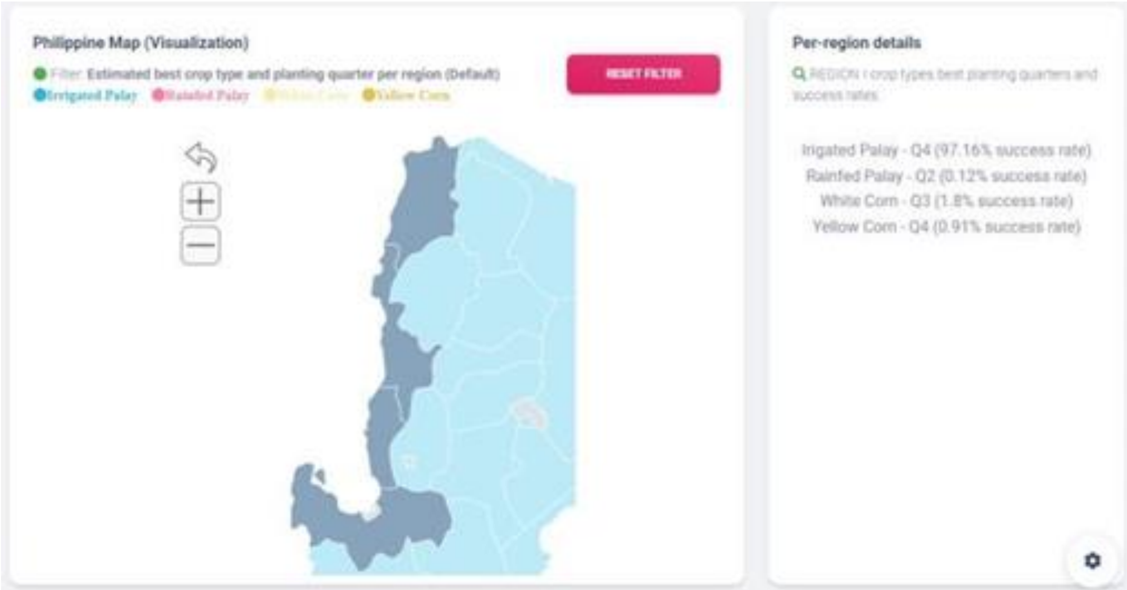

Figure 1. Philippines Map (Visualization) of Palay and Corn Per Region

This is because the default value for the optimal yield prediction, quantified in metric tons, has been established at its maximum conceivable magnitude (1,234,567,890). Consequently, the k-NN process led to the identification of the nearest neighbor as Q4.

However, if we set a designated value of an optimal yield prediction is set, it will accordingly find the nearest neighboring value for it according to the algorithm's classification.

If the optimal yield prediction is set to be 300,000 metric tons, it will pick Quarter 1 as it is the closest neighboring value.

III. Results And Discussion

The crop yield volume for a total of 16 regions (excluding NCR) in each of the 4 crops are gathered from PSA. These raw data from PSA are classified into regions, crops, quarter, and from year 2019 – 2020. The result that is formulated from k-NN algorithm was presented through a website using a heat map where the colors are classified based on what crop it is.

The tables that follow provide the result of implementing k-NN on the PSA's data on crop yield volume per region quarterly. The tables include the crop type and its success rate on a specific region. The algorithm also determines the ideal quarter of the year for the crop to be cultivated. These are with a set optimal yield production of 80,000 metric tons

Table II. Crop success rate in Cordillera Administrative Region (CAR).

Crop type – Idea quarter	Success rate
Irrigated Palay – Q3	52.39%
Rainfed Palay – Q1	15.46%
White Corn – Q2	0.74%
Yellow Corn - Q2	31.41%

Table III. Crop success rate in Region I (Ilocos Region)

Crop type – Idea quarter	Success rate
Irrigated Palay – Q3	92.69%
Rainfed Palay – Q2	0.32%
White Corn – Q3	4.65%
Yellow Corn – Q4	2.34%

Table IV. Crop success rate in Region II (Cagayan Valley)

Crop type – Idea quarter	Success rate
Irrigated Palay – Q3	51.77%
Rainfed Palay – Q3	3.2%
White Corn – Q4	0.61%
Yellow Corn – Q4	44.41%

Table V. Crop success rate in Region III (Central Luzon)

Crop type – Idea quarter	Success rate
Irrigated Palay – Q3	97.98%
Rainfed Palay – Q2	0.32%
White Corn – Q4	0.77%
Yellow Corn – Q4	0.93%

Table VI. Crop success rate in Region IV-A (CALABARZON)

Crop type – Idea quarter	Success rate
Irrigated Palay – Q1	79.65%
Rainfed Palay – Q3	10.83%
White Corn – Q2	2.1%
Yellow Corn – Q2	7.43%

Table VII. Crop success rate in MIMAROPA

Crop type – Idea quarter	Success rate
Irrigated Palay – Q3	68.52%
Rainfed Palay – Q2	22.83%
White Corn – Q1	1.73%
Yellow Corn – Q4	6.92%

Table VIII. Crop success rate in Region V (Bicol Region)

Crop type – Idea quarter	Success rate
Irrigated Palay – Q2	43.57%
Rainfed Palay – Q2	42.15%
White Corn – Q2	3.89%
Yellow Corn – Q2	10.4%

Table IX. Crop success rate in Region VI (Western Visayas)

Crop type – Idea quarter	Success rate
Irrigated Palay – Q1	65.07%
Rainfed Palay – Q3	20.49%
White Corn – Q2	4.13%
Yellow Corn – Q1	10.32%

Table X. Crop success rate in Region VII (Central Visayas)

Crop type – Idea quarter	Success rate
Irrigated Palay – Q4	73.04%
Rainfed Palay – Q3	7.34%
White Corn – Q2	19.16%
Yellow Corn – Q2	0.46%

Table XI. Crop success rate in Region VIII (Eastern Visayas)

Crop type – Idea quarter	Success rate
Irrigated Palay – Q3	53.1%
Rainfed Palay – Q3	39.08%
White Corn – Q1	7.05%
Yellow Corn – Q2	0.77%

Table XII. Crop success rate in Region IX (Zamboanga Peninsula)

Crop type – Idea quarter	Success rate
Irrigated Palay – Q2	61.58%
Rainfed Palay – Q2	22.23%
White Corn – Q2	13.58%
Yellow Corn – Q2	2.61%

Table XIII. Crop success rate in Region X (Northern Mindanao)

Crop type – Idea quarter	Success rate
Irrigated Palay – Q2	40.73%
Rainfed Palay – Q2	3.15%
White Corn – Q2	19.98%
Yellow Corn – Q2	36.14%

Table XIV. Crop success rate in Region XI (Davao Region)

Crop type – Idea quarter	Success rate
Irrigated Palay – Q2	61.11%
Rainfed Palay – Q1	6.92%
White Corn – Q2	22.76%
Yellow Corn – Q2	9.2%

Table XV. Crop success rate in Region XII (SOCCSKSARGEN)

Crop type – Idea quarter	Success rate
Irrigated Palay – Q2	52.18%
Rainfed Palay – Q2	6.53%
White Corn – Q2	8.63%
Yellow Corn – Q2	32.67%

When considered in the context of the designated optimal yield prediction, the success rate for each region will consistently reach 100%. In this framework, the crop with the highest percentage will emerge as the dominant choice. The dominant crop, therefore, holds the greatest likelihood of prospering in terms of cultivation and yield output. As mentioned earlier, the researchers have already organized the crops based on the most suitable quarter of the year for cultivation. Consequently, solely the optimal quarter is subjected to k-NN processing, minimizing errors and processing demands. Irrigated palay (rice) displays a more favorable success rate across diverse regions of the Philippines in comparison to rainfed or non-irrigated palay, as well as white and yellow corn. This discrepancy can be attributed to a variety of factors that contribute to enhanced crop yields and stability in irrigated zones. The triumph of irrigated palay hinges on variables such as the effectiveness of the irrigation system, soil quality, local climate conditions, and the agricultural techniques embraced by farmers. Government initiatives aimed at promoting irrigation development and efficient water management play a pivotal role in upholding the ongoing prosperity of irrigated rice cultivation, particularly in a country like the Philippines where rice holds vital importance as both a staple crop and a critical element of food security.

Numerous factors require careful consideration while progressing and exploring crop prediction. Farmers can benefit from a precise model for predicting crop production, aiding them in deciding which crops to cultivate and when to initiate planting. Diverse approaches exist for predicting crop production. In this section, a concise overview of research, literature, data, and analyses conducted by other researchers were provided that could elucidate the concepts utilized in this inquiry. The review paper also delves into the examination of machine learning's application in predicting agricultural yields, as explored within the existing literature.

The criteria applied in both the analysis and this review pertain to the interconnection of the paper with other review papers or publications. In a publication by [12], they presented a study outlining the procedure for developing targeted seasonal climate forecasts for rice production in the Philippines during both dry and wet seasons across three geographical scales. Their objective also encompassed the assessment and quantification of plausible predictive abilities through retrospective forecast evaluations. Within this study, they formulated crop prediction models consisting of two components. The initial segment is grounded in empirical factors, drawing from actual preceding climatic conditions, while the subsequent segment is semiempirical, relying on precipitation projections obtained from general circulation models (GCMs) encompassing the Philippines. This paper not only effectively showcases the considerable potential linked to crop forecasting in the Philippines, primarily based on climate predictions, but it also highlights the limitations encountered at the regional and provincial levels.

Researchers employed trend analysis to validate the precision of forecasts rooted in diverse elements. While each study employs machine learning to predict yields, the specifics of these endeavors exhibit variations. Varied attributes are utilized based on the datasets accessible. Aspects like crop production, temperature, humidity, soil moisture, agricultural activities, and anticipated rainfall all come into play. Furthermore, it's worth noting that the selection of these attributes is influenced by both the dataset's accessibility and the objectives of the study [13].

The presence of extra attributes in models did not consistently result in the most optimal yield prediction performance. Evaluating models with both more and fewer features is essential to identify the top-performing approach. Although a multitude of algorithms have endeavored to forecast crop production, it's important to highlight that the outcomes illustrate a lack of definitive determination regarding the superior model. However, these results do notably indicate a prevalent preference for certain machine learning models over others [13].

Liakos et al. [14] published a a comprehensive review paper discussing the application of machine learning in the agricultural domain. They performed an analysis by drawing from literature related to crop management, animal management, water management, and soil management.

A study was conducted on the different data mining approaches utilized for crop yield prediction. Beulah's findings established that the issue could be addressed using data mining techniques [15].

As an illustration, consider the work of [16], a review article delving into the application of data mining in broader agricultural decision-making. Their findings highlighted the necessity for further research to ascertain the potential utilization of data mining within extensive agricultural databases.

In the 2018 Syngenta Crop Challenge, research demonstrated enhanced results by employing extensive datasets of corn hybrids and utilizing a machine learning methodology for predicting crop production [17].

The comparison of crop yield prediction may be done using the whole set of existing accessible data, and will be dedicated to appropriate ways for enhancing the efficiency of the suggested strategy [18].

The effectiveness of a predictive model is impacted by the dynamic nature of agricultural production data, which can vary across regions. Consequently, crop yields might fluctuate due to the geographical characteristics of the areas [19]. Numerous recent research studies [20,21,22] underline the vital importance of enabling farmers to accurately anticipate crop choices, particularly for imports and exports, which plays a crucial role in global food production and sustainable urban planning. These estimations are pivotal for a nation's food security. In order to develop improved crop varieties, breeders necessitate precise forecasts that can gauge the performance of new hybrids across diverse environments. Accurate anticipation of crop type and yield empowers growers and farmers to make well-informed decisions pertaining to management and financial matters [23]. However, due to the multitude of intricate factors involved, precise agricultural production forecasting remains a challenging endeavor [24]. As outlined in [25], there's a pressing need to establish an objective methodology for preharvest crop forecasting. Developing an appropriate model offers distinct advantages compared to traditional forecasting techniques.

Based on the analysis of review papers and an examination of existing review articles, this paper stands out as the inaugural work concentrating on specific data spanning the years 2019 to 2021. Certain publications lacked an all-encompassing exploration of the literature, with certain ones honing in on specific aspects of crop production prediction. Across these studies, there's a shared focus on utilizing machine learning for yield forecasting, although the attributes considered exhibit variations.

IV. CONCLUSION

This study primarily centered on predicting crop outcomes in the Philippines and determining their yields through the application of a geographic trend analysis algorithm. The analysis underscored the utility of the datasets acquired from PAGASA's website and the Philippine Statistics Authority database in achieving the necessary accuracy calculations. The proposed approach can be of significant assistance to farmers in choosing the appropriate crops for cultivation on their fields. This endeavor serves to enhance understanding of specific crops, enabling efficient and effective harvesting practices. Precise crop forecasting across diverse regions stands to benefit farmers in the Philippines, contributing to heightened crop production rates. This, in turn, holds the potential to bolster the Philippine economy.

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