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A Decision Support System for Benguet's Upland Vegetable Crop Prediction using Machine Learning Techniques

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***Abstract*—Food security has been a long-standing problem in the Philippines, with the agricultural sector having constant issues with transporting and distributing produce, a huge mismatch between supply and demand, dealing with damages from natural calamities or outbreaks, poor crop planning and management, and other economic and political problems that have negatively affected our farmer folk. In recent times, technologies such as machine learning and decision support systems (DSS) have been helpful in mitigating these problems. This paper presents a DSS for Benguet's upland vegetable crop prediction using machine learning techniques. It will utilize these technologies to help farmers in optimizing their crop yields providing assistance to the farmers of Benguet in decision making on potential crop yield for a particular climatic scenario. Multiple linear regression algorithm was used for the prediction of crop yield and was done on a dataset that contained important commodity information per municipality for the years 2015 to 2020. Data mining techniques such as data pre-processing, data transformation, data aggregation and crop prediction were performed using Microsoft Excel, Python, and WEKA. The accuracy of prediction was evaluated through R-squared and Root Mean Squared Error. We got an accuracy of 97.73% for the prediction algorithm.**

Keywords—DSS, data mining, machine learning

I. INTRODUCTION

The traditional work of majority in the Philippines, particularly in the province of Benguet, is known as mixed farming, an agricultural method that includes livestock and crop farming. Benguet is popularly called the "Salad Bowl" of the Philippines, because each form of vegetable employed in salads is made here. Benguet remains as the leading producer of vegetables in the Cordillera Administrative Region owning 83.34% of the total vegetables production [1]. The vegetables from Benguet are sold daily not only in Baguio City, but also in nearby provinces and Metro Manila. There is, however, a noticeable difference of 4.10% change compared to last year's produce [1].

Difficulties in agriculture have always been an issue but as of late, decline in food security [2] has taken the lead. The factors that affected food security [3] listed conflict, climate variability and extremes, and economic slowdowns and downturns. In addition, the COVID-19 pandemic also contributed to the threat especially to the developing countries [4,5,6] where the supply and demand of agricultural products are in collapse. Restaurants were closed, markets had no way of getting supplies because of lockdown, and farmers had no choice but to throw away their rotting produce. Furthermore, [7] the pandemic had also resulted in the Gross Regional Domestic Product (GRDP) of the Cordillera Region dropping to its lowest at -10.2%.

The world is now recovering from the pandemic, yet another problem arises leaving not only farmers but also consumers no room to breathe. Recently, fuel prices had been increasing as a byproduct of the Ukraine-Russian war. This led to the price increase of transportation fees thereby influencing the cost of vegetables on the market.

In addition to these agricultural crises, the available resources for crop production are decreasing, but the population of the world increases so fast. There's an enormous inadequacy between the quantity of food we tend to turn out these days and therefore the amount required to feed everybody in 2050. There'll be nearly ten billion individuals on Earth by 2050—about three billion additional mouths to feed than there have been in 2010 [8].

Because of the convergence of these global, national, and local challenges, the need to boost the country's food security has been higher than ever. As per FAO's report (2017), the growth rates of agricultural production and crop yields have been decelerating for the past years. The general agreement is that international agriculture production has got to be boosted by 60 up to 70 percent from the present levels to satisfy the demand of food in 2050.

Despite the gift given by nature, the unpredictable climate and environmental changes in the Philippines have become a major threat to the agricultural economy. Specifically, in the province of Benguet, farmers have been constantly plagued with the issue of overproduction [9], forcing them to either go back to their farms with their harvest, sell it for an extremely low price, or even throw it away.

A lot of the problems with overproduction either come from delayed sowing and harvest because of natural calamities or low demand. Since these problems revolve around needing future data, prediction or forecasting could be a tool to aid farmers in preparing and deciding their next actions based on future events such as typhoons or high demand. Various studies have also shown the applications of Machine Learning in successful crop yield predictions. The advancement of science and technology has paved the way to address the gaps for further refinement of crop prediction methodologies to generate more accurate crop forecasting.

With these concerns, a decision support system (DSS) is a tool that could benefit the farmers of Benguet and its stakeholders during times of agricultural crisis. As defined by [10] Terrible, et. al (2015), a DSS is a smart system that provides operational answers and supports decision-making to specific demands and problems based on collected data. With the help of datasets obtained from various local government units (LGUs), along with crop inputs from the farmers, a DSS will guide the beneficiaries in choosing the most advantageous commodities to plant. It would aid decision-makers in creating a better farming plan that adjusts to the needs of the crops and farmers. The project will collect data such as crop trends, yields, patterns, factors affecting crop production, and other farmers' experiences to inform and guide other farmers in choosing profitable agronomic decisions. This helps farmers become involved in both the production and economic side of agriculture, shaping them to become agricultural entrepreneurs who are both knowledgeable about the supply and the demands of the market. The study will focus on the top ten (10) vegetables indicated in the value chain analysis (VCA). Project's name is PASYA: Prediction And Sustainability for Agriculture.

II. LITERATURE REVIEW

Agriculture is critical to every country's economic success. FAO states that COVID-2019 is affecting agriculture in two significant aspects: the supply and demand of food which is directly associated with food security. With increasing population, frequent fluctuations in weather conditions, and limited resources, meeting the current population's food needs has become a problematic issue and continues to impede global efforts to achieve the UN Sustainable Development Goal, Zero Hunger. Increasing food production alone to attain the goal is not sustainable, as 30% of the global food supply is wasted (World Bank Group, 2020). To withstand the impact of the pandemic on food security and agricultural supply and demand, each must take part in building a resilient and food-secure nation. Smart farming has emerged as an innovative tool to address current agricultural sustainability issues. It allows the machine to learn without human intervention. The next agricultural revolution could rely heavily on machine learning and IoT (Internet of Things) [11].

Farmers can manage their crops and farms better if they can communicate their experiences, both positive and negative, with each other and with experts. It is a potentially useful tool that farmers and agricultural practitioners can use to manage their crops and farms better, reduce risk, increase productivity and improve their livelihoods. In a study by Patil and Shirsath (2017), an agricultural DSS using data mining [12] was implemented that assists farmers for the selection of crops for cultivation using multiple parameters such as soil type, average rainfall required, temperature range, water consumption, etc. In another study by Arshad and Aziz (2021), they constructed a networking based DSS for recommendations to farmers leading to optimum sustainable yields [13]. The system focuses on sensors such as humidity sensor, soil moisture sensor, soil conductivity sensor, and NPK sensor. This study provides real-time data that can show past patterns, monitor climate trends, and check fertilizer consumption which assists the users for proper yields.

Whereas Majumdar et al. [14] conducted a study on the application of data mining techniques on agricultural data. Their paper discussed the various decisions farmers and agribusinesses make each day with multiple parameters that include environmental conditions, soil types, different combinations, and commodity prices to produce accurate yield estimates. A similar study done by Kodeeshwari and Ilakkiya [15] compared various data mining techniques used in agriculture for decision making such as classification, clustering, association rule mining and regression. Their paper discussed that data mining provides major advantages in agriculture as it provides insights into related topics such as disease detection and pesticide optimization. They further added data mining in agriculture is used to find patterns and trends in different domains. They analyzed the different data mining techniques and discussed the usage, needed data, learning methods and applications.

These similar DSS often employed a subset [15] of Artificial Intelligence (AI) known as Machine Learning (ML). AI is a term used to build artificial human brains that can learn, plan, perceive, and analyze natural language. It is the study and creation of computer systems capable of performing activities that need human intelligence, such as visual perception, speech recognition, decision-making, and language translation [16]. ML and deep learning are the most often utilized AI technologies. Individuals, organizations use these approaches, and government agencies to predict and learn from data. ML models for the complexity and diversity of data in the food business are currently being developed.

Machine learning is not only used for crop prediction and planning, but studies have shown that it could be used on managing pesticide control to better the quality of crops. In a study by Lomotey and Deters (2014), they have created a mobile app [17] that facilitates pesticide control by informing farmers on how, when, where, and what chemicals should be applied based on collected data. In another study conducted by Fenu and Mallochi (2020), the DSS was able to forecast the period in which it is appropriate to carry out treatments useful against a potato disease outbreak using two disease prediction models and climatological data [18] , which allowed for more efficient and cost-effective pesticide control.

Competition is a common aspect of the economy. To remain in the competitive scene, multiple vital information must be gathered such as fertilizer management, crop protection systems, water management, harvest calendars, and specific crop details. Most farmers rely on professional advisors and agricultural specialists to gather information needed for decision-making. Challenging and burdensome efforts such as these are noble causes for the creation of Decision Support Systems (DSS). A DSS specifically created to provide dynamic information and ever-changing elements can reduce farmers' data gathering time and could provide

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greater yields which significantly improve the UN's sustainable goal: Zero Hunger.

Proposals that advocate for an integration of AI and ML as an assistive tool for both public and private sectors are not a foreign area of study, as shown by the emergence of academic papers, business ventures, and political discussions that aim to foster this kind of innovative solution within their respective country. For the Philippines, Rosales et.al [19] observed that these technologies in the industrial, agricultural, and service-centered sectors, but the study also concluded that the people must be fully aware of the advantages to off-set the possible negative effects of its implementation into the workforce.

Efforts to introduce AI within the country, however, have gradually taken shape. Republic Act No. 11293, the "Philippine Innovation Act" aims to foster innovation in the country as a vital component of national development and sustainable economic growth. Also, the Department of Trade and Industry (DTI) drafted the National Artificial Intelligence Roadmap [20] with the Philippines AI Taskforce that included multiple government agencies, with the goal of elevating the country as an "AI Centre for Excellence" through entrepreneurship, innovation, and local talent as a means of achieving global competitiveness.

The COVID-19 pandemic that limited human interaction was cited as one among the many justifications of utilizing AI and ML as a vital innovative solution [21].

III. RESEARCH METHODS

A. *The Study Area*

Benguet is located at the southern end of the Cordillera Region. It is bounded by Pangasinan to the south, La Union and Ilocos Sur to the west, Mountain Province to the north, and Ifugao and Nueva Vizcaya to the east. Located 5,000 feet above sea level, the province lies on top of the Cordillera Mountain. The area is characterized by its rugged and sloping terrain and deep valleys. As of 2010, Benguet has a total land area of 2,833.0 square kilometers mostly covered with forest land. The map of the study area is shown in Fig. 1.

A wide plateau in these mountain peaks can be found hosting the capital town, La Trinidad, is located. Benguet makes up a total of 1 city, 13 municipalities and 140 barangays. The 13 municipalities are Atok, Bakun, Bokod, Buguias, Itogon, Kabayan, Kapangan, Kibunga, La Trinidad, Mankayan, Sablan, Tuba and Tublay. According to the Department of Agriculture (2018), they have determined the main commodities of highland vegetables of Benguet are cabbage, Chinese cabbage, broccoli, carrots, cauliflower, garden pea/ sweet pea, bell pepper, lettuce, and snap beans (pole). The study focuses on the production of the top ten (10) vegetable crops of the province of Benguet.

B. *The Dataset*

All datasets used are gathered from the records of the Philippine Government, specifically from the Office of the Provincial Agriculture (OPAG) and Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA). For each of the crops cultivated on the farm of Benguet, historical commodity production data for the past six (6) years, from the years 2015 to 2021, are consolidated and gathered from OPAG. Whereas, the data on weather and other climate related parameters are gathered from PAGASA. Commodity production data include year, municipality, area harvested (hectares), production (metric tons), productivity (metric tons/hectare).

Fig. 1. Benguet - the study area

While climatological data include rainfall unit, maximum temperature, minimum temperature, relative humidity, wind speed, and wind direction.

C. *The DSS Architecture*

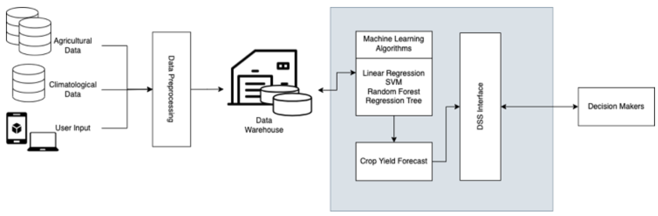

Fig. 2. Conceptual framework

From the theories and ideas gathered in the review of literatures, the researchers designed a conceptual framework. It tackles different parameters related to the problem statement. The collection of climatological and agricultural data was performed. Various data mining techniques such as data preprocessing, data transformation, data summary, and data analysis are performed to understand the data cleanly, discover knowledge, and perform predictions. Data wrangling was also executed so that the complex data is transformed into a usable format for performing analysis on it before finally store the data into a data warehouse. The task of data mining in this study was to create predictive power that is using features to predict unknown or future values of the same or other feature. The researchers tested and evaluated machine learning algorithms such as Multiple Linear Regression, Decision Tree and Random Forest using WEKA, Microsoft Excel and Python to determine model accuracy.

The DSS provides the users forecasted crop yield. Defining trends in crop yields and determining factors affecting production are byproducts of the transformation process and is supplemental to the study. Agricultural decision making is then provided with more actionable insight allowing better options to be more visible which leads to crop production and yields improvement as seen in the studies [22, 23, 24].

D. The Datawarehouse

DSS helps farmers and other stakeholders make sense of data so they can undergo more informed management decision-making. For making a big-picture decision making, a data warehouse needs to be created to store data in the organization as well as external sources such as climatological and crop production dataset.

One consideration in the design of the data warehouse of the project is the dimension. Dimensions can be attributed to the crop production, such as the farmer who produced the crop, the type of crop produced, the season when the crop is produced, and the location where the crop is planted and harvested. The following descriptive dimensions will be used in the project and its descriptive attributes of each dimension are described in Table 1.

TABLE I. DIMENSION TABLES

No.	Dimensions	Descriptive Attribute
1	Crop	cropID, cropName, cropStart, cropMaturity, cropSeason, cropMun
2	Season	seasonID, seasonName, seasonStart, seasonEnd
3	Municipality	munID, munName, munLat, munLong
4	Farmer	farmerID, farmerLname, farmerFname, farmerContactNo
5	Harvest	harvestID, harvestYear
6	Organization	orgDI, orgName, orgType
7	CommodityProduction	prodID, prodArea, prodMt, prodProductivity
8	Climatological	climID, climYear, climMonth, climRainFall, climTMax, climTMin, climRH, climWSpeed, climWDirection

The monthly and/or yearly production of each crop will be the fact that will include production measure in metric tons, the area harvested measure in hectares, and productivity measured in metric tons per hectare. The fact table is presented in Table 2.

TABLE II. PRODUCTION FACT TABLE

Crop Production Fact
cropID (FK)
seasonID (FK)
munID (FK)
farmerID (FK)
harvestID (FK)
orgID (FK)
prodID (FK)
climID (FK)
cropProduction(mt)
cropArea(ha)
cropProductivity (mt/ha)

A data warehouse that contains data that is used to support agricultural decisions that could be used as data visualization tool for reports and dashboards and crop yield predictions.

E. The Prototype

The proposed system has six (6) modules that include 1) dashboard; 2) management of crop, farmer, and commodity production data; 3) historical data of commodity production and climatological data (Fig. 3); 4) crop trends and predictions on commodity production using various climatological parameters (Fig. 4) ; and 5) news module; and 6) a community module.

It has user access levels that define what users can do in the system with access levels. Admins have full access to all functionality. Staff from Department of Agriculture (DA) on the management level can access the system, they are responsible in the management of crop and farmer's information, view dashboard and historical data, view crop

Fig. 3. Data visualization on historical data

Fig. 4. The predicted crop production amount based on climatological parameters

trends and predictions, disseminate news and other programs for the farmers, and post announcements or events for the farmers. They will also input in the crop management the crop calendar that will indicate the following parameters: 1) time of planting, 2) maturity, and 3) volume of production for each crop. While staff from OPAG on the management level enjoy similar functionality except that they can do only the management of crop production data. Farmers can also access the system's dashboard with data visualizations to assist them in crop planning. Results and other announcements can also be send directly to the farmers through a simple Short Message Service (SMS).

The project aims to construct an agricultural decision support system likewise considered a regression model as the foundation for the system's predictive features which corresponds to other similarly designed decision support systems mentioned in the study.

Table 3 contains the Mean Squared Error and R2 score of the three models, which were obtained through WEKA, when applied to the dataset with a percentage split of 80% for training and 20% for testing. Crop production was labeled as class. According to the results, Random Forest with Out-Of-Bag (OOB) estimates has the lowest Mean Squared Error (MSE), but its R2 score has a negligible difference between it and Linear Regression. It was later determined that due to the visual nature of the project, a random forest model would prove too complicated to visualize [25] as opposed to Multiple Linear Regression (MLR).

TABLE III. REGRESSION MODELS

Regression Model	**Root Mean Squared Error**	**R2 Score**
Multiple Linear Regression	2106.1026	97.73%
Decision Tree	2160.8527	96.98%
Random Forest (OOB)	1230.4652	99.30%

Due to the mostly categorical nature of the dataset, the project implemented a variant of Linear Regression, Multiple Linear Regression (MLR), in order to derive a single numerical prediction in the form of the metric tons produced

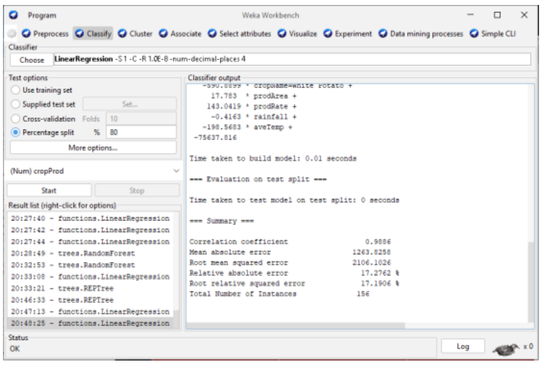

Fig. 5 Linear Regressiona result using WEKA

per crop. MLR is a model that shows the relationship between a dependent variable and multiple independent variables. The model was used for the prediction of each crop yield in each municipality. Data mining techniques such as data pre-processing, data transformation, data aggregation and prediction were performed using Excel, Python, and WEKA. The accuracy of prediction was evaluated through R-squared and Root Mean Squared Error.

IV. CONCLUSION AND RECOMMENDATIONS

There is corroboration for the implementation of a better DSS to provide a more accurate prediction of vegetable crop yield. It could be used for analysis to recommend the most appropriate actionable insights. It has been presented in this study that the adoption of innovation and technology and the application of various machine learning techniques could be a possible way for national development and sustainable economic growth.

The prototype provides farmers and other users with a DSS platform. Data mining techniques such as data preparation, data transformation, data summary, and data wrangling are useful techniques in the analysis stage prior to the utilization of machine learning algorithms in the prediction of crop yield. Crop predictions for each municipality and for each crop were successfully achieved using various climatological parameters particularly the average amount of rainfall and average temperature.

An important factor for the future enhancement of the DSS is the continuous integration of updated climatological and agricultural data. Farmers are expected to continuously input crop production information, best practices or experiences, and other factors affecting good and bad production for the upland vegetables. Collaboration of regional/national agricultural experts, information technology specialists, and other stakeholders particularly local knowledge will be an important source of information and decision-making.

The DSS is currently in the early stage, but plans are underway to enhance the system to assess its use in the province. Future enhancements will permit the researchers to confirm the performance of various machine learning algorithms and deployment of the best predictive model to respond to challenges to the emerging agricultural issues not only in the province of Benguet but in the Cordillera Administrative Region (CAR).

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