Eco: Digitization of Organic Farming in Sri Lanka

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ABSTRACT
From the beginning, Sri Lanka has been an agrarian civilization. When Sri Lanka was colonized, the plantation sector, which specialized in rubber, tea, and coconut, was given precedence. Following independence in 1948, a greater focus was placed on the production of food crops. A significant portion of the Sri Lankan population works in agriculture, and there is a growing need to promote organic farming. Low economic growth has come from farmers and out-growers incapacity to make educated and productive judgments quickly. As a result, they're having trouble deciding what to grow next, as well as client consumption trends and the most in-demand locations for a certain crop. Farmers also require a reliable communication system to coordinate a variety of operations related to their crops, such as fertilizing, planting, and harvesting. Due to a lack of information exchange, farmers are now uninformed of the behavior of the Sri Lankan market and worldwide agricultural trends. Because of assessing these scenarios, a system for forecasting demand for certain vegetables is needed. As a consequence of this study, it is suggested that the major variables driving vegetable demand and price variations in Sri Lanka be identified and that a model be trained using machine learning to predict demand and price. Additionally, determine the optimum cultivation for current land and recommend favorable circumstances depending on the crop, making this computerized method more reliable and convenient. The system's ultimate goal is to assist users in making high-quality, timely judgments to achieve the sector's optimum growth.

Keywords
Agriculture demand forecasting; Price prediction; Neural network; Sri Lanka; Regression approach; crop favorable conditions, best crops for existing lands.

1. INTRODUCTION
Sri Lanka's agricultural industry dates back to the ancient kingdoms when it was one of the world's leading agrarian societies. Sri Lanka rose to prominence as a paddy-growing location. Agriculture was first restricted to home consumption and was carried out on a small scale in dwellings or nearby landmasses. Sri Lanka had substantial changes in every industry, including agriculture, during the colonial period. In Sri Lanka, commercial goods such as coffee, rubber, coconut, and tea were introduced.

Agricultural was separated into four primary categories: agriculture (plantation), fisheries, livestock, and forestry, which were further divided into 16 subcategories to make national accounting easier to compile and understand.

Experts say that the agriculture business is either stagnant or declining in terms of income. However, successive administrations have prioritized the development of this industry since it provides food security and work possibilities for the country. Many farmers are reporting major difficulty in securing a regular price for their products, as well as crop damage as a result of extreme climatic conditions and wildfires. Some farmers are unable to recover their fixed expenditures and prepare for the following harvest [1].

Overall, the agriculture sector contributes around 7 percent of the national GDP, with the fisheries sector contributing 1.2 percent and the livestock business contributing 0.6 percent. Moreover, a quarter of Sri Lankans work in the agriculture industry. Even though Sri Lanka is a fertile tropical location with the capacity to cultivate and process a wide range of crops, productivity, and profitability remain difficult [2].

Sri Lanka's major food crop is rice. Rice is cultivated throughout two seasons. Tea is an important source of foreign cash and is cultivated in the central highlands. Fruits, vegetables, and oilseeds are also cultivated in abundance over the nation. Mechanization in agriculture has been sluggish to take hold. Sri Lanka imports a variety of agricultural and food goods, including wheat, lentils, sugar, fruit, milk, and milk products. Imports of food and beverages made up 7.2 percent of total imports in 2018. Sri Lanka is quickly developing itself as a major international commerce and tourism destination. A wave of luxury foreign and local hotels, resorts, and restaurants have opened in Colombo, Kandy, Galle, and the surrounding districts. They are an excellent venue for presenting new imported foods to the market. In addition, premium retailers are creating distribution channels for international goods and drinks. Sri Lanka imports animal feed as well. Imports of agriculture, food, and beverages totaled 1.6 billion USD in 2018 [3]. Certain agricultural commodities are occasionally in high demand, but meeting that needs is difficult for several reasons, some of which are unavoidable and others that are less obvious. Adverse and damaging weather conditions, as well as the unpredictability of agricultural product demand by key export destinations, exacerbated the issue.

2. LITERATURE REVIEW

Research on hybrid neural networks and the H-P filter model for short-term vegetable price forecasting was carried out and the focus of this research is on time series data on vegetable costs, which have a significant impact on people's lives. There are both linear and nonlinear patterns in the time series pricing data. As a result, neither a contemporary linear forecasting model nor a neural network can be used to model and predict time series data. The linear forecasting model cannot handle nonlinear relationships, while the neural network model cannot manage both linear and nonlinear patterns simultaneously. From time series data, the linear Hodrick-Prescott (H-P) filter may extract the trend and cyclical components. They forecasted both linear and nonlinear patterns, then linearly mix the two components to give a forecast from the original data. The model is evaluated using data from vegetable prices in the trial. According to this research paper, their method outperforms the auto-regressive integrated moving average method and back propagation artificial neural network methods, according to comparisons [4]. A study on the prediction of vegetable price based on a neural network and genetic algorithm was conducted and they used four distinct types of models.

- BP neural network model
- The neural network model based on the genetic algorithm
- RBF neural network model
- An integrated prediction model based on the three models above

The four models are used to forecast the price of Lentinus edodes for the Xinfadi wholesale market in Beijing. 84 total records have used to train and test the four models, which were collected between 2003 and 2009. In conclusion, the BP neural network model has the weakest predictive ability. The RBF neural network model was generally more accurate than the genetic algorithm neural network model. The outputs of the integrated prediction model are the best [5].

Another research was done on Alternative Forecasting Techniques for Vegetable Prices in Senegal. Based on this research paper Dr. Alioune DIENG evaluate the effectiveness of parametric models for projecting specific vegetable prices and making recommendations to potential users. Two approaches to predicting are used. The methodologies' forecasts were evaluated using both qualitative and quantitative criteria. Three alternative parametric models and a non-parametric model are considered forecasting methodologies. The naïve, exponential, and Box and Jenkins autoregressive integrated moving average (ARIMA) models are among the parametric models. The spectrum analysis technique is used in the non-parametric model. According to the findings of this study, among parametric models, Box and Jenkins' auto-regressive integrated moving average model will be a good technique to utilize in providing vegetable price forecasts for producers and consumers. But more study is needed to compare the accuracy of parametric and non-parametric models in forecasting other crops [6].

It is critical to understand existing applications before developing a solution. Based on performance analysis, a study was conducted to select the appropriate forecasting model at the retail stage for selected vegetables [7]. Various forecasting models, including the Box–Jenkins-based autoregressive integrated moving average model, and machine learning-based algorithms, including long short-term memory (LSTM) networks, support vector regression (SVR), random forest regression, gradient boosting regression (GBR), and extreme GBR (XGBoost/XGBR), were proposed and applied at the retail stage for selected vegetables to forecast demography. The performance analysis was carried out to select the best forecasting model for selected vegetables at the retail stage. Based on the results obtained for a case environment, it was discovered that the machine learning algorithms, namely LSTM and SVR, produced superior results when compared to other different demand forecasting models. Implementing LSTM and SVR for the case scenario at the retail stage will reduce forecast error, daily retail inventory, and fresh produce waste, while increasing daily revenue [7]. Another study focused on managing change and addressing the different expectations of domestic and foreign stakeholders in the context of Indian agriculture [8]. A seasonal autoregressive integrated moving average (SARIMA) model surpassed other contenders in terms of forecasting accuracy on both in-sample and two out-of-sample data sets among the models designed and tested. The model's results demonstrate that it can forecast with a mean absolute percentage error (MAPE) of 14 percent, which is regarded as acceptable for products with stochastic demand like fresh vegetables [8].

A Fuzzy Based Decision Support System for Evaluating Land Suitability and Selecting Crops was carried out and the focus of this research is to give the best suggestion for farming in lands using a few variables. Such as climate, landscape and soil, topography, and wetness. The proposed system has six phases.

- Identification of the decision maker's requirements
- Determination of membership functions of each criterion.
- Determination of performance rating of each land limitation
- Determination of performance rating of landscape and soil hmita1ion
- Evaluation of land suitability class
- Selecting the appropriate crop

All land characteristics are considered as having defined fuzzy sets. Hence the real-valued input variables arc transformed into fuzzy sets. This stem is applied to each land characteristic factor considered m the solution to the problem. The next step is the inference process it relates systematically pairwise all the factors that take place in the solution depending on the purpose of the problem. This part includes many fuzzy conditional statements to describe a certain situation. Land suitability class 1s determined through a two-phase inference based on input data expressed as crisp value and fuzzy set. First, the inference process is done to set the limitation level and second, it is done to determine the suitability class of the land [10].

Another study on Geographic information system-based identification of suitable cultivation sites for wood-cultivated ginseng was done. Wood-cultivated ginsengs are perennial plants that are semi-heterophonic and commonly used in Chinese medicine. To identify suitable sites for the propagation of wood-cultivated ginseng, the factor combination technique (FCT) and linear combination technique (LCT) were used with a geographic information system and the results were superimposed onto an actual wood-cultivated ginseng plantation. The LCT more extensively searched for suitable sites of cultivation than that the FCT; further, the LCT probed wide areas considering the predominance of precipitous mountains in Korea. In addition, the LCT showed a much higher degree of overlap with the actual cultivation sites; therefore, the LCT more comprehensively reflects the cultivator's intention for site selection. On the other hand, the inclusion of additional factors for the selection of suitable cultivation sites and experts' opinions may enhance the effectiveness and accuracy of the LCT for site application [11].

Integration of an artificial neural network and geographical information system for an intelligent assessment of land suitability for the cultivation of a selected crop is another study that was carried out in this domain. The main objective of this study is to investigate the potential of artificial neural networks (ANN) for integration with geographical information systems (GIS) to assess the suitability of the land to cultivate a selected crop. For this purpose, the requirements of a system for an intelligent assessment of land suitably were determined and the architecture of the integrated system was designed according to the capabilities of ANN and GIS [12].

A study on Best Crop Rotation Selection with GIS-AHP Technique Using Soil Nutrient Variability was done earlier. Crop selections and rotations are very important in optimizing land and labor productivity, enhancing higher cropping intensities, and producing better crop yield. This is a land suitability analysis system based on the analytical hierarchy process (AHP) technique coupled with the Geographic Information System (GIS) software environment that can be a unique tool for better crop selection. The AHP-GIS technique was used in land suitability analysis in crop rotation decisions, for rice-jute (Kharif season) and potato-lentil (Rabi season) crops in the Hooghly District, West Bengal, India. The study area covering 291 ha was classified based on eight major soil nutrient levels with 70 randomly selected plots for soil sampling and analysis [13].

A Fuzzy Based Decision Support System for Evaluating Land Suitability and Selecting Crops is evaluating land suitability and selecting crops in modem agriculture is of critical importance to every organization. This is because the narrower area of land, the more effective planting 1s required following the desires of the land. The process of evaluating land suitability class and selecting plants by decision marker's requirements is complex and unstructured. Approach: This study presented a fuzzy-based Decision Support System (DSS) for evaluating land suitability and selecting crops to be planted. A fuzzy rule was developed for evaluating land suitability and selecting the appropriate crops to be planted considering the decision maker's requirements in crop selection with the efficient use of the powerful reasoning and explanation capabilities of DSS. The idea of letting the problem be solved determines the method to be used and was incorporated into the DSS development. As a result, effective decisions can be made for land suitability evaluation and crop selecting problems an example was presented to demonstrate the applicability of the proposed DSS for solving the problem of evaluating land suitability and selecting crops in real-world situations [15].

3. METHODOLOGY

3.1 Forecasting demand for specific vegetables

Historical Product Demand is a sample dataset used to forecast retail vegetable demand. A CSV file is used to forecast retail vegetable demand. The shape of the dataset was substantially distorted when evaluating it due to the imbalanced number of records. There were 1306 records in the Historical Product Demand file, with data spanning five years.

Table 1. The data file's attributes

Attribute	Description
Commodity_Name	Vegetable Category
Centre_Name	Hector Kobbekaduwa Agrarian Research and Training Institute
Period	2015-2019
Demand	Demand of Vegetables

Filling in missing values is an important part of the data-cleaning procedure before training the model. There are a few solutions to this problem, including discarding the entire tuple, but most of them will likely bias the results. Because the number of missing values is less than 1 percent, hence, make the 'executive choice' to remove them. In addition, adjustments such as deleting redundant columns and splitting the date time column into two were made. To facilitate data transformation, all category data was condensed into a numerical format that could be understood. The data set contains a variety of data kinds with varying ranges. As a result, data transformation entails data normalization.

Time series models are used to predict the future values of variables by looking at their previous movements. The Voting Ensemble approach was employed to forecast vegetable demand in this case. Because of its great performance and simplicity, this approach has been employed in the literature. After the forecast, the accuracy was calculated as a percentage. Actual data for the 30 days predicted at the start was obtained from the same source and compared to determine the accuracy. To calculate the accuracy, the research team employed the Mean Absolute Error (MAE) [18] technique. The prediction system performs better when the MSE and MAE values are near zero.

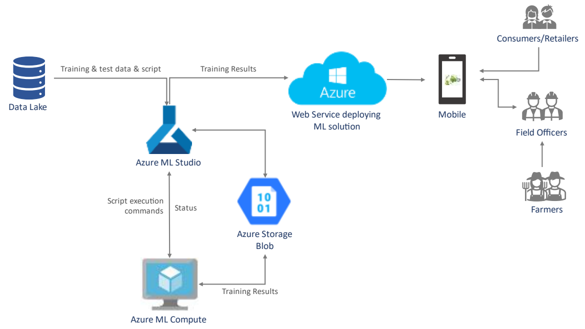

Fig 1: System Diagram

3.2 Forecasting prices for specific vegetables

A sample data set used to forecast retail vegetable prices with Historical Product Prices. To forecast retail vegetable prices, a CVS file with the dimension of 1306 x 6 is employed. team chose the most relevant data set for the model.

Table 3. The data file's attributes

Attribute	Description
Commodity_Name	Vegetable Category
Centre_Name	Hector Kobbekaduwa Agrarian Research and Training Institute
Period	2015-2019
Price	Price of Vegetables

Before training the model, filling in missing values is a crucial element of the data-cleaning process. Although there are a few solutions to this problem, such as tossing the entire tuple, the majority of them will certainly prejudice the results. Team made the 'executive decision' to eliminate missing values because the number is far less than 1 percent. In addition, changes were made, such as the deletion of duplicate columns and the splitting of the date time column into two. All category data was condensed into a numerical format that could be comprehended to make data transformation easier. The data collection includes a wide range of data types and ranges. As a result, data normalization is a part of data transformation.

Time series models are used to forecast future values of variables based on their past movements. In this scenario, the exponential smoothing approach was used to forecast the vegetable price. This methodology has been used in the literature because of its high performance and simplicity. The accuracy was calculated as a percentage after the forecast. To measure the accuracy, actual data for the 30 days anticipated at the start was gathered from the same source and compared. Mean Absolute Error (MAE) [18] was used as an approach to calculate the accuracy. When the MSE and MAE values are close to zero, the prediction system performs better.

3.3 Identify the best cultivation for existing land

To identify the best cultivation for existing land, a comprehensive dataset was obtained from National Agriculture Information Communication Center - Gannoruwa (NAICC). A CVS file with a dimension of 1000 x 11 is used to recommend the optimal crop for the current land and this is pertinent data set to train the model.

Table 3. The data file's attributes

Attribute	Description
Commodity_Name	Vegetable Category
Centre_Name	National Agriculture Information Communication Center - Gannoruwa
Period	2015-2019
Recommendation	Recommended crops for existing land

Before training the appropriate model using the dataset, the dataset was cleaned and examined for missing data. Following that, 80 percent of the data in the dataset was chosen at random. The dataset has 11 columns, 10 of which provided numerical data, while the last column specifies the crop on which the data is based. As a result, data normalization as part of data transformation was simple.

The neural network regression model was used for the recommendation system to calculate the accuracy and employed the Mean Absolute Error (MAE) [18] method. The prediction system works better when the MSE and MAE values are near zero.

3.4 Favorable conditions based on the crop

Before planting something, it is not easy to decide all the conditions at a 100 percent of accuracy level for a relevant crop by looking at the surface alone. This component will be providing a solution for this case. Here when someone searches for a crop by its name and enters the land area and quantity of the harvest this system will provide all the required conditions such as Nitrogen Level, Phosphorus Level, Potassium Level, PH of soil, and Temperature.

Table 4. The data file's attributes

Attribute	Description
Commodity_Name	Vegetable Category
Centre_Name	National Agriculture Information Communication Center - Gannoruwa
Period	2015-2019
Nitrogen, Prosperous, and Potassium levels according to to yield	Favorable conditions based on the crops

The records of Dambulla Pelwehera Agricultural training school which is affiliated with the Agricultural Department in Gannoruwa from 2015 to 2020 are used in training the model. The data set was collected with the help of agricultural instructors. The process was discussed with the instructors of Hayles, CIC, and Bowers to gain more information about fertilizers and soil. They also agreed to the concept. CIC instructors also helped us in testing the composition of fertilizer.

In the beginning, the dataset was as a cluster. First, the dataset was normalized. Then trained them. The dataset was containing only the relevant things without even a single empty detail. Therefore, the accuracy and the training result were 100 percent. XGBoost algorithm is used in training the model. As all possible conditions are not mentioned for all measurements, and providing an algorithm through XGBoost to calculate conditions for any quantity which is entered into the system. The quantities are categorized into several groups. They are

- Less than 1000 – Small
- 1000 to 10000 – Medium
- 10000 to 50000 – Large
- Above 50000 – Huge

4. RESULTS

During the testing rounds, the application was regularly tested in its natural context. Several testing rounds were conducted by analyzing the outcomes as the team followed the agile methodology. To produce more accurate outputs with the best user experiences, the team made sure to develop the system with a high level of user interaction. The next stage was to justify the idea based on the solutions discovered after developing the hypothesis. Many of the researchers to whom the research team turned for advice were at the theoretical level. As a result, supplying the extended theorems, as well as the proof and conclusion, is critical for putting it into practice. We've developed improved solutions for each component of the research that, when combined, leads to research solutions. The following are some of the findings in brief.

With the acquired data set, the demand prediction system that was constructed using the Voting Ensemble model was evaluated to get demand projections for carrot and beetroot for five years (from 2015 to 2019). As previously stated, figure 06 and Figure 07 show the expected demand fluctuation findings for carrot and beetroot.

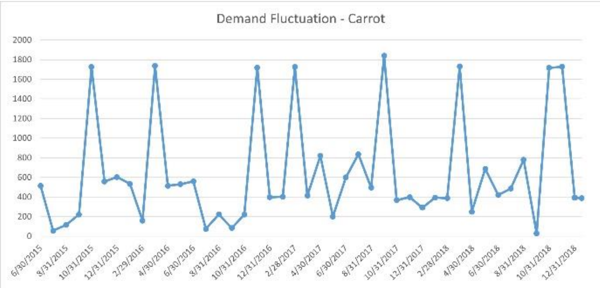

Fig 2: Demand Fluctuation of Carrot

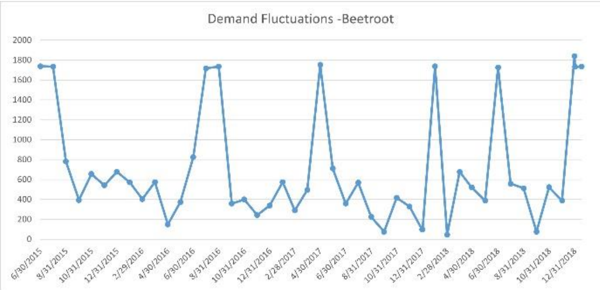

Fig 3: Demand Fluctuation of Beetroot

Fig 4: Real vs Predicted demand for Carrot

Fig 5: Real vs Predicted demand for Beetroot

Figure 04 and Figure 05 show a comparison of real demand vs. expected demand for carrots and beetroot. The expected needs, according to the graphs, are very near to the actual demand. This suggests that for a limited length of time, this model can be used to predict more dependable and legitimate demand.

The application was constantly evaluated in its native surroundings during the testing rounds. The team used the agile technique to conduct several rounds of testing and analyze the results. The team made efforts to create a system with a high level of user interaction to produce more accurate outputs with the best user experiences. After developing the hypothesis, the following step was to substantiate the notion using the solutions discovered. Many of the researchers that sought help from were on a theoretical basis. In a nutshell, it's vital to include the extended theorems, as well as the proof and conclusion, to put it into reality. We've enhanced solutions for each component of the research, resulting in research solutions when they're combined.

The price prediction system, which was built using the time series approach, was assessed using the obtained data set to obtain price estimates for carrots and beetroot for the next five years (from 2015 to 2019). Figure 10 and Figure 11 demonstrate the projected price fluctuation findings for carrot and beetroot, as previously mentioned.

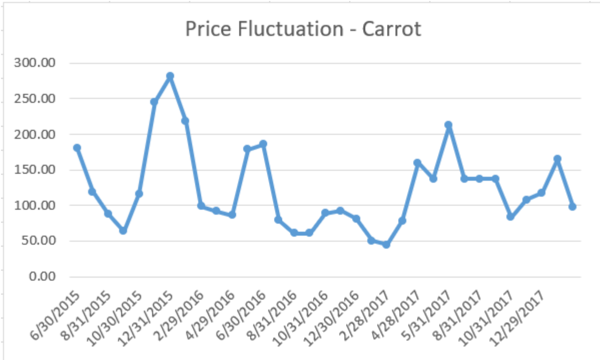

Fig 6: Price Fluctuation of Carrot

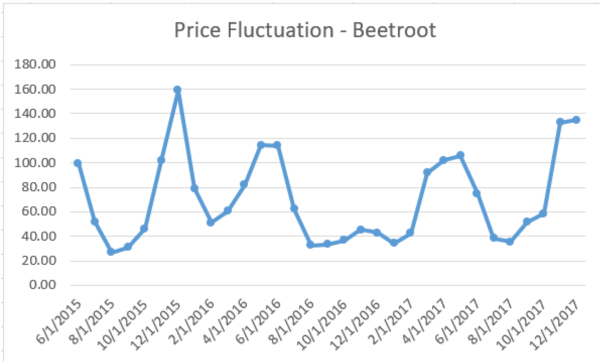

Fig 7: Price Fluctuation of Beetroot

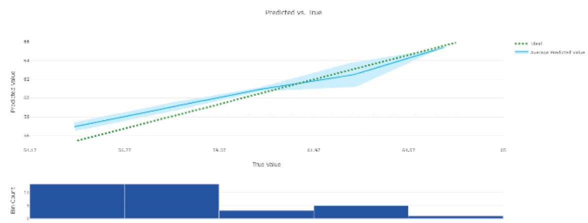

Fig 8: Real vs Predicted price of Beetroot

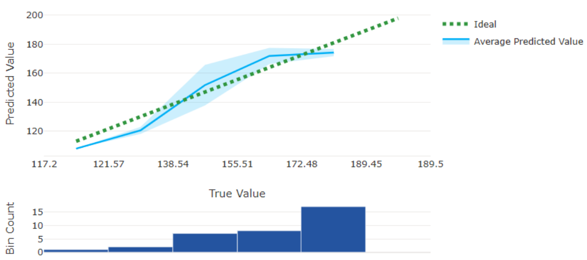

Fig 9: Real vs Predicted price of Carrot

For carrots and beetroot, figure 08 and Figure 09 illustrate a comparison of true price vs predicted price. According to the graphs, the projections are fairly close to the actual price. This implies that, for a limited period, this model can be used to forecast more reliable and legit prices.

Finally, the model trained on the dataset for crop predicting was given a table containing the following dataset. "Scored label" is the column in the table that corresponds to the crop value that hopes to predict after training.

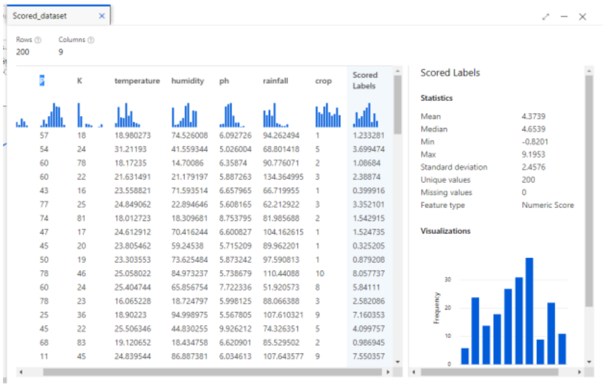

Fig 10: Score Dataset of Crop Recommendation

The required conditions for any quantity that is entered into the system are calculated by XGBoost according to the algorithm which are introducing. Once someone enters any amount of cultivation quantity within the ranges with the name of the vegetable, the calculations will happen and will show the results. The following figure 15 and Figure 16 show the yield of carrot and beetroot for five years related to all the components.

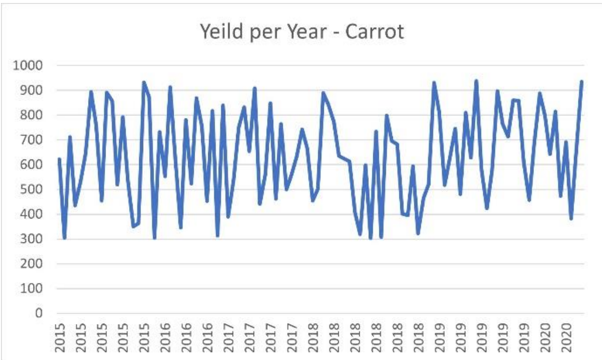

Fig 11: Yield per year – Carrot

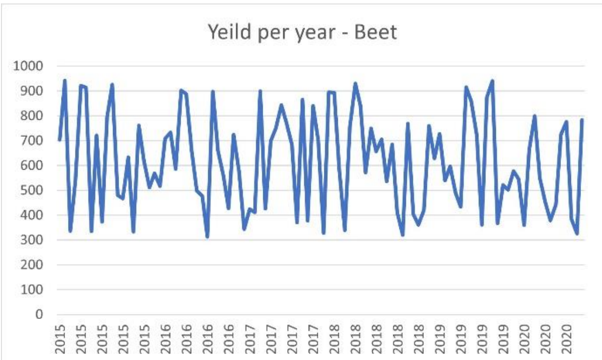

Fig 11: Yield per year – Beetroot

5. DISCUSSION

This section mostly discusses the concerns that arose during the design and implementation process, as well as how those issues were overcome. In addition, how to develop the system and achieve success is discussed in this section. The "ECO" project began in July 2021 as a final-year group project. Over several weeks, the research team investigated the problem behind the research topic by obtaining important information from targeted audiences, documents, and online users. After identifying the problem, members of the research team had to devise an appropriate strategy for resolving it within the time constraint. A literature review was conducted to see if similar products were available and, if so, what limitations they had. After that, an analysis was conducted to identify and test current technologies to find a solution to the concerns mentioned above.

Because of the pandemic situation, the main challenge that faced was obtaining an accurate data set for predicting expected results through the mobile application. As a result, team was able to obtain some previous datasets from Hector Kobbekaduwa Agrarian Research and Training Institute (HARTI) and Horticultural Crops Research and Development Institute, Gannoruwa (HORDI). According to the records of the Horticultural Crops Research and Development Institute, Gannoruwa, choosing higher-demand crops among Sri Lankan vegetable producers and consumers (HORDI). Also had a lot of trouble deciding between Azure and Python Stat modules when it came to selecting technology.

Team want to expand the solution in the upcoming version by adding a few additional crops and introducing Sinhala and Tamil versions of ECO. Although ECO currently only serves the Android platform, it will be enhanced in the future to accommodate other operating systems as well. Team ECO, expects that ECO would provide a large helping hand to farmers to help them overcome their difficulties and misery.

6. CONCLUSION

Farmers have forecasted future vegetable pricing and demand based on their previous experiences and knowledge. They also tend to plan their future crops based on their findings. However, research team may conclude that these predictions are inaccurate since the human brain can only handle a finite amount of data and is unable to evaluate linked factors that influence it. As a result, anticipating future market predictions has always been a time-consuming and complex undertaking in Sri Lanka. As a result, rather than using traditional hand-out testing, a smart device that can assess patterns and forecast future market demands for vegetables is a much-needed alternative. Overall, the ECO smart mobile application contains a price prediction system, a demand forecasting function, a system for determining the best cultivation for current land, and a system for recommending favorable crop conditions. ECO is the first automated program in Sri Lanka to employ Neural Network Regression to estimate vegetable demand, to the best of the knowledge. ECO can act as a platform for future agricultural research, allowing subsequent studies to explore deeper into the area.

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