Synergetic Innovation in Gherkin Cultivation Based on Machine Learning Algorithms

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***Abstract*— Gherkin cultivation, while a significant contributor to the agricultural sector, remained underutilized in Sri Lanka despite high international demand, particularly for pickles. Gherkin farmers faced many challenges from pests, diseases, unpredictable harvest and production costs. The main reasons identified were farmers' lack of knowledge, different weather conditions and inability to identify the danger. The proposed system provided a smart agriculture solution included with computer vision, machine learning and object detection for improving gherkin production. The solution enabled pest identification and control, disease diagnosis, accurate harvest estimation, and cost determination, addressing the underutilization of gherkin cultivation in Sri Lanka despite high international demand, especially for pickles. The system provided the capability for pest identification and control, disease diagnosis, real-time estimation of actual harvest and the cost determination remains underutilized in Sri Lanka despite high international demand, particularly for pickles. By leveraging YOLOv8, Random Forest, and CNN architectures, the system returned reliable predictions and recommendations for the farmers. The outcomes revealed that using the system enhanced productiveness and diminished the pollution in gherkin farming with high accuracy rate of various functionalities.**

Keywords*— *Gherkin farming, Pest identification, Disease detection, Random Forest, YOLOv8, Harvest prediction, Cost forecasting, Machine learning, Computer vision.

I. Introduction

Gherkin cultivation is a significant element in the world's agriculture sector because it has a universal demand as a multifaceted crop. Gherkins are mostly famous for pickles. They are not identical to common cucumbers but share similar characteristics. Most of the countries including Sri Lanka exports Gherkins pickles to European, Asian and American countries which have huge exaction for pickles.

Sri Lankan Gherkin pickles have a great demand in the international industry because of the excellent natural taste and aroma of the products. The naturally placed geographic location, year-round sunlight and most favorable atmospheric conditions are causing that. Therefore, Sri Lanka placed a significant exporting brand in the foreign market. However, Gherkin cultivation is not widely popular among Sri Lankan farmers, due to the lack of knowledge. Only two to three companies are involved in gherkin cultivation and exporting process across Sri Lanka. The aim of this research is to address this gap by monitoring the cultivation process and providing guidance to new farmers throughout the cultivation period.

Therefore, the thesis introduces an innovative mobile application to the farmers who are willing to cultivate gherkins. It contains four main functionalities including disease identification, pest identification, actual harvest prediction and production cost prediction which implements with the machine learning and computer vision technologies. The proposed solution can give complete guidance about gherkin cultivation to make the production more efficient and sustainable. By using the object detection algorithms and productive analysis mechanisms, the system can provide the most accurate information to make the right decision thus improving yield and minimizing the production risk. It will boost not only the economic prospects of farmers but also Sri Lanka's position as a high-quality gherkin pickles exporter in the international market.

II. Literature Review

This research paper deals with synergetic innovation in cucumber farming specifically focusing on identifying diseases on the leaves of cucumbers. This subject is important since diseases can have serious effects on the growth of gherkins, leading to economic losses to farmers. The research aims at contributing towards management of disease in Gherkin cultivation through employment of most recent technologies such as Convolutional Neural Networks (CNNs).

In agriculture domain, Machine learning, deep learning, and Computer Vision methods are utilized precisely to perceive pests and various types of pest testing and detection research have also been done on the same subjects [1]. Digital image processing tools aided photos of crop insects by performing the pre-processing, segmentation, and feature extraction steps, to evaluate the insect shape. In the early stage of pest recognition, handcraft-feature methods were the primary solutions. Mayo et al. proposed an automatic identification method using support vector machines (SVM). It has a novel approach for the early detection of whiteflies, aphids, and thrips on greenhouse crops [2]. Yufeng Shen et al. [3] presented implementing a system for detecting and identifying stored-gran insects by applying a deep neural network. They used Faster R-CNN for disclosing the corresponding genus of these insects. Hence, the developed innovative procedure can identify the kind of poisonous insects under grain storage. These conventional methods have some disadvantages in terms of practicality, contributing to delayed pest identification, recognized accurate pest, provided farmer friendly solutions.

This Research carried out by other scholars serves as a basis upon which this study builds. Mohanty (2016) shows that CNNs can be employed to detect illnesses on crops such as cassava and rice [4]. Debates over the choice of CNN architectures for disease identification are evident in the existing literature. For example, Mohanty et al. (2017) compared ResNet, VGG16, and Inception architectures and found differences in their performances and computational efficiency. Additionally, Zhou (2017) found transfer learning to be useful in fine-tuning pre-trained models for plant disease recognition thus improving its classification accuracy [5]. The major strength of previous works is an illustration of how deep learning and transfer learning techniques can be used in plant disease identification. However, some limitations are identified like larger annotated datasets, model generalization, and real-time applicability for agricultural purposes. In fact, there is a gap in the understanding of diseases specifically affecting gherkin leaves. While some crops have been successfully treated using CNN-based methods, the actual worthiness of these models in gherkin disease diagnosis has not been extensively studied yet. Based on the literature, this research will employ CNN architectures including Inception , EfficientNet, ResNet and DenseNet to recognize diseases in gherkin leaves.

The study [6] aims to predict the crop yield using Random Forest algorithm by considering the machine learning approach depending on the productivity, changes in climate, and humidity in the agricultural field. It shows the capability of handling large datasets and making crop-yield predictions using Random Forest.The thesis published by N. Rale et al. (2019) [7] shows how climatic predictions can be knitted with artificial intelligence to provide better solutions in crop farming, hence improving yield results.

The research [8] tries to use machine learning algorithms with concentration on the Random Forest model to accurately estimate crop yields. According to the results of economic indices in combination with agricultural data, the goal of the research is to have credible forecast to possibility indicate the shortages and needs of agricultural planning and management, especially in the context of urbanization.Thesis [9] contributes to giving the understanding about Parallel and complex parallel factor analysis. The research discusses the convergence and separation performance of these algorithms, particularly in scenarios involving blind source separation and monitoring tasks.

The thesis [10] highlights the integration of experiential, procedural, and descriptive knowledge into a knowledge-based system, aiming to enhance reliability and decision-making in maintenance engineering and pathology. The platform leverages big data and smart computing to create a system that can assist experts in making informed decisions based on accumulated knowledge and experiences. Over time, gherkin production research has changed dramatically [11]. Studying varietal screening of gherkins by D. Kuruppuarachchi (1993) set the foundation for knowledge on variations in gherkin farming and their effects on crop yields. Important insights into the agronomic features of gherkin farming were gained from this early research.

The use of machine learning in agricultural forecasting has grown in popularity in recent years. The potential of multivariate LSTM models for price forecasting in Sri Lankan agricultural markets was illustrated by the work of Shriram Navaratnalingam and colleagues (2022) [12], demonstrating how sophisticated algorithms can increase predicted accuracy. This is consistent with work done in 2013 by Vikas Deswal et al. [13], who used machine learning techniques to anticipate stock market prices and showed how predictive modeling is similar in many fields.

The Socio Economics and Planning Center, Department of Agriculture, Peradeniya, issued "AgStat, Agricultural Statistics Volume XV" (2018) [14], which highlights the significance of precise agricultural data. This publication emphasizes the need for trustworthy statistical data in the development of efficient forecasting models by providing crucial data that enables predictive modeling in agricultural research. Furthermore, A.K. Iftekharul Haque (2020) [15] investigated how trade volumes of important agricultural commodities were affected by exchange rate and commodity price volatility, highlighting the importance of larger economic issues in agricultural commerce. These results offer a thorough insight of the economic issues facing the industry and are essential for comprehending the market dynamics influencing gherkin output and pricing.

III. METHODOLOGY

This Figure 1 presents a system designed to support agriculture through the integration of computer vision and machine learning models. This proposed solution provides minimal time and maximal productivity, as well as quality assurance in the gherkin production. The approach combines smart pest identification and classification, actual harvest prediction, disease detection, and cost prediction based on modern machine learning algorithms and object detection models. Every component utilizes advanced technologies to solve cultivation related issues and enhance production results to produce synergetic innovation in gherkin farming.

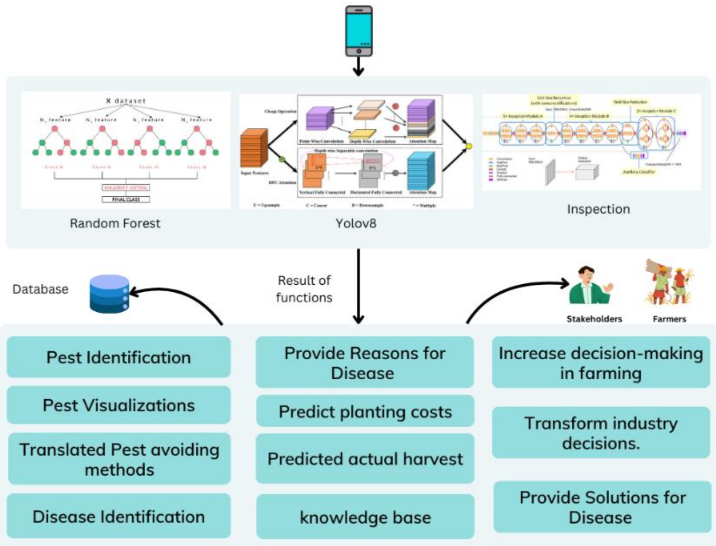

Fig. 1. Overall System diagram of the proposed solution

A. *Smart Pest Identification and Classification*

The application's primary goal is to develop and evaluate a comprehensive system for smart pest identification and management in the Gherkin industry. The main challenge in the gherkin industry is pest infestations and waste a lot of time and money to avoid pest infections. This solution can accurately identify five types of pests: aphids, thrips, caterpillars, mites, and whiteflies [16]. This system integrates machine learning algorithms and image processing techniques to enhance the pest control efficiency and accuracy for farmers. The pest dataset contains primary and secondary datasets. To identify the accurate pest, that system uses Look Only Once (yolov8) object detection algorithm. It is a state-of-the-art model that uses a single CNN for both object classification and localization [17]. YOLO is developed on the Darknet architecture, that consists of 24 convolutional layers. That model was trained using images of newly collected pests and online resources. Given that training has been completed, the machine learning (ML) model will give the binary outputs. The below Figure 2 is used to depicted F1-Confidence Curve which is used to measure the accuracy level of the given model by plotting the values of F1 score with respect to the confidence levels of the different classes. X-Axis (Confidence) - Represents the confidence threshold, Y-Axis (F1)- F1 stand for the F1 score, and Colored Lines stands for how the F1 score for each class varies with different threshold values.

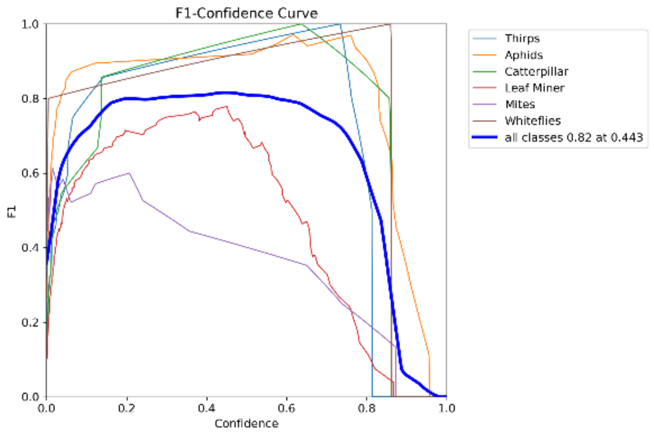

Fig. 2. F1-Confidence Curve

This system provides high accuracy answers with a secondary analysis. This is conducted using the Inspection algorithm, which re-evaluates the identified images to enhance accuracy and reliability. Inspection is a deep convolutional neural network architecture that involves Depth wise Separable Convolutions. Re-identification, the app provides tailored recommendations for pest management based on the detected pest species. That extra layer of scrutiny and an optimized pest identification process improved the overall efficacy and accuracy of the answer.

Depending on the pest it has identified, the application will recommend management actions. The outcome will be shown in Sinhala voice command and English text. Expo-speech, which provides an API that allows you to utilize Text-to-speech functionality in this app. This especial feature helps that app to be step forward because most of the users of this app based on Sri Lanka. This makes it possible for the recommendations and insights developed by the app to go beyond the realm of those who fully understand the technical details of the software.

B. Actual Harvest Prediction

The primary objective of the Actual Harvest Prediction functionality is to reduce the gap between the expected and actual harvest by optimizing the main factors including soil composition, fertilizer combinations and weather forecasts. Also, this functionality classifies the factors that contribute directly and indirectly to the variance between the expected and actual yields.

The harvest of gherkin cultivation exists based on several factors. They are the pH value of the soil, the percentage of minerals including Nitrogen(N), Phosphorus(P), Potassium (K), rainfall, temperature, the fertilizer combination including the percentage of Urea, Triple superphosphate (TSP), Muriate of Potassium (MOP) and Calcium nitrate. Based on these combinations, the actual harvest can be more or less than the expected harvest. It can be deficient or in excess causing losses to the farmers. To avoid this risk, the actual harvest prediction functionality has been provided.

The prediction methodology is, therefore, developed from a machine learning (ML) model trained to predict the actual harvest. The first difficulty, in this context, was the generation of an extensive database. This dataset comprises of data from gherkin cultivations in the past and has various attributes such as cultivation area, soil pH, acreage, Calcium (Ca), Magnesium (Mg), Zinc (Zn) and N-P-K in the soil, and Urea, TSP, MOP and CaNO3 in percentage [6]. Also, information inserted comprise of the season, grade, rainfall, temperature, anticipated yield, as well as the actual yield [7].

On building the prediction model, four regression models namely, ‘Random Forest’, ‘Lasso Regression’, ‘Linear Regression’, and ‘Decision Tree Regression’ were used. Analyzing the output of those models, it has been found that the Random Forest model has given the highest accuracy of 95.56% compared to the other models. The evaluation matrix and the comparison of accuracies of these models is illustrated in F2 and F3 respectively in Figure 3. Therefore, Random Forest model was used in the actual ‘harvest prediction’ functionality [8].

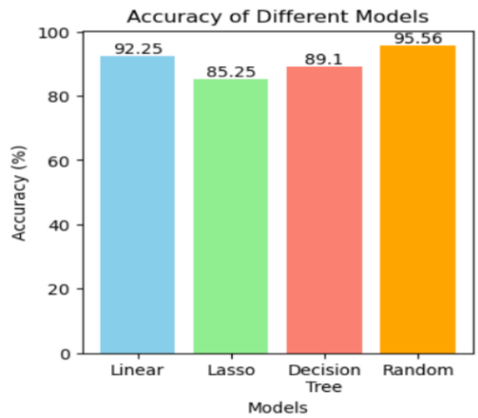

Fig. 3. F3-Accuracy chart of different models

When the actual harvest is predicted, the system performs an assessment with a view to determining the actual and projected harvest. The above analysis is then succeeded by the suggested most appropriate fertilizers to reduce this gap using factor analysis to ascertain the appropriate blend [9]. In addition to them, decision support for farmers is an improved functionality of this system where a knowledge base that contains more on how farmers can go about has also been incorporated [10].

C. Disease Identification and control

The proposed solution aims to provide an advanced and reliable system for identifying gherkin leaf diseases and providing appropriate solutions depending on environmental factors such as humidity and temperature. In this regard, the system enables users, including farmers and agricultural experts, to submit images of gherkin leaves which are then processed through object detection and CNN models.

The first thing done by the system is to figure out if the leaves are gherkin leaves. It does this using a YOLOv8 object detection model that has been trained on a dataset of gherkin leaves. The model finds out whether there are gherkin leaves in the input image. If the system confirms that this is an image of a gherkin leaf, then it goes into disease identification mode. Four different CNN architectures were used to find out which architecture worked best. These include Inception (GoogLeNet), EfficientNet, ResNet, and DenseNet due to their high performance in image classification tasks related with disease identification. This paper focuses on two specific diseases downy mildew and bacterial wilt, only, therefore used these four architectures alone for both training and testing purposes as part of the experiments. Each model was trained and tested using a dataset of disease infected gherkin leaf images with labeled disease information associated with each image. The dataset is divided into train, valid and test sets so that strong models can be effectively evaluated. The input to the system is temperature and humidity data. It will use previously set limits and patterns to assess if these abiotic factors can be considered as causes of the noticed disease. If humidity levels and temperature are within ranges which promote diseases, such cases are flagged as possible causes of a condition.

The data set was divided into three sets: training (80%), validation (10%), and testing (10%). To prepare the images for analysis, they were scaled to 300 × 300 pixels on all sides and normalized by dividing all pixel values by 255 to ensure they were between 0 and 1. To avoid overfitting and improve generalization of the model, simple augmentation techniques such as rotation, flipping or zoom were applied. Gherkin plants grown in the fields are equipped with sensors that capture humidity and temperature. These thresholds are defined through expert consultation with agronomists and plant pathologists who understand bacterial wilt as well as downy mildew.

Train this YOLOv8 model using a dataset of annotated gherkin leaf images so that it can differentiate them from other objects contained in the pictures. The other models used are Inception, EfficientNet, ResNet, DenseNet which have been trained on labeled gherkin leaf datasets with specific indications for bacterial wilt as well as downy mildew. The hyperparameters are adjusted during training to tune up all aspects of model performance requirements. Algorithms come in handy when comparing real-time sensor measurements against pre-defined thresholds that define whether conditions are favorable for disease development by way of temperature or moisture levels within the atmosphere. The Gemini model is fine-tuned with agricultural data to generate solutions tailored to the detected disease and current environmental conditions. Solutions are translated using a machine translation API ensuring accurate and context-appropriate language use. This comprehensive methodology ensures that the system can effectively identify gherkin leaves, diagnose diseases, analyze environmental factors, provide solutions, and communicate them in a language accessible to the end-users.

D. Cost Prediction

Gherkin cultivation is an important part of global agriculture, providing a key source of income for farmers worldwide while supporting pickle manufacturing. However, the cost of planting gherkins is subject to fluctuations due to various factors, including labor availability, weather, soil quality, input costs (such as seeds, fertilizers, and pesticides), insecticides, and fungicides. For farmers, merchants, and other stakeholders to make educated decisions regarding production methods, budgeting, and resource allocation, an accurate forecast of gherkin planting costs is vital.

Advanced cost prediction methodologies become even more important in this sector because traditional forecasting methods are severely challenged by the inherent unpredictability and complexity of agricultural production expenses. To directly address these difficulties, this research study proposes a data-driven strategy for cost forecasting in Gherkin farming. To give farmers early warning about the possible profit or loss of their investment before they commit to the planting procedure, our goal is to create a machine learning algorithm for gherkin planting cost prediction. We hope to provide stakeholders with actionable insights that can help lower risks and take advantage of market opportunities, guaranteeing more thoughtful and strategic decision-making throughout the production cycle. We do this by integrating modern analytics with industry knowledge of the gherkin market.

Beyond its approach, this research is important because it could change the way the gherkin sector makes decisions, which would increase the efficiency, sustainability, and resilience of agricultural markets. By enabling stakeholders to foresee cost patterns and market dynamics, our predictive models help improve risk management, investment planning, and resource allocation methods. The study helps with cost prediction for gherkin agriculture, including its implications for production trade, rural development, and food security, which is of immeasurable value to exporters and industry participants.

The proposed system objective is to demonstrate the efficacy of our approach in forecasting gherkin planting expenses by means of empirical confirmation and practical application. We want to precisely navigate the complexity of gherkin production costs by utilizing data-driven insights, giving stakeholders the resources they require to prosper in an agricultural environment that is continuously changing. Our strategy aims to improve predictive analytics in this industry by providing useful tools for wise choices and long-term expansion.

IV. Result And Discussion

In this research, identification and classification of pests employed the YOLOv8 model based on object detection. The YOLOv8 model was used for pest detection and identification in gherkin cultivation with over 85% accuracy. The performance of the YOLOv8 model is presented in the result image Figure 1. Analyzing the loss functions such as box_loss, cls_loss DFL_loss for training and validation, all the parameters are declining in the model signifying a good training and validation of the model [6]. Other measures such as precision and recall also support the functionality of the model by attaining good scores as the training continues. Figure 4 shows the validation batch labels predicted by the YOLOv8 model. Figure 5 is evidence of the model's effectiveness in labeling diverse pests like Aphids, Leaf Miners, Thrips, Whiteflies, Mites, and Caterpillars.

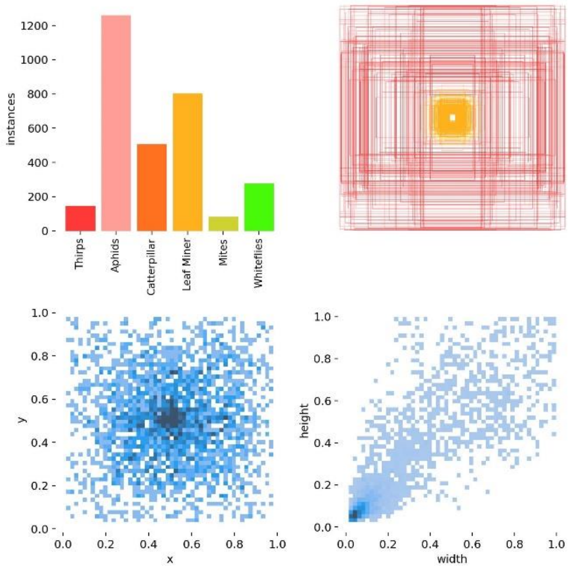

Fig. 4. Result values in Yolov8

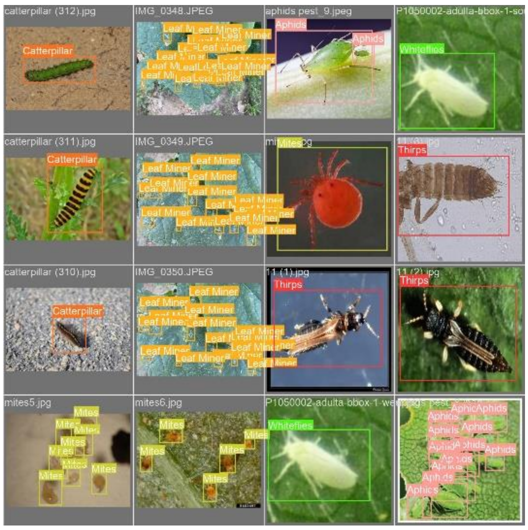

Fig. 5. Validate Pest Result

The classification of the particular pest detected by YOLOv8, Inception v3 model was adopted to re-identify the pests. This re-identification step boosted the accuracy higher than 90% for improving pest classification's accuracy level. The use of YOLOv8 for the primary identification and Inception v3 for re-identification makes for a wholesome integration that powers up the pest identification process in a remarkably efficient manner. Once the pest is correctly identified, the system provides a pest control solution that is interpreted to Sinhala through the use of the React Native expo speech library. This makes it easier and straightforward for the farmers that are basis the local individuals to understand and implement the pest management solution. The solution provides an AR view of the pests detected for helping the farmers. This feature enables farmers to see the pests in relation to the surrounding environment, making it easier for them to identify and manage them.

The Actual Harvest Prediction functionality was effective in reducing the likely gap between the expectation and the real harvester for gherkin farming. Employing a Random Forest model algorithm, the high accuracy of 95.56% was realized, relative to other models including Lasso Regression, Linear Regression, Decision Tree Regression models. This high accuracy proves that the model has a unique ability to handle large amounts of data input including the soil pH, nutrient content, and weather factors and can offer accurate predictions. More specifically, the researchers found that the differences between the anticipated and the real harvested yields may be caused by unequal distribution of nutrients in the soil and improper application of fertilizers, which seemed to call for accurate approaches to the issue at hand [6].

The Table1 denotes the difference between the expected harvest and actual harvest and the relative equality of predicted harvest and the actual harvest.

TABLE I. The Details of the Harvest of Yala Season -2024 of Cultivations in Sri Lanka

Cultivation	A	B	C	D
pH	5.1	4.9	7	4.2
Acreage	13.49	120.83	94.6	57.29
N (μg/g (ppm))	1	3.77	8.87	6.77
P(μg/g (ppm))	7	9.7	20.2	14.2
K (meq/100g)	0.07	0.1	0.1	0.3
Urea (kg/acre)	2300	5200.5	4800	3100
TSP (kg/acre)	1800	3900	2200	2000.5
MOP (kg/acre)	3200	6100.5	5000	4200.5
CaNo3 (kg/acre)	250	380	350	320
Expected Harvest	80000	820000	600000	120000
Predicted Harvest	94500	758300	650380	100500
Actual Harvest	93562	767230	63825	101523

To minimize this excess or deficiency of the harvest, the system doing an analysis to select the best fertilizer combination for the expected harvest. The implications of factor analysis in predicting the best fertilizer combination to use has helped in nose-diving yield variances. Making them understand some of the critical factors like pH of the soil and nutrients keeps them informed on how to avoid future short falls on yields and how to improve on yields. This approach does not only assist in the process of reconciling the amount of produce expected to be harvested with the amount that is actually produced but also assists farmers in the decision-making process of the number of resources to use and how to manage them to enhance production [9]. The implementation of the above suggestions within the mobile application means that farmers are ready and able to do what is best suited for their situation in an effort of preventing or minimizing on potential losses while at the same time enhancing production yields.

Also, this paper suggest a data-driven method for gherkin cultivation cost predictions. The goal is to give stakeholders useful insights by combining modern analytics with industry expertise. The prediction models improve investment planning and risk management, which improve the agricultural markets' resilience. The efficacy of our strategy is validated by empirical validation and practical use. In order to promote sustainable gherkin farming, this study integrates econometrics, statistical analysis, machine learning, and agricultural economics.

Future Work

As the future work, explore economic and societal impacts of gherkin farming which effects for cost prediction models. Also improve high quality user experience by using augmented reality (AR) to show the predicted outcome and give suggestions using artificial intelligence models.

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