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A Precision Agriculture Framework Using DoubleGAN and Machine Learning for Grape Leaf Irrigation Scheduling and Yield Prediction

Jing Yue
School of Electronics Science and Engineering, Xiamen University, Xiamen, Fujian, China, 361005.
jingyueese@hotmail.com

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Corresponding author(s):
Jing Yue, School of Electronics Science and Engineering, Xiamen University, Xiamen, Fujian, China, 361005.
Email: jingyueese@hotmail.com

Abstract – We propose an integrated Double Generative Adversarial Networks (DoubleGAN) machine learning framework used to improve the irrigation timing of grapevines and disease classification, as well as predict yields. High-resolution grape leaf images were enhanced by DoubleGAN to eliminate class imbalance because field data, such as irradiance, soil pH, crop type, rainfall, temperature, and humidity, were normalized. We tested irrigation scheduling using Naive Bayes, Random Forest, and Decision Tree models, with the latter achieving the highest accuracy at 75%. In the detection of the disease, both VGG16 and ResNet50 achieved better performances using DoubleGAN-augmented datasets, achieving an accuracy of 99.39%. Gaussian Process Regression (GPR), Support Vector Regression (SVR), Random Forest Regression (RFR), and Boosted Regression Tree (BRT) participated in the prediction of crop yield, and BRT had minimum errors. Findings affirm that DoubleGAN enhances model robustness, allowing accurate data-driven decision support in viticulture.

Keywords – DoubleGAN, Machine Learning, Irrigation Scheduling, Grape Leaves, Disease Detection, Yield Prediction, Deep Learning, Precision Agriculture.

I. INTRODUCTION

The economy heavily depends on agriculture, as its backbone. Agricultural automation is a major concern and an expanding topic in all countries. The world is growing at an alarming rate, thus increasing the food demand. The growing demand for food and shifting consumer tastes have made it extremely difficult for the farming industry to come up with policies and schemes that are sufficient to satisfy rising demands and expectations. Agriculture is one of the core sectors in civilization that contributes to progress. As such, there are necessary enhancements in this business that would bring improvements in its net effects and outcomes. Technology in food production should encourage serious improvement and innovation to address the changing needs of consumers [1]. The use of agricultural resources is a necessity, as most countries rely on the agricultural sector.

Three main factors affecting irrigation include crop, weather and soil, which play a significant role in determining the irrigation schedule requirements. The nature of farming and soil will determine the manner in which the fertilizer will be billed and the irrigation procedure. Next, there will be other influences such as weather and soil that will influence the manner in which irrigation is conducted. The need for irrigation for a crop varies every year, and this is where the field of smart irrigation is emerging. It is becoming a novel field of science in which techniques and practices rely on data to increase agricultural productivity and minimize environmental degradation. Smart irrigation automates irrigation systems and increases the efficiency of irrigation systems while decreasing the overuse of water. The enhancement of agricultural systems is one of the main priorities of several nations, and in this regard, the appropriate systems to make the smart irrigation systems user-friendly are being implemented [2]. In addition, efficient crop irrigation practices need to be developed, based on these real-time data, to eliminate unnecessary water use and improve crop yield.

Furthermore, the use of machine learning is not limited to just what has been mentioned. It has a bigger scope and a lot of applications, particularly in agriculture. For example, in crop monitoring, specific ML algorithms can use data given from remote sensing devices, such as satellite and spectral imageries, to predict and track the attributes of a crop, including, but not limited to, the yield, quality, and incidence of pests/diseases. ML algorithms can be applied to optimize irrigation, fertilization strategies, and the effectiveness of precision farming solutions. The timing of irrigation plays a vital role in vegetable production. Irrigation can also result in reduced yields and substandard products.

On the other hand, over irrigation increases the susceptibility of the crop to diseases, increases the cost of energy used to pump water, leads to wastage of water, and causes pollution of the environment through leaching. Bonachella et al. [3] established that poor management of drip irrigation was one of the factors that led to the leakage of nitrate in tomato production in the greenhouse in Almeria which is the most concentrated greenhouse region in the world. Central among these reasons is the fact that many producers use experience to schedule irrigation; as opposed to actual crop water needs. Due to the close association between the nutrient use and the water relations, higher water use efficiency tends to result in greater nutrient use efficiency. Moreover, managed deficit irrigation requires proper scheduling as it aims to induce moderate water stress to plants to conserve water and increase crop yield and quality.

The remaining sections of this study have been organized as follows: Section II reviews related work on irrigation scheduling, and its AI and ML technologies. In Section III, we present the materials and methods used to obtain our results. Section IV provides a discussion of the findings to determine (i) performance evaluation of irrigation scheduling algorithms, (ii) effect of data expansion approaches on plant disease detection accuracy, and (iii) comparison of ML approaches in the estimation of crop yields. Section V concludes the study and highlights the significance of the proposed DoubleGAN-ML approach in enhancing reliability and accuracy of irrigation scheduling, disease detection, and crop yield estimation.

II. RELATED WORK

According to Zhao et al. [6], irrigation scheduling technology is a significant decision-making process aimed at optimizing the efficient and effective usage of water. The quality and production of crops are substantially influenced by water timing and quantity. The aim of this technology is to provide an appropriate volume of water at the optimal moment for a particular crop. Scholars investigated US DoA (Department of Agriculture) findings and concluded that over 75% of the technology employed by American farmers uses the checkbook method, along with visually assessing crop conditions, crop calendars, and observing nearby fields. Poor irrigation scheduling techniques may cause excessive or insufficient irrigation.

Dehghaniansani et al. [7] have stated that the application of ML in irrigation scheduling increased the productivity of farms as well as the working efficiency in terms of water usage. Novel methods of data collection have created an unprecedented increase in the amount of data available at a shorter temporal and spatial ontology, termed big data. With regard to water scarcity, crop management, and cost management, big data should be able to offer solutions to the problems that farmers face. The predictive modelling of irrigation water consumption can be achieved with ML through the utilization of massive data. The amalgamation of ML technologies with big data enables more intelligent and effective irrigation estimate, hence assuring water sustainability for the burgeoning global population.

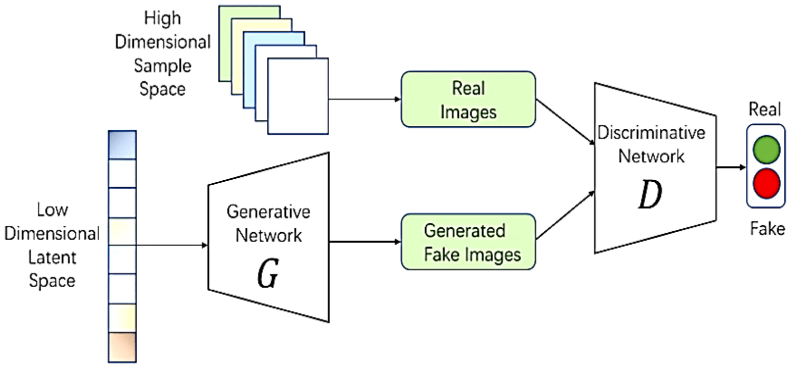

Fig 1. Generative Adversarial Networks.

In reference to a study by Nkwocha and Chandel [8], the early identification of plant diseases is advantageous as it offers timely predictions that cultivators may use to avert potentially detrimental occurrences via proactive management. Advancements in AI enable the development of a model capable of extracting aspects of each symptom and classifying plants as healthy or ill, even those affected by abiotic stressors. Early diagnosis by AI will avert big food crises by preventing the transmission of illnesses among plants and crops.

Recently, Alqahtani, Kavakli-Thorne, and Kumar [9] introduced generative adversarial networks (GANs) to address the constraints in the availability and variety of CNNs see **Fig. 1**. Following the introduction of GAN architecture, other comparable structures have been created, yielding remarkable results. Conditional Generative Adversarial Network (cGAN) and Deep Convolutional Generative Adversarial Network (DCGAN) may be considered extensions. The sophisticated GANs include the WGAN (Wasserstein Generative Adversarial Network), BigGAN (Big Generative Adversarial Network), CycleGAN (Cycle-Consistent Generative Adversarial Network), SG (Style-based Generative) and SG-2 adversarial network. The DCGAN enhances the basic GAN by using CNN configurations, which stabilize the learning process; nevertheless, this introduces a mode collapse challenge, resulting in the model generating a singular type or limited range of outputs.

According to Jenkins and Roy [10], DCGANs have a reducing gradient phenomenon, when generators are unable to learn owing to data deprivation, leading to ineffective generators and strong discriminators. The WGAN addressed the challenges of mode reduction, training stability, and vanishing gradients; nonetheless, it extended the training duration and sometimes yielded suboptimal outputs. BigGAN provides enhanced stability during training and superior outcomes compared to WGAN, although necessitates more large data samples and time.

According to Yuan et al. [11], SG architecture enhances the training methodology and conventional GAN model by reconfiguring generators standardization, altering advanced development, and normalizing generators. They presented a sophisticated technique for high-resolution picture synthesis; nonetheless, it sometimes produces inconsistent regions within images and necessitates a substantial quantity of quality data. SG2 identifies the anomalous blob-based artifact produced by SG by alleviating high-resolution learning; in addition, the use of short datasets results in classifier overfitting. SG2-ADA yields superior outcomes with a limited data while attaining enhanced findings.

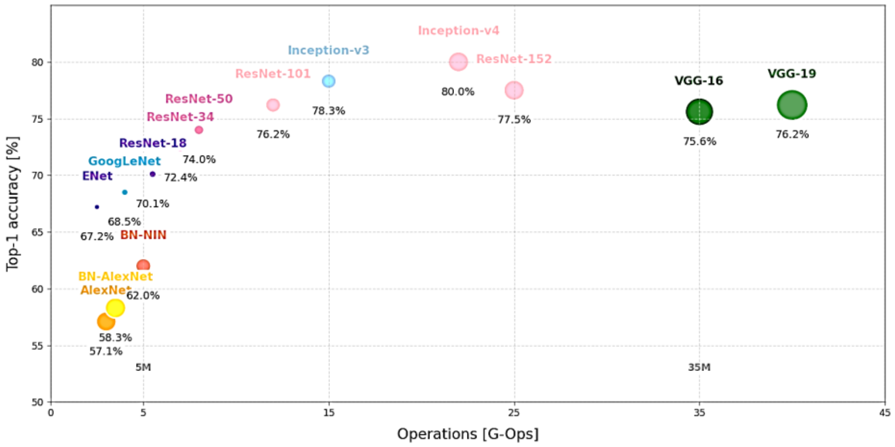

Fig 2. CNN Model Evaluation.

Research conducted by Alruwaili and Mohamed [12] assessed the classification accuracy of several advanced classifiers along with convolutional neural networks (CNNs) such as EfficientNet b0, MobileNet v2, DenseNet 161, and ResNet 18, while analyzing the influence of extension on the classification of grape leaves. Still, the implementation of transfer learning did not significantly improve the classification accuracy. Hence, finding an appropriate and ideal classifier for identifying diseases in crops becomes a considerable challenge when a pre-trained model does not appropriately retain the essential features needed for classification. **Fig. 2** illustrates the most recent comparison combinations of CNN models.

As depicted by Tammina [13], VGG-16 is recognized for its robust efficacy and simplicity in image detection tasks. It has 16 layers, including many convolutional layers succeeded by fully linked layers that facilitate the acquisition of intricate patterns from images. The model was selected for its capacity to autonomously extract intricate characteristics from leaf photos without requiring operator input. VGG-16 accepts input pictures of 224×224×3, making it appropriate for leaf disease classification applications. The design employs tiny 3×3 filters and ReLU activation features to capture local patterns, succeeded by max-pooling layers to minimize complexity. Beji et al. [14] used DoubleGAN and achieved superior accuracy in illness picture detection compared to the original dataset. Plant foliage may be employed to detect infections in plants.

Fig 3. (a) DoubleGAN Phase 1 Produced Grape Leaf Images; (b) DoubleGAN Phase 2 Generated Grape Leaf Image.

Nonetheless, there are often inconsistent representations of disquieting leaves derived from various plants. Plant diseases characterized by uneven sets of data are difficult to identify. We used a double generative adversarial network (DoubleGAN) to balance these data sets.

Zhao et al. [15] recommended employing DoubleGAN to produce high-quality images with a reduced number of sick leave samples see **Fig. 3**. The two phases of DoubleGAN are delineated. In phase 1, the authors employed unhealthy and healthy leaves as components. Initially, the pre-learned system was provided with WGAN employing healthy images (Wasserstein Generative Adversarial Network). The system then employed ill leaves to generate 64 by 64-pixel leaves. In the second step, 256 by 256-pixel frames were acquired to enhance imbalanced data configurations.

Khan et al. [16] identified that a lack of training photos was the primary barrier impeding enhancements in the detection accuracy of grape leaf diseases. Nonetheless, their dataset was augmented using DoubleGAN, resulting in crisper produced pictures and improved recognition accuracy. Due to the issue of an inadequate dataset, together with the challenges of acquiring 'disease' images on a wide scale and manually annotating them, Zheng et al. [17] used MergeModel to augment the illness image collection. They indicated an augmentation in the diversity of phytonematode species (classes) within the dataset. This was undertaken to augment the dataset. As a consequence, their model attained superior outcomes relative to leading models in the field.

III. MATERIALS AND METHODS

Grape leaf data were procedurally measured in field locations and each sample consisted of annotated data of humidity, temperature, Rainfall, crop type, pH of soil, and soil irradiance. Images of grape leaves at a high resolution were captured in variable field conditions to allow accurate diagnosis of plant conditions and detection of diseases. All tabular records were normalized so as to have equal feature scaling. Image preprocessing involved resizing, normalization, and intensive data augmentation, including flipping, rotation, and translation to increase sample diversity and overcome class imbalance. High-resolution images were also synthesized using the DoubleGAN architecture which greatly increased the dataset size and avoided constraints imposed by traditional augmentation see **Fig. 4**.

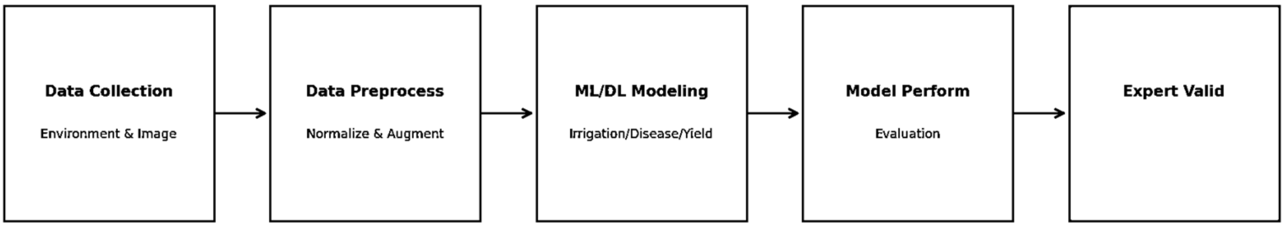

Fig 4. Grape Leaf Irrigation Scheduling and Disease Detection Workflow.

To schedule irrigation, the researchers used normalized tabular information in Naïve Bayes, random forest, and decision tree models. The grid search optimized hyperparameters, and resilient accuracy estimates were determined through 10-fold cross-validation. Accuracy measure showed that the Random Forest performance was better than that of the other classifiers as indicated in **Fig. 5**. RMSE (root mean square error), MAE (mean absolute error), R^2 (R-squared), and MSE (mean square error) further validated the model performance. The outputs of these models were independently validated by an expert agronomist; this ensured that the models were relevant in fields.

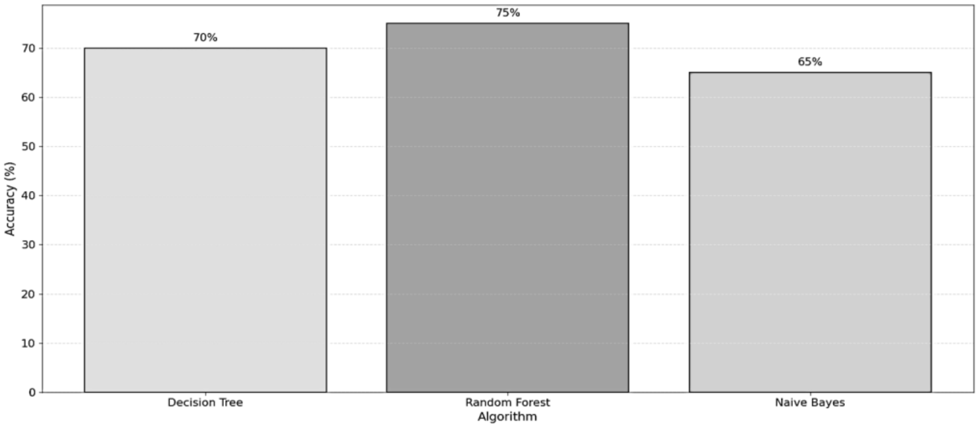

Fig 5. ML Model Accuracy in Irrigation Scheduling.

Detection of plant diseases was conducted using deep learning architectures, i.e.: VGG16 and ResNet50, and was assessed on three datasets, i.e.: original images, traditional augmented images, and images produced by DoubleGAN. Crosscomparison between plant types demonstrated enhanced accuracy on expanded data; the DoubleGAN-enhanced set provided the best accuracy with both deep learning setups see **Fig. 6**.

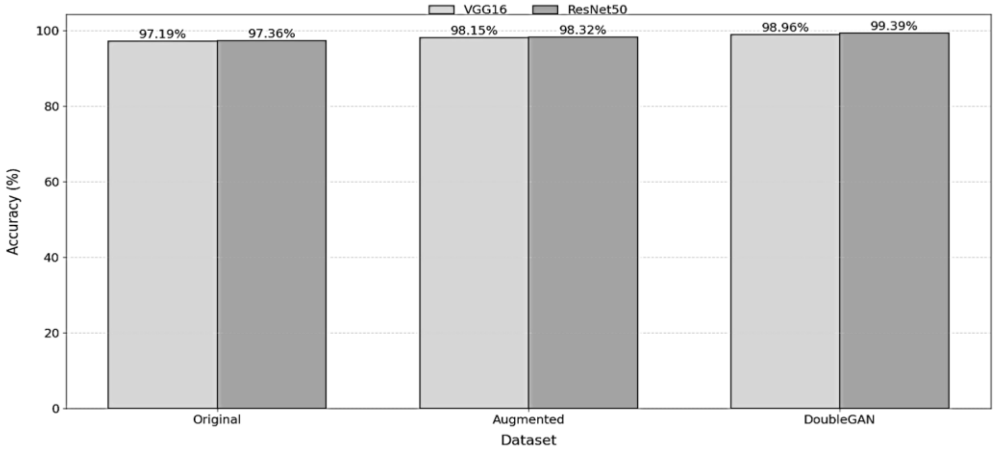

Fig 6. Accuracy of Plant Disease Prediction with Varying Dataset Scale and Models.

Regression models, Gaussian Process Regression, Support Vector Regression, Random Forest Regression, and Boosted Regression Tree using tabular and image-derived knowledge, were used to predict crop yield. Quantitative measures of model performance were the coefficient of determination (R^2), RMSE, and MAE. All experiments were written using Python, scikit-learn and TensorFlow. Training and test sets were segregated in data partitions and the relevance of the segregation was achieved by use of the relevant tests in statistical significance. Agricultural experts were involved in the workflow, to ensure that outputs would be viable in practicable viticulture.

IV. RESULTS AND DISCUSSION

The proposed method is measured on the grape leaves with soil irradiance, pH, crop type, rainfall, temperature, and humidity as a measure to establish the time to water it. Image collection is employed to assess plant health and agricultural productivity. The assessment of the proposed approach will be conducted using classification algorithms, namely the Naïve Bayes (NB), Random Forest (RF), and Decision Tree (DT) technique. Plant disease identification is conducted via DoubleGAN and assessed with VGG and ResNet algorithms. The crop yield forecast is ultimately conducted by employing the Boosted Regression Tree approach.

Performance Evaluation of Irrigation Scheduling Algorithms

The appropriate irrigation schedule is assessed with NB, RF, and DT methodologies, with the metrics of MSE, MAE, R2 error, RMS, and correctness. However, it still necessitates critical evaluation to ascertain the precise irrigation timing. We may also evaluate other parameters such as crop yield timing and plant disease identification to provide accurate estimates about irrigation schedule. This subsection and **Table 1** provide the performance results of several ML algorithms for grape leaf irrigation scheduling.

Table 1. Comparative Analysis of ML Models in Irrigation

Algorithm	**Accuracy (%)**	**R^2**	**MSE**	**RMSE**	**MAE**
DT	70	−0.87	7.63	2.77	2.16
RF	75	−0.82	7.51	2.74	2.14
NB	65	−1.62	10.82	3.29	2.58

All three graphs illustrate the values of the metrics: RF, DT, and NB. Undoubtedly, RF showed superior accuracy among the three algorithms, suggesting its use throughout the irrigation season. The Mean Square Error is calculated by averaging the squares of the anticipated and actual dataset numbers, using Eq. (1).

$$MSE = \frac{a}{n}\sum\nolimits_{e_i p_i}^{2} E1 \tag{1}$$

The expected value of dataset i is represented by e_i, but the forecasted value is shown by p_i Due to the direct proportionality of RMSE and other error score units to the expected target value, mean absolute error has emerged as a significant statistic. The MAE can be computed using Eq. (2) below.

$$MAE = \frac{a}{n}\sum\nolimits_{abs(e_i p_i)} E2 \tag{2}$$

In this case, the absolute function is $abs()$, the anticipated value of dataset i is e_i, the proposed value of dataset i is p_i, and so on. The variance amount within the dependent variable, which a regression model variable, or independent variable can account for is shown by the R-squared (R^2) statistic. To get the RMSE, we use the formula in Eq. (3) below.

$$RMSE = sqrt\left(\frac{1}{n}\sum_{e_i p_i}^{2} E3\right) \tag{3}$$

where e_i signifies the expected dataset value for the i-th element and p_i signifies the predicted value of the i-th element. Accuracy is described as the proportion of accurate forecasts made by a test dataset. The quantity of accurate forecasts may be easily calculated by grouping them by the entire number. Accuracy (Acc) is determined as the proportion of effectively classified cases, as shown in Eq. (4).

$$Acc = \frac{x}{y} E4 \tag{4}$$

where x represents the aggregate of TP (true positives) and TN (true negatives), whereas y denotes the total of TN, FP (false positives), and TP see **Fig. 7**.

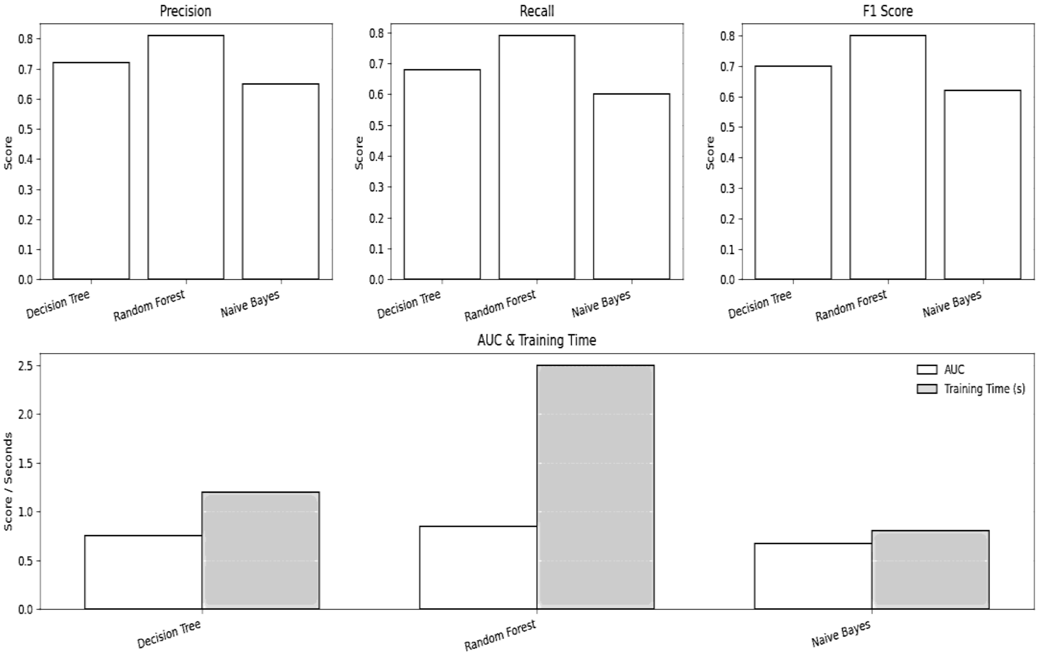

Fig 7. (a) Measures of MSE, (b) Metrics of MAE, (c) Metrics of RMSE, and (e) Precision Metrics.

Impact of Data Expansion Techniques on Plant Disease Identification Accuracy

DoubleGAN is employed to enhance low-resolution grape leaves images into high-quality images. Accuracy is then assessed using ResNet50 and VGG16. The outcomes of the different algorithms are established in **Table 2**.

Table 2. Accuracy of the Plant Disease Detection Model

Plants		**Tomato**	**Corn**	**Potato**	**Acc. average**
Initial DataSet	VGG16	96.45	97.48	97.65	97.19
	ResNet50	96.65	97.61	97.83	97.36
Flipping and Translation Expansion	VGG16	98.45	97.85	98.15	98.15
	ResNet50	98.75	97.85	98.35	98.32
DoubleGAN Expansion	VGG16	97.83	99.8	99.25	98.96
	ResNet50	98.85	99.88	99.45	99.39

The results show that the independence classifier gains improvement as data gets generated by DoubleGAN. Of the neural networks employed, VGG16 and ResNet50 achieved the most predictive accuracy on the datasets, leading to DoubleGAN-generated images that were visually similar to the real images. They were the most efficient of datasets that were contributed with high predictive accuracy since DoubleGAN has the advantage of not being restricted to manually engineered datasets because it can produce multiple images using a fixed-dimensional noise vector, unlike augmentation-oriented datasets made by mere rotation and other acts. Farming must be improved because we can see that irrigation and agricultural productivity depend on each other see **Fig. 8**. We can see that understanding agricultural plant disease images can make a difference.

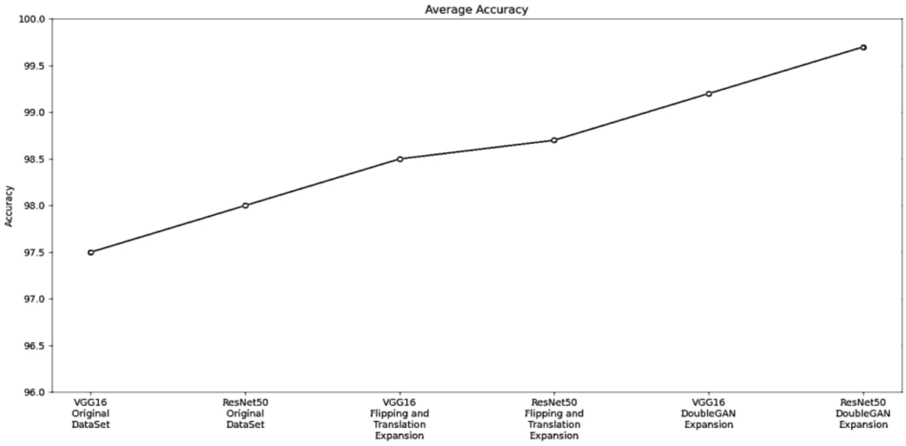

Fig 8. Identification Models Data Accuracy/Precision.

Comparison of ML Strategies for Predicting Crop Yields

It was observed that enhancements were attained in independence classifier when data was produced employing DoubleGAN. VGG16 and ResNet50 are two of the most utilized neural networks providing the greatest prediction accuracy across several datasets, that enabled spectacular differentiated original images, using DoubleGAN. VGG16 and ResNet50 performed quite effectively on this data and, in particular, the explanation is that DoubleGAN is not hindered with augmentation-based datasets which are straining dataset constructions that only rotate the images, and similar methods. The images of the identified plant diseases could improve prediction outputs in the context of irrigation and crop productivity. See **Fig. 8**.

Ojo and Zahid [19] analyzed deep learning in the context of precision farming in congested environments, demonstrating its efficiency and precision in undertaking tasks, such as plant recognition and yield estimation. Deep Learning, especially CNNs, surpassed other techniques in dense farming environments, highlighting its significance in computer vision applications. They assess the application of DL approaches, highlighting its significance in predicting agricultural crop yields. They assert that AI may enhance yield forecasting and crop control, with hybrid networks and RNN such as RNN-LSTM demonstrating more predictive accuracy than alternative networks.

Patrício and Rieder [20] examine computer vision and DL in precision agriculture for crop production estimate, emphasizing the advantages of automation in picture processing and remote sensing. Their findings indicate that the use of deep learning in conjunction with machine vision enhances the precision of automated agriculture systems. This work used sophisticated ML algorithms, including SVR (Support Vector Regression), BRT (Boosted Regression Tree), and DPR (Gaussian Process Regression) with grape plants. Additionally, we compare these ML algorithms against R, RMSE, and MAE, which are all considered measures of academic error.

Fig. 9 and the following subsection show that BRT, compared to RFR, SVR, and GPR, has achieved low rates of error. In the end, the results of these applications may be used to improve the final outcome. As demonstrated in **Table 3**, the outputs of predicting the timing of crop yields and the identification of plant diseases can be used to predict irrigation schedule production in an accurate and timely manner.

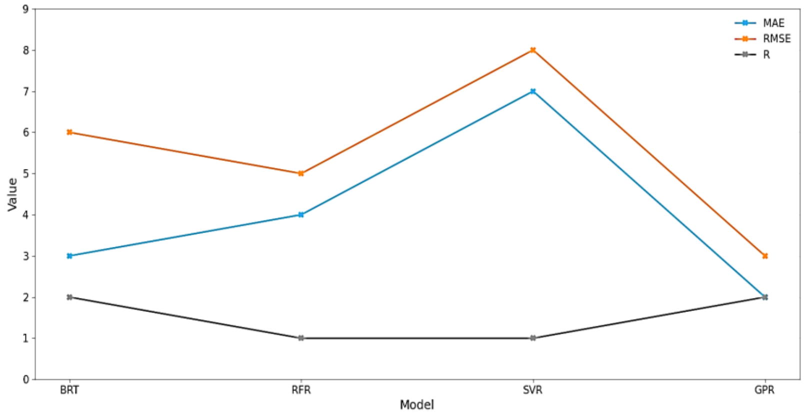

Fig 9. Error Rate of Yield Forecast Methodologies.

Classification methods such as NB, DT, and RF will be used to assess the suggested technique. The random forest model surpassed the other two ML alternatives. The DoubleGAN technique is used for the identification of plant diseases, whilst the ResNet and VGG algorithms are utilized for performance assessment.

Table 3. Error Rate of Yield Prediction Techniques

ML Model	R	RMSE	MAE
GPR	0.75	5.48	2.85
SVR	0.43	8.21	6.02
RFR	0.71	3.63	1.91
BRT	1.21	4.96	2.32

Utilizing the DoubleGAN image dataset with VGG and ResNe models results in superior precision rates compared to both the initial dataset and traditional boosted images. The error rate of agricultural production forecasts is determined using multiple ML techniques, such as GPR, SVR, RFR, and BRT. SVR has a significantly reduced error rate compared to other methodologies.

V. CONCLUSION

The proposed DoubleGAN-ML presented substantial successful outcomes in increasing accuracy and reliability of scheduling irrigation, disease diagnostics, and yield estimation of grapevines. Random Forest was the classification model that showed the highest success at optimizing irrigation. Deep-learning-based models, specifically, the ResNet50 and VGG16, enjoyed significant enhancement with the use of DoubleGAN-enhanced data sets, achieving approximately 99 percent of accuracy when it comes to plant disease recognition. On the same note, the Boosted Regression Tree model performed better, in terms of crop yield projections, in comparison to other regression methods as it managed to produce the lowest error predictions. The results indicate the worth of integrating synthetic image generation with ensemble learning and regression methods to support decision-making in agricultural management.

CRediT Author Statement

The author reviewed the results and approved the final version of the manuscript.

Data Availability

The datasets generated during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interests

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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Competing Interests

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