

Enhancing Agricultural Yield Forecasting with Deep Convolutional Generative Adversarial Networks and Satellite Data

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Abstract—Ensuring food security amidst growing global population and environmental changes is imperative. This research introduces a pioneering approach that integrates cutting-edge deep learning techniques. Deep Convolutional Generative Adversarial Networks (DCGANs) and Convolutional Neural Networks (CNNs) with high-resolution satellite imagery to optimize agricultural yield prediction. The model leverages DCGANs to generate synthetic satellite images resembling real agricultural settings, enriching the dataset for training a CNN-based yield estimation model alongside actual satellite data. DCGANs facilitate data augmentation, enhancing the model's generalization across diverse environmental and seasonal scenarios. Extensive experiments with multi-temporal and multi-spectral satellite image datasets validate the proposed method's effectiveness. Trained CNN adeptly discerns intricate patterns related to crop growth phases, health, and yield potential. Leveraging Python software, the study confirms that integrating DCGANs significantly enhances agricultural production forecasting compared to conventional CNN-based approaches. Against established optimization methods like RCNN, YOLOv3, Deep CNN, and Two Stage Neural Networks, the proposed DCGAN-CNN fusion achieves 98.6% accuracy, a 3.62% improvement. Synthetic images augment model resilience by exposing it to varied situations and enhancing adaptability to diverse geographic regions and climatic shifts. Moreover, the research delves into CNN model interpretability, elucidating learnt features and their correlation with yield-related factors. This paradigm promises to advance agricultural output projections, advocate sustainable farming, and aid policymakers in addressing global food security amidst evolving environmental challenges.

Keywords—Agricultural yield prediction; DCGANs; CNN; satellite imagery; data augmentation; synthetic image generation

I. INTRODUCTION

Accurate and effective agricultural techniques are more important than ever in light of the problems posed by climate change and the world's expanding population [1]. Accurately predicting agricultural yields is essential to maintaining sustainable resource management and food security [2]. While

historical data and fundamental environmental elements are still important components of traditional yield prediction systems, technological improvements have made more advanced techniques possible [3]. An inventive way to improve the precision and granularity of agricultural production forecasts is to combine satellite images with the deep learning capabilities of DCGANs [4].

In the realm of precision agriculture, satellite imaging has become a game-changer by providing a thorough perspective of agricultural fields at many sizes [5]. These images record important details on the health of the crop, its growing habits, and its surroundings [6]. But there are difficulties in deciphering and drawing useful conclusions from such large and intricate databases [7]. This is when using DCGANs becomes essential. With the use of DCGANs, satellite imagery processing may be automated, making it feasible to retrieve fine features that may be missed by more conventional techniques. This combination might completely change our understanding of and approach to managing agricultural landscapes [8].

Particularly well-suited for processing satellite photos are DCGANs, which are renowned for their ability to produce realistic images [9]. By learning hierarchical representations of visual characteristics, these neural networks are able to recognize intricate patterns in the photos. When it comes to agriculture, DCGANs may be trained to provide artificial satellite photos that capture important details about crop conditions. This generating capacity is particularly useful in situations when it is difficult to gather large and varied labelled datasets. Agricultural yield prediction models may successfully adapt and generalize across diverse geographic and climatic situations by leveraging the distinct characteristics of DCGANs [10].

There are several benefits of using DCGANs for agricultural yield prediction [11]. In addition to producing artificial pictures to alleviate data shortages, DCGANs enhance model accuracy by automatically identifying subtle patterns in the data. DCGANs' ability to generate hypothetical

situations adds to their usefulness by allowing stakeholders to investigate optimization methodologies and arrive at well-informed judgments. The ramifications for global food security, resource optimization, and sustainable agricultural techniques grow as this field of study develops. The use of DCGANs to satellite images in agriculture marks a revolutionary step towards a day when technology will be crucial to maintaining the productivity and resilience of agricultural systems all over the world.

Over the years, satellite imagery has developed into a remarkable technical wonder that has revolutionized our daily lives by changing the way we see and interact with the outside world. It can now see the planet from orbit thanks to the installation of Earth-observing satellites, which has given us precious knowledge about its varied and dynamic landscapes. Satellite imaging has proven useful in many domains, from tracking changes in land use to monitoring weather patterns. Its widespread use in everything from crisis management and urban planning to scientific research and environmental monitoring shows how versatile it is [11].

The capacity to reveal Earth's mysteries from above is at the core of satellite imagery's potency. These photos, which were taken from circling satellites with sophisticated sensors, provide a distinct and in-depth look at the surface of the planet. The information extracted from these photos offers crucial details regarding environmental shifts, natural occurrences, and human activity. By advancing our knowledge of geological processes, ecosystem health, and climate dynamics, satellites help scientists, researchers, and politicians make decisions that will benefit society and the environment alike [12].

Satellite imaging is now an essential component of modern life and has outlived its use as a scientific instrument in the modern period. The applications of satellite images are numerous and include disaster relief, precision farming, and navigation system guidance [13]. High-resolution satellite data is now widely available, enabling people, organizations, and governments to make global decision-making decisions with knowledge and insight. The role that satellite imagery plays in influencing our perception of the world and spurring innovation across a range of industries is only going to increase as we continue to leverage the power of satellites orbiting high above. This bodes well for a time when the frontiers of knowledge will be continuously pushed by the perspective of technology derived from space.

The ability to accurately forecast and maximize crop yields is a continuous issue for agriculture, which is essential to the world's food security. For efficient resource allocation, risk management, and sustainable agricultural practices, accurate yield prediction is essential [14]. Conventional techniques frequently depend on historical data, soil conditions, and weather patterns, but integrating cutting-edge technology like deep learning has enormous promise. A subset of deep learning algorithms called Deep Convolutional Generative Adversarial Networks (DCGANs) has become highly effective tools for image processing jobs in recent years. An inventive way to improve the precision and granularity of agricultural

yield forecasts is to combine the power of DCGANs with satellite images.

In contemporary agriculture, satellite photography has proven to be an important tool, providing a broad overview of agricultural fields. The images offer insightful information on the health of the crop, its growth habits, and its surroundings. Through the use of satellite imagery, which is rich in data, scholars and professionals may get a comprehensive comprehension of the agricultural terrain. However, because these pictures are complicated and provide a large quantity of data, it can be difficult to extract useful information from them. This opens the door to the possibility of autonomously learning and extracting pertinent characteristics from imagery from satellites using deep learning techniques, especially DCGANs, which might lead to more precise and effective yield estimates [15].

As an extension of conventional CNNs, DCGANs are made to produce lifelike images through the hierarchical encoding of visual information that they learn. DCGANs may be taught to analyze and produce synthetic satellite images with detailed information on crop health, growth phases, and environmental elements in the setting of agriculture. Because DCGANs are generative in nature, they may produce a wide range of realistic pictures, which improves the model's comprehension and adaptation to the inherent variety of agricultural landscapes. Because of its versatility, DCGANs are a good choice for agricultural production prediction in a variety of climatic and geographic settings.

There are several benefits of using DCGANs for agricultural yield prediction. First off, the capacity to produce artificial satellite images enables the enhancement of training datasets, hence resolving the constraints associated with a lack of data. Moreover, DCGANs can automatically recognize and learn intricate patterns from the photos, which enhance the model's capacity to recognize nuanced markers of crop health and prospective production. Because DCGANs are generative, they may also be used to create hypothetical situations, which can be useful for exploring what-if possibilities to optimize agricultural techniques. Precision and efficiency are increased by including DCGANs into the prediction pipeline, which helps farmers, agricultural researchers, and politicians make well-informed decisions.

The use of DCGANs in conjunction with satellite images to forecast agricultural production is a major step towards more precise and data-driven farming methods. The goal of on-going research in this area is to improve the model's interpretability, scalability, and performance. The system's predictive capabilities are further enhanced by the investigation of real-time applications and the incorporation of additional data sources, such as soil and climate model information. The combination of deep learning, satellite technology, and agriculture promises to transform our understanding, prediction, and optimization of crop yields worldwide, supporting our efforts to ensure a sustainable and food-secure future.

In recent years, ensuring global food security has become an increasingly critical challenge due to the growing world population and the impact of environmental changes on

agricultural productivity. Accurate forecasting of agricultural yield plays a vital role in resource allocation, risk management, and the promotion of sustainable farming practices. Traditional methods of agricultural yield prediction often rely on historical data and statistical models, which may not capture the complex spatial and temporal dynamics of crop growth. With advancements in deep learning and remote sensing technologies, there is a growing interest in leveraging high-resolution satellite imagery and deep learning techniques to enhance the accuracy and reliability of agricultural yield forecasting.

Despite the potential of deep learning and satellite data, there are several challenges in accurately predicting agricultural yields. One major challenge is the limited availability of labelled data for training deep learning models, especially for tasks involving complex spatial and spectral features from satellite images. Additionally, traditional deep learning approaches may struggle to generalize across diverse environmental conditions and crop types, leading to reduced predictive performance. Furthermore, existing methods often lack interpretability, making it difficult to understand the underlying factors influencing yield predictions and limiting their practical utility for farmers and policymakers.

To address these challenges, this research proposes a novel approach that combines DCGANs with CNNs to enhance agricultural yield forecasting using satellite data. The proposed model leverages DCGANs to generate synthetic satellite imagery that closely resembles real-world agricultural settings, thereby enriching the dataset for training CNN-based yield estimation models. By augmenting the dataset with synthetic images, the model can learn to generalize across different environmental conditions and crop types, improving its predictive performance. Additionally, the research explores the interpretability of the CNN model, providing insights into the learned features and their associations with yield-related factors. Overall, the proposed solution aims to provide more accurate and interpretable predictions of agricultural yields, thereby contributing to improved resource allocation, risk management, and sustainable farming practices.

The following are the research study's principal contributions:

- Employing histogram-equalized images as input to DCGAN-CNN models for effective feature extraction and learning in agricultural yield prediction.
- Utilizing DCGANs for generating synthetic satellite images that closely resemble real-world agricultural landscapes, acting as data augmentation tools.
- Incorporating CNNs to learn spatial and hierarchical representations from artificial and real-world satellite imagery, resulting in more reliable and accurate agricultural yield prediction models.
- Applying Adam optimization algorithm for enhancing the efficiency and performance of DCGAN-CNN models, especially in dealing with the intricate and dynamic nature of satellite imagery datasets.

II. RELATED WORKS

The literature review section provides a comprehensive overview of existing research and studies related to agricultural yield forecasting, remote sensing technologies, and deep learning techniques. It highlights key findings, methodologies, and advancements in the field, laying the groundwork for understanding the current state of knowledge and identifying gaps in research. By synthesizing and critically analyzing the existing literature, this section aims to contextualize the proposed approach within the broader academic landscape and elucidate the rationale behind its development.

For the food industry, it is essential to be able to quickly and non-destructively predict how much oil is in a single maize kernel [16]. Unfortunately, gathering a large number of maize kernel oil content reference values is costly and time-consuming, and the model's limited data set also makes it difficult for it to generalize. Here, the oil content of a single maize kernel was predicted using a combination of DCGAN and hyperspectral imaging technology. They simultaneously expanded their spectral and oil content data using DCGAN. Fake data that was strikingly similar to the experimental data was produced after numerous iterations. The performance of the support vector regression (SVR) and PLSR models was compared before and after the augmentation of the data. The outcomes demonstrated that this approach not only enhanced the functionality of two regression models, but also resolved the issue of needing a substantial quantity of training data.

Before starting a farming endeavour, crop selection is a crucial step. Reliable weather data plays a major role in crop output in India by assisting farmers in scheduling their labor to maximize crop productivity [17]. According to a number of researchers, changes in temperature, precipitation, winds, humidity, and carbon dioxide levels all have an immediate impact on crop productivity. Any deviation in the weather creates atmospheric stresses, which increases the risk of financial loss for these farmers. In response to these issues, this manuscript suggests two new methods for predicting weather: the Cycle Consistent GAN with Color Harmony algorithm for choosing crops in the selected in WB, India, and the Recalling Improved Sigmoid RNN with Manta Ray the enhancement for weather prediction. The results show that compared to the conventional methods, the introduced model achieves a higher accuracy. Tests like the Cochran's Q test and the Chi-square test are conducted to demonstrate the statistical analysis of the suggested strategy.

Plant diseases significantly reduce agricultural yields and cause a great deal of damage. Plant disease detection has benefited from the recent development of deep learning techniques, which provide a reliable tool with incredibly accurate results [18]. Images were shot in a variety of weather conditions, at different angles, during the day, and against a variety of backgrounds to simulate real-world scenarios. The number of images in the dataset was increased using two different strategies: cutting-edge generative adversarial networks and conventional augmentation techniques. In order to evaluate the effectiveness of controlled training and application in real-world scenarios for accurately recognizing

plant diseases in a complicated context and under varied conditions including the identification of multiple diseases in a single leaf—a number of experiments were carried out. Lastly, novel neural network architecture with two stages was put forth for the classification of plant diseases with an emphasis on the real world. With training, the model's accuracy was 93.67%.

In order to identify plant leaf diseases using leaf images, we developed a brand-new 14-layered DCNN) in this study. Several public datasets were used to create a new dataset. The dataset's individual class sizes were balanced through the application of data augmentation techniques [19]. The following three methods of image augmentation were applied NST, DCGAN, and basic image manipulation. The dataset distinct leaf classes—one without any leaves as well as images of sick and healthy plants. The suggested model underwent 1000 epochs of training in the context of MGPU. The best hyperparameter values were chosen using a random search using the coarse-to-fine searching technique in order to enhance the suggested DCNN model's training performance. Furthermore, the suggested DCNN model outperformed the current transfer learning techniques in terms of overall performance.

UAV aerial survey technology is widely used in agricultural production; however, signal interference, environmental changes, and other factors can cause missing flight data in aerial survey missions [20]. The paper proposed a complementary model based on VAE-CGAN optimization that employs a new discriminator structure, adds PSA to reduce computational complexity, and uses a combination of conditional CGAN and VAE as a regressor for VAE-CGAN reduction in order to accurately complement the time-series data. The model performs better than other comparable models in terms of sample generation capacity and prediction results with real aerial survey project datasets, according to comparative experiments. The algorithm is universally applicable on data that has various parameter time series missing rates.

It is difficult to carry out recognizing modeling and diagnosis of leaf diseases by directly using in-situ images from the agricultural Internet of things system because of the complex environments found in real fields. To address this drawback, a method for identifying cucumber leaf diseases in the field was suggested that relies on a deep convolutional neural network and a small sample size [21]. To obtain the lesion images, a single two-stage segmentation method was introduced, which involved removing diseased spots from cucumber leaves. The lesion images were then fed into the activation reconstruction GAN for augmenting the data to produce new training samples after rotation and translation had been applied. Lastly, we suggested using the generated training samples to train a dilated and inception convolutional neural network, which would increase the identification accuracy of cucumber leaf diseases. The experimental results demonstrated that the proposed approach significantly outperformed those of its existing counterparts. The average identification accuracy of 96.11% was achieved.

GANs are prominent in DL, particularly for their capacity to create realistic images and learn complex ST correlations within MTS [22]. Forecasting vegetation, crucial for understanding ecosystem dynamics and land cover changes, presents challenges due to non-stationary ST correlations and external factors like weather. Addressing these challenges, we propose a novel multi-attention GAN model composed of an encoder network to encode input sequences, a generator for long-term temporal pattern extraction, and an improved discriminator for classification and feedback. Extensively tested with real-world data, the model demonstrates superior performance, yielding a Coefficient of Determination (R^2) of 0.95, RMSE of 0.04, MAE of 0.01, and MAPE of 15.35, showcasing its effectiveness and robustness compared to existing methods.

Crop classification using remote sensing data has become increasingly important, with studies indicating that combining SAR and optical images improves classification accuracy. However, a key challenge is the scarcity of training data, particularly for minority crop classes, which impacts classifier performance [23]. Traditional methods struggle to address this issue, as they often fail to effectively generate synthetic data for minority classes. In this study, we investigate the efficacy of conditional tabular generative adversarial networks (CTGAN) in synthesizing data for minority crop classes. Our results demonstrate that CTGAN produces high-quality synthetic data, effectively increasing sample size for minority classes and improving classifier performance in crop classification using SAR-optical data fusion.

The studies that have been discussed all have significant limitations. The use of artificial data raises questions about the way the model captures variations in the real world. In a similar vein, the robustness of the model in real-world meteorological applications may be impacted by the manner in which DCGAN-generated images perform as data augmentation in the tropical cyclone recognition framework. The accurate modeling of weather patterns is a challenge for weather prediction methods utilizing GANs and RNNs, and the specificity of the training data may have an impact on the methods' practicality in real-world scenarios. Despite their innovation, plant infection detection models may not be able to handle a variety of environmental conditions or identify several diseases in a single leaf. Although it outperforms transfer learning techniques, plant leaf disease identification raises concerns about its generalizability beyond particular datasets. Finally, the complementary model for aerial survey data completion may be affected by real-world environmental factors that are not fully accounted for, and careful validation in a variety of agricultural contexts is necessary to ensure its applicability across varying missing rates in time-series data.

III. PROBLEM STATEMENT

From the reviewed literatures that problem addressed that the traditional agricultural yield prediction models have limitations. These include difficulty accurately extracting features from satellite data and inability to generalize across a wide range of environmental conditions. The inhomogeneous pixel intensity distributions in images, which are impacted by variables like shadows and lighting, provide substantial

makes it easier for the model to identify minute differences in the types of soil, vegetation, and other critical components that affect agricultural productivity. Histogram equalization is therefore applied as a pre-processing step to ensure that the input data is more conducive to efficient feature extraction and learning, which helps to optimize DCGAN-CNN based crop-yield prediction models. By extending the intensity range throughout the image, it effectively distributes the levels of intensity and improves the image. When adjacent contrast data reflect the operational values of a picture, this approach increases the image's universal contrast.

Histogram with equalization, a smaller localized intensity differential can yield more contrast. It aims to increase the image's visual appeal and readability. A picture's intensity spreading values can be thought of as arbitrary numbers between 0 and L-1. An additional meaning of "random calculation" is the cumulative distribution function that goes along with it.

Denote the input picture f as an array of numerical pixels with intensities values within the range of 0 to $L - 1$, where L is the intensity probability value. Additionally, q denotes regularized histogram of the primary image (f). Eq. (1) represents the general formula for q and g .

$$qn = \frac{\text{number of pixels with intensity } n}{\text{total number of pixels}} \quad n=0, 1 \dots, L-1 \quad (1)$$

Eq. (2) represents the histogram equalization of the image

$$h_{i,j} = \text{flor}(L - 1) \sum_{n=0}^{f_{i,j}} qn \quad (2)$$

The $\text{flor}()$ changed to the closest down integer as a result. This is equivalent to applying the following Eq. (3) to the values of the densities, k , of 'f':

$$S(k) = \text{flor}(L - 1) \sum_{n=0}^k qn \quad (3)$$

Considering the densities for f and h as continuous arbitrary values Y, Z over a time span from 0 to $L - 1$, where Z is a variable, served as the inspiration for this conversion. The intensity formula, represented by Eq. (4), is provided below.

$$Z = S(Y) = (L - 1) \int_0^x q(x) dx \quad (4)$$

where, $q(x)$ is the probability intensity formula for g . S is the product of Y 's collective distribution values and product of $(L-1)$. It will be easier to suppose that the variable T is differentiable and invertible. While the function $T(X)$ denotes Y , which is normally distributed.

C. Deep Convolutional Generative Adversarial Networks for Data Augmentation

One of the areas of artificial intelligence research that has seen the most development recently is GANs, which are used extensively in a variety of fields including visual forecasting of typhoon clouds, image generation, and image repair. A discriminator and a generator are components of a GAN. The discriminator's goal is to discern among actual and artificially produced pictures as much as possible, while the generator's goal is to render the discriminator incapable of differentiating

between true and image generated. An image is the generator's output, and it requires an n -dimensional vector as input.

Any model capable of producing images, like the basic fully connected neural network, can serve as the generator. An image serves as the discriminator's input, and its label serves as its output. The discriminator structure is comparable to the generator structure in a similar way, resembling a network with convolution, etc. Advancement over the original GAN is represented by DCGANs. The following are the improvement's primary contents; rigorous mathematical proof is not included. Convolutional neural networks are used by both the discriminator and the generator. Both discriminators and generators employ batch normalization. The pooling layer is not utilized by either the discriminator or the generator. The generator substitutes fractionally strided convolution for the convolution layer, while the discriminator maintains the CNN architecture. The loss functions of discriminator D and generator G are included in the DCGAN's loss function. The discriminator's parameters are set after the generator has been trained. The generator's parameters are set while the discriminator is being trained.

The generator's goal is to prevent the discriminator from being able to tell the difference between generated and actual TC images as shown in Eq. (5).

$$L_D^{adv} = \log(1 - D(G(X))) \quad (5)$$

The discriminator can be tricked by the generator by minimizing Eq. (6), which prevents the discriminator from differentiating between generated and real images. The L1 loss function is then presented in order to calculate the difference between the generated and actual images as shown in Eq. (7).

$$L_1 = \sum_{a=1}^{q_w} \sum_{b=1}^{q_h} |G(X)(a, b) - Y(a, b)| \quad (6)$$

$$L_G = \lambda_1 L_D^{adv} + \lambda_2 L_1 \quad (7)$$

where, the empirical weight parameters are λ_1 and λ_2 . By reducing Eq. (8), the generator can produce high-quality images.

Differentiating between the generated and actual images is the aim of the discriminator D . The discriminator's adversarial loss function is as follows in order to accomplish this goal:

$$L_D^{adv} = -\log(D(Y)) - \log(1 - D(G(X))) \quad (8)$$

In Eq. (8), an infinite situation will arise if the generated image is incorrectly judged as the real image, or if the real image is incorrectly judged as the generated image. This implies that the discriminator needs to be optimized. A progressive decrease in Eq. (8)'s value indicates that the discriminator is becoming increasingly well-trained.

In the field of agricultural yield prediction, Deep Convolutional Generative Adversarial Networks are effective instruments for feature extraction from satellite imagery. An improvement on conventional GANs, DCGANs are made expressly to extract and assimilate hierarchical features from large, complex datasets. With regard to satellite imagery, DCGANs are particularly good at identifying complex spatial and spectral features that may be difficult for traditional

methods to extract. In this context, subtle patterns and nuanced information are critical for accurate yield predictions.

DCGANs are made up of a discriminator and a generator that collaborate through adversarial training. The discriminator assesses the authenticity of these generated images in comparison to real ones, while the generator attempts to replicate the true distribution of the input data by synthesizing realistic images from random noise. This competitive process forces the generator to continuously enhance its capacity to generate images that are identical to real satellite data, efficiently recognizing and encoding complex patterns present in the imagery.

DCGANs are especially useful for extracting features like crop health indicators, vegetation distribution, and soil properties when it comes to agricultural yield prediction. The model can automatically recognize and abstract complex features at different scales, capturing both local and global patterns within the satellite imagery, thanks to the hierarchical structure of the convolutional layers in DCGANs. Subsequently, these acquired characteristics can function as comprehensive depictions for subsequent assignments, contributing to precise crop yield forecasting.

The spatial relationships and contextual information found in satellite images are naturally utilized by DCGANs. Convolutional layers give the network the ability to detect spatial hierarchies, which is essential for figuring out how crops are arranged, pinpointing specific areas, and encapsulating the diversity of agricultural landscapes. As a result, the generated features offer a thorough depiction of the fundamental features and structure of the agricultural terrain, enabling more accurate yield predictions. The application of DCGANs to feature extraction from satellite imagery presents a refined method for identifying and encoding complex spatial relationships and patterns in the data. DCGANs are especially well-suited for the intricate and nuanced task of agricultural yield prediction because of their hierarchical feature learning capabilities, which provide a solid basis for further model

training and optimization. The DCGAN's architectural diagram is illustrated in the Fig. 2.

D. Convolutional Neural Network for Agricultural Yield Prediction

CNNs play a pivotal role in leveraging satellite imagery to make accurate predictions. CNNs excel in learning hierarchical and spatial representations from images, making them particularly effective for capturing intricate patterns and features present in agricultural landscapes. Trained on a dataset comprised of real and synthetic satellite images, where the latter is generated using a DCGAN to augment the available data, the CNN learns to automatically extract relevant features associated with crop health, growth, and other factors influencing yield. The convolutional layers of the network act as localized feature detectors, identifying distinctive spatial patterns in the images, while subsequent layers integrate these features for high-level representation and prediction. Through this process, the CNN becomes adept at discerning subtle variations in satellite imagery, contributing to a robust and accurate model for agricultural yield prediction, which is crucial for informed decision-making in precision agriculture and resource optimization.

The source data is passed through a series of "filters" by convolutional layers. Every filter is made to identify a particular pattern or feature, like corners, edges, or, in the case of deeper layers, more intricate shapes. These filters result in a map that shows the locations of the characteristics as they move across the image. The output of the convolutional layer is a feature map, which is a representation of the source data with the filters applied. Convolutional layers can be stacked to create more complex models with a higher capacity to extract finer details from images. Convolutional layers, put simply, are in charge of extracting features from the input images. These characteristics could be corners, edges, textures, or intricate patterns. Eq. (9) represents the input pixel, filter and the value at the position

$$A(p, q) = \sum x \sum y B(p + x, q + y) * E(x, y) + b \quad (9)$$

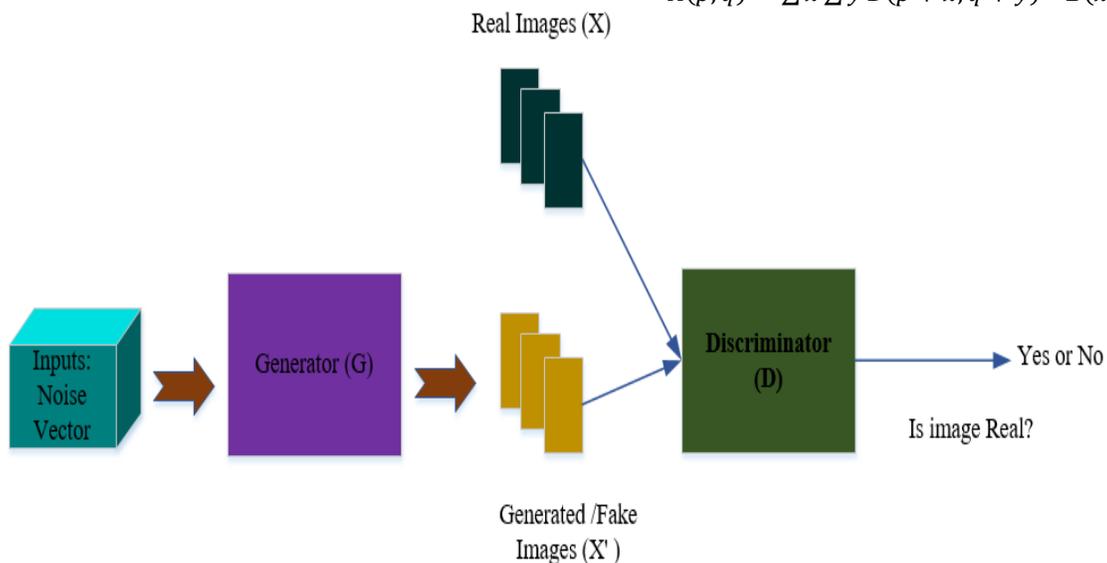


Fig. 2. DCGAN's architectural diagram.

where, $A(p, q)$ is the value in the future map at position (x, y) .

$B(p + x, q + y)$ is the input image pixel at position $(p = x, q = y)$

$E(x, y)$ is the filter/kernel at position (x, y) .

b is the bias term

Pooling layers are used to speed up analysis and decrease the spatial extent of the user's input. They are the next in the processing hierarchy after convolutional layers. In the context of images, "spatial dimensions" refers to the height and width of the image. The fundamental units of an image are called pixels, which resemble rows and columns of tiny squares. By reducing the spatial dimensions, pooling layers help lower the number of factors or weights in the system. This expedites the model's training process and helps avoid overfitting. Because max pooling reduces the size of the feature map and makes the model invariant to small transitions, it aids in lowering computational complexity.

The network wouldn't be able to identify features regardless of slight rotations or shifts without max pooling. This could potentially reduce accuracy by weakening the model's resistance to changes in object positioning within the image.

For example, if the pooling window is 2 by 2, the highest-valued pixel in that 2 by 2 region will be selected. Max pooling effectively captures the most notable feature or characteristic within the pooling window. Using average pooling, the sum of all values within the pooling window is found. It provides a picture of typical, rounded features. Eq. (10) denotes the maximum pooling function. The CNN architectural diagram is given in Fig. 3.

$$F(p, q) = \max(F(2r, 2s), F(2r, 2r + 1), F(2r + 1, 2s), F(2r + 1, 2s + 1)) \quad (10)$$

E. Adam Optimization for Enhancing DCGAN-CNN Model

Adam is ideally suited for the intricate and dynamic nature of deep neural network training since it combines adaptive learning rates with momentum. The algorithm's adaptive features facilitate the efficient adjustment of learning rates for

individual model parameters by utilizing the historical gradients. This leads to a stable and robust convergence. This flexibility comes in handy when working with datasets of satellite imagery, where intricate spatial patterns and variable data distributions call for an optimization algorithm that can navigate a wide range of complex and subtle terrain. Adam's scalability to manage massive amounts of high-dimensional satellite imagery data is further enhanced by its efficient memory usage, which is attained by preserving moving averages of gradients and squared gradients. Moreover, compared to conventional optimization techniques, Adam's simple implementation and reduced hyperparameter requirements make it a practical and effective option for remote sensing and agricultural analytics professionals. By using Adam, researchers and practitioners can improve DCGAN-CNN performance and training efficiency, which will lead to more accurate and dependable predictions in satellite-based applications.

It combines the advantages of momentum and Root Mean Square Propagation, two other optimization techniques. Adam works well in a range of machine learning scenarios by adjusting the learning rates of individual model parameters based on the historical gradients.

Two moving averages, one for the gradients (first moment) and another for the squared gradients (second moment), computed exponentially over time, are essential components of Adam. Setting hyper parameters during initialization includes determining the learning rate (α), the decay rate in the first moment estimate (β_1), and the decay rate in the second moment estimate (β_2). The algorithm uses exponential decay to update the first and second moment estimates at each iteration and computes the gradient of the loss with respect to model parameters. Adam presents terms for bias correction in order to address biases towards zero.

Using exponential decay, update the first moment estimate (mean of gradients) and the second moment estimate (mean of squared gradients) is expressed in Eq. (11) and Eq. (12).

$$n_t = \beta_1 \cdot n_{t-1} + (1 - \beta_1) \cdot g_t \quad (11)$$

$$o_t = \beta_2 \cdot o_{t-1} + (1 - \beta_2) \cdot (g_t)^2 \quad (12)$$

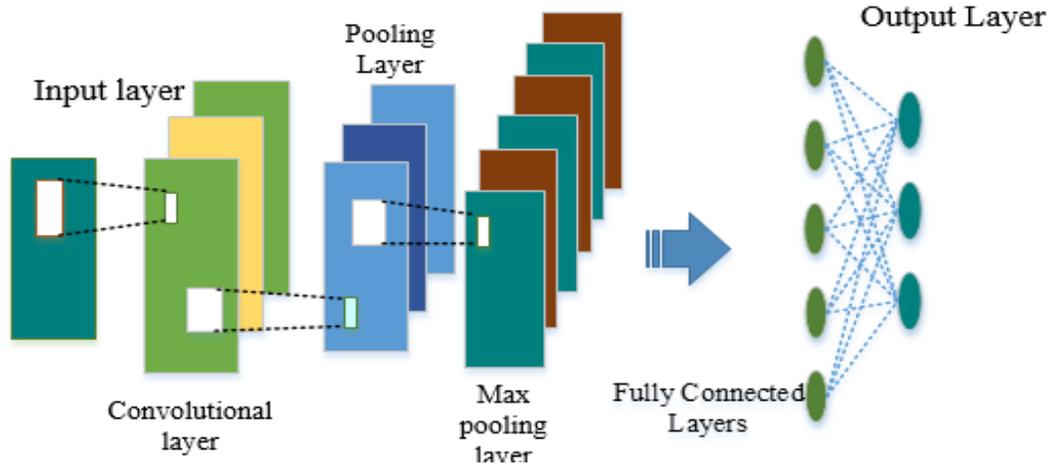


Fig. 3. CNN architectural diagram.

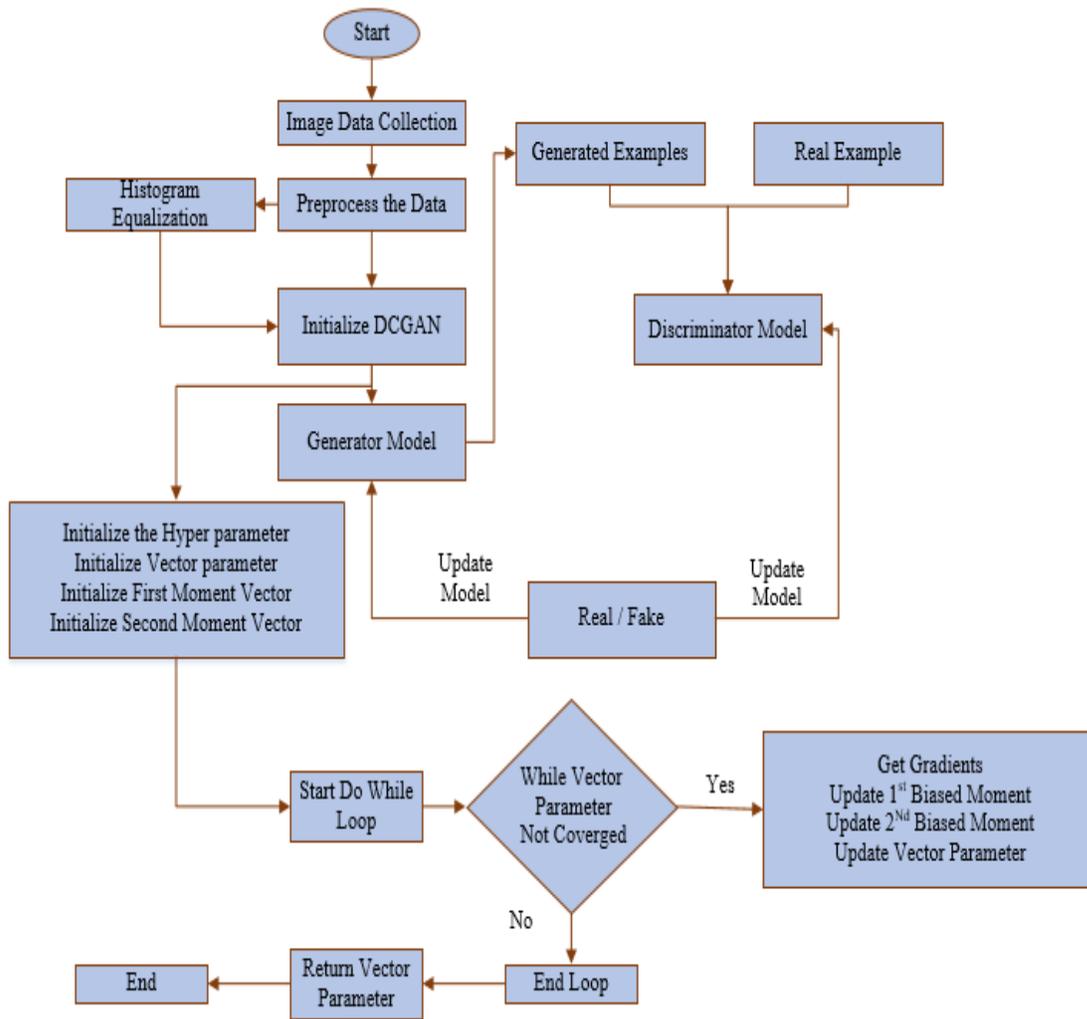


Fig. 4. Flowchart of the proposed AO optimized DCGAN method.

where, the gradient is denoted by g_t , and the first and second moment estimates at iteration t are represented by n_t and o_t , respectively. Particularly in the early iterations, there is a bias towards zero in the estimates of n_t and o_t .

Adam presents terms for bias correction in order to address this bias. Eq. (13), Eq. (14) and Eq. (15) represents,

$$\hat{n}_t = \frac{n_t}{1-\beta_1^t} \quad (13)$$

$$\hat{o}_t = \frac{o_t}{1-\beta_2^t} \quad (14)$$

$$\theta_{t+1} = \theta_t - \alpha \cdot \frac{\hat{n}_t}{\sqrt{\hat{o}_t + \epsilon}} \quad (15)$$

The model parameter at iteration t is represented by θ_t , the learning rate is represented by α , and division by zero is maintained by the small constant ϵ . The final step updates the model parameters using the bias-corrected estimates. Adam is a powerful optimizer because of its adaptability, real-world efficacy, and combination of momentum and RMSprop. The best results require experimentation and fine-tuning because task-specific characteristics and hyper parameter selection determine its performance. Adam is a good neural network

training optimizer due to its momentum incorporation and adaptive features. Fig. 4 shows the flowchart of the proposed AO Optimized DCGAN Method.

V. RESULTS AND DISCUSSION

The results section presents the outcomes of the empirical analysis conducted in this study, elucidating the effectiveness and performance of the proposed methodology in agricultural yield forecasting. It provides a detailed overview of the model's predictive accuracy, robustness, and generalization capabilities across different environmental conditions and crop types. Additionally, the results section offers insights into the interpretability of the model, highlighting key features and factors influencing yield predictions, thereby contributing to a deeper understanding of the underlying dynamics of agricultural production.

In this section, the research present the results obtained from our novel approach integrating DCGANs with satellite imagery for the purpose of optimizing agricultural yield prediction. The utilization of DCGANs allowed us to generate synthetic satellite images, enabling the augmentation of our training dataset and enhance the model's ability to generalize

across diverse agricultural landscapes. Through extensive experimentation, we evaluate the performance of our proposed methodology in comparison to traditional yield prediction models. Our results shed light on the efficacy of DCGANs in extracting meaningful features from satellite imagery, providing valuable insights into the potential advancements and improvements that can be achieved in the realm of precision agriculture. When combined, the metrics that the research evaluates provide a strong basis for assessing and maximizing the efficiency of DCGANs in satellite imagery-based agricultural yield prediction. The performance of the model across these crucial metrics will be thoroughly examined and its implications will be discussed in the results section that follows, providing insight into the model's potential to improve agricultural prediction processes.

A. Performance Metrics

Metrics that quantify the accuracy, precision, and overall efficacy of the model are essential when assessing the way a DCGAN predicts agricultural yields from satellite imagery. The objectives of the agricultural yield prediction task should be taken into consideration when designing these metrics. The following metrics are frequently employed when assessing DCGANs and contrasting them with conventional techniques

1) *Mean squared error*: The average squared difference between the model's predicted agricultural yield values and the dataset's actual observed yields is measured by a performance metric called mean squared error, or MSE. A lower MSE value reflects a higher degree of accuracy in the DCGAN's agricultural productivity predictions by indicating that it is better at minimizing the overall difference between predicted and true yield values. The following Eq. (16) is the formula for mean squared error:

$$MSE = \frac{1}{n} \sum_{p=1}^n (y_p - \hat{y}_p)^2 \quad (16)$$

where,

The total number of instances in the dataset is represented by n .

For p th instance, y_p represents the actual agricultural yield that was observed.

For p th instance, \hat{y}_p denotes the expected yield calculated by the DCGAN.

The mean squared error (MSE) is computed by averaging the squared deviations between the observed and anticipated values for every example in the dataset. This metric provides a quantitative assessment of the model's accuracy in predicting agricultural yields by penalizing larger errors more severely.

2) *Accuracy*: Assessing the accuracy by contrasting the predicted class labels your model generates with the ground truth (actual) labels for your test dataset. After processing all of the test photos to determine accuracy, increase the "Number of Correct Predictions." and divide this count by the "Total Number of Predictions" if the projected label for an image in the test dataset matches the actual label. Accuracy is commonly determined by applying Eq. (17).

$$Accuracy = \frac{RN+RP}{RP+AP+RN+AN} \quad (17)$$

The accuracy metric assesses the percentage of correctly classified instances, offering valuable information about the DCGAN's capacity to identify and replicate significant patterns associated with crop yield throughout the complete dataset. A high accuracy shows that the model is able to learn and generalize from the satellite imagery in an efficient manner, resulting in dependable predictions for the evaluation of agricultural yield.

3) *Precision*: Precision is a commonly measured quantity, primarily in statistics and machine learning. It assesses a model's ability to make positive predictions about the future. The ratio of accurate forecasts to all reliable forecasts is known as precision. It is commonly combined with other classification model metrics like accuracy, F1-score, and recall. The formula for precision in Eq. (18) is as follows:

$$Precision = \frac{True\ Positives}{(True\ Positives+False\ Positives)} \quad (18)$$

The number of correctly predicted positive outcomes is known as True Positives. The number of negative events that the model misinterpreted as positive is known as False Positives (FP). The precision level is a number between 0 and 1, where 1 represents perfect precision (all correct positive predictions) and 0 represents no correct positive predictions. To use this equation, a dataset containing the ground truth labels and the model's predictions is required. Next, ascertain precision by counting the true positives and negatives using the previously described method.

A high precision value indicates that the DCGAN minimizes false positives by being effective in identifying regions of interest linked to high crop yield. Precision is particularly important in agriculture because it highlights the model's capacity to offer reliable and accurate insights into regions where ideal yields can be anticipated, assisting farmers and other stakeholders in making well-informed decisions.

4) *Recall (sensitivity)*: Recall is also known as sensitivity and true positive rate. The ability of the model to correctly identify each relevant instance of a given class that is present in the dataset is referred to as recall. It determines the percentage of true positive predictions, or correctly detected instances of a class, out of all real positive occurrences for that class. Recall can be defined as mathematically in Eq. (19)

$$Recall(sensitivity) = \frac{True\ Positives}{True\ Positives+False\ Negatives} \quad (19)$$

A high recall value means that the DCGAN minimizes false negatives by effectively capturing a sizable portion of the regions linked to optimal agricultural yields. To ensure that the model can consistently identify and highlight areas of interest in agricultural applications and help farmers and decision-makers optimize their resource allocation and management strategies, a high recall is necessary.

5) *Specificity*: The proportion of accurately anticipated negative observations to all actual negative observations is defined as specificity. Eq. (20) is used to compute it:

$$Specificity = \frac{True\ Negatives}{True\ Negatives + False\ Positives} \quad (20)$$

Specificity is frequently shown against sensitivity (True Positive Rate) at different categorization levels within the framework of the ROC curve. A high specificity number means that the occurrences of the negative class are accurately identified by the model, and they are not being incorrectly classified as positive.

6) *F1-Score*: The F1 score is particularly useful in datasets that are unbalanced meaning that one class significantly outnumbers the other. The following Eq. (21) is used to determine the F1 score:

$$F1\ Score = 2 * \frac{(Precision * Recall)}{(Precision + Recall)} \quad (21)$$

A model that successfully strikes a balance between the accuracy of positive predictions and the capacity to record all pertinent cases is indicated by a higher F1 score, which provides a thorough indicator of overall predictive accuracy.

7) *AUC*: The ROC curve, which plots the True Positive Rate (sensitivity) versus the False Positive Rate (one-specificity), provides a graphic representation of a model's performance across different classification thresholds. The range of the AUC is 0 to 1, where:

The model performs no better than chance, according to an AUC of 0.5.

AUC > 0.5 denotes performance that is superior than chance, and higher values signify improved discriminative capacity.

The capacity of a model to distinguish between positive and negative occurrences, such as a DCGAN in agricultural yield prediction, an improved model's ability to distinguish pertinent agricultural features is indicated by an AUC value that is closer to 1, which makes it a useful metric for assessing the model's overall discriminatory power.

TABLE I. THE SUGGESTED METHOD'S PERFORMANCE METRICS ARE COMPARED TO THOSE OF EXISTING METHODS

Method	Accuracy (%)	Precision (%)	Recall (%)	F1 Score
YOLO v3 [25]	93.96	80.64	85.9	89
Deep CNN [21]	96.11	90.67	93.90	89.56
Two Stage Neural network [18]	95.38	90.18	85.52	86
Proposed AO-DCGAN+CNN	98.6	98.2	97	96

Compared to YOLO v3, Deep CNN, and Two Stage Neural Network, the proposed AO-DCGAN+CNN model achieves the highest accuracy of 98.6%, outperforming the other methods is given in Table I. Compared to state-of-the-art methods, it demonstrates superior precision (98.2%), recall (97%), and F1 Score (96%), demonstrating its efficacy in precise object detection and classification.

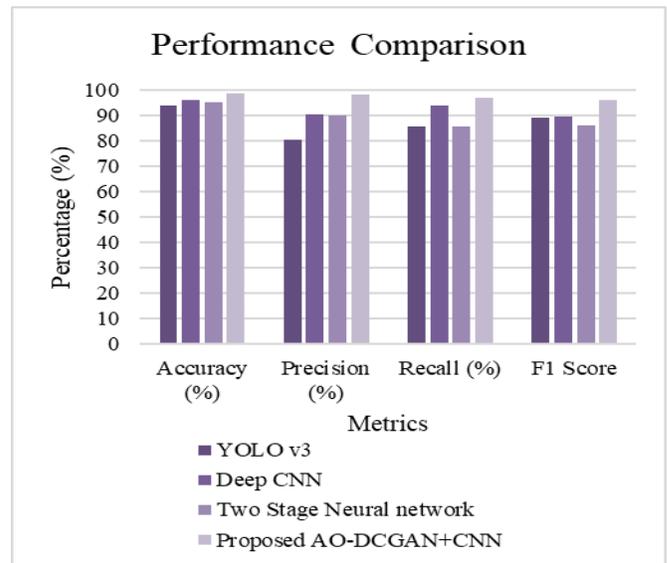


Fig. 5. Visual representation of the performance measures of the suggested DCGAN+CNN's using traditional methods.

Fig. 5 shows the performance metrics of the proposed DCGAN+CNN model in comparison to conventional techniques. The graphical representation highlights the proposed model's superior accuracy; precision, recall, and F1 score over traditional methods, demonstrating how effective it is at advancing agricultural yield prediction.

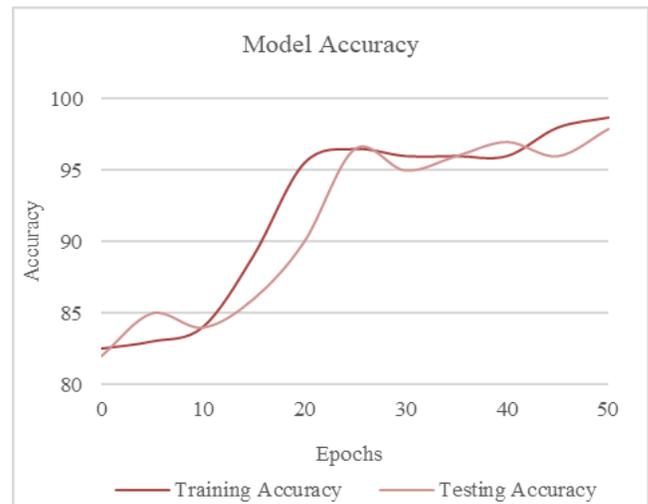


Fig. 6. The suggested DCGAN+CNN method's graphical representation for both training and testing accuracy.

The suggested DCGAN+CNN method is graphically represented in Fig. 6, which shows the accuracy of both training and testing. In addition to confirming the model's effectiveness in maintaining high accuracy during testing, the visual highlights the model's performance dynamics throughout the training process, offering insights into its learning behavior.

Table II provides an extensive analysis of the performance metrics of the Proposed DCGAN+CNN, demonstrating its superior MSE of 8.20% in comparison to conventional techniques.

TABLE II. EVALUATION OF PROPOSED DCGAN+CNN PERFORMANCE METRICS USING TRADITIONAL METHODS

Methods	MSE (%)
Random Forests	17.98
KNN	25.64
Proposed DCGAN+CNN	8.20

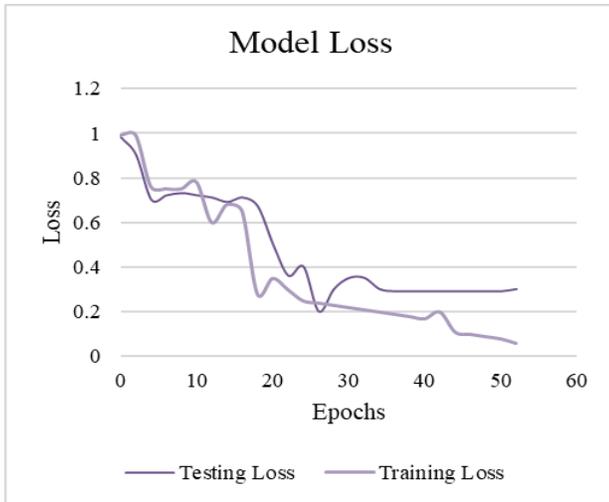


Fig. 7. The proposed Adam optimized DCGAN+CNN's training and testing loss is illustrated graphically.

The training and testing loss of the suggested Adam Optimized DCGAN+CNN model is shown graphically in Fig. 7. The graphical display provides a thorough understanding of the convergence and generalization capabilities of the model, demonstrating the efficient optimization and performance stability attained in the training and testing stages.

The ROC curve for the suggested DCGAN-CNN model is shown in Fig. 8, demonstrating how well it can differentiate between true positive and false positive rates.

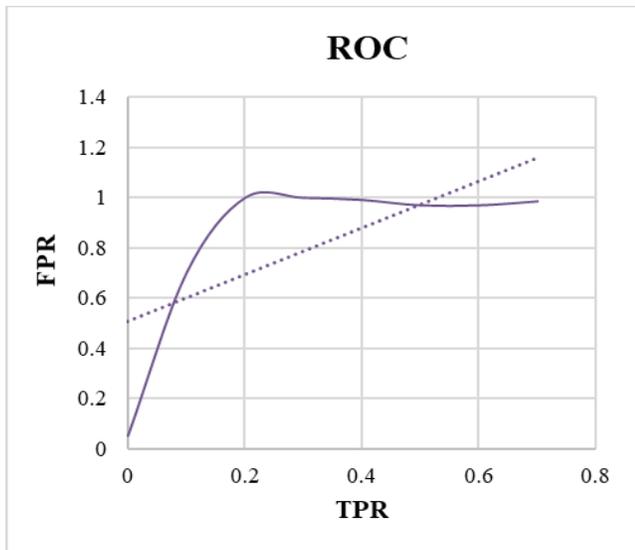


Fig. 8. The proposed DCGAN-CNN's ROC Curve.

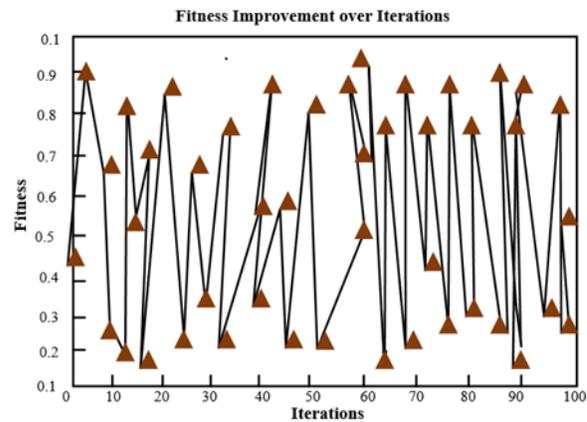


Fig. 9. Graphical illustration of proposed Adam optimizer's fitness graph.

The fitness graph for the suggested Adam optimizer is shown graphically in Fig. 9. The figure illustrates the way optimization algorithm works, highlighting how it can adjust and improve the DCGAN+CNN model's training efficiency, which leads to better overall performance in agricultural yield prediction.

B. Discussion

In order to improve agricultural yield prediction, a novel method that combines DCGANs with satellite imagery is presented in this study. By creating synthetic satellite images, DCGANs improve the training dataset and the model's ability to generalize across various agricultural landscapes. A thorough assessment of the model's effectiveness is provided by the performance metrics, which include Mean Squared Error, Accuracy, Precision, Recall, Specificity, F1 Score, and AUC. The findings show that the suggested AO-DCGAN+CNN model outperforms the current techniques, attaining high F1 Score (96%), recall (97%), accuracy (98.6%), and precision (98.2%). To further demonstrate the efficacy and learning behavior of the model, visual representations of performance metrics, training accuracy, testing accuracy, and ROC curve are provided. According to the research, there is great potential for improving precision agriculture through the integration of DCGANs with satellite imagery. This integration can provide valuable insights into managing strategies and allocating resources optimally for better agricultural yield prediction.

The performance metrics of various methods, including YOLO v3 [25], Deep CNN [21], Two Stage Neural Network [18], and the proposed AO-DCGAN+CNN, for agricultural yield forecasting is discussed. The proposed approach outperforms existing methods, achieving an accuracy of 98.6%, precision of 98.2%, recall of 97%, and F1 score of 96%. This indicates the superior predictive accuracy and robustness of the AO-DCGAN+CNN model compared to YOLO v3, Deep CNN, and Two Stage Neural Network, highlighting its potential to enhance agricultural yield forecasting and contribute to sustainable farming practices.

VI. CONCLUSION AND FUTURE WORK

In conclusion, the integration of DCGANs, CNNs, and satellite imagery proves to be a promising approach for optimizing agricultural yield prediction. When DCGANs are used to generate synthetic images for data augmentation, the model's capacity to generalize to a variety of environmental conditions is improved, leading to predicted outcomes that are more accurate. Using CNNs makes it easier to extract features that are useful for crop health assessment, as they can capture complex patterns and spatial representations. The model is even more flexible in different lighting conditions appreciations to the pre-processing method of histogram equalization. The framework that has been suggested exhibits promise in tackling issues related to unequal distributions of pixel intensity in satellite imagery. In the future, the scope will include investigating more sophisticated methods to improve model performance and generalization across various geographic locations, such as transfer learning and attention mechanisms. Furthermore, the model's predictive abilities could be improved by adding weather parameters and real-time satellite data, which would make it a useful tool for precision agriculture in the face of changing climate conditions. It is possible to improve agricultural technology, guarantee food security, and promote sustainable farming practices by carrying out more research in this area. Despite the promising results, several limitations and avenues for future research exist in enhancing agricultural yield forecasting with DCGANs and satellite data. Firstly, the effectiveness of the proposed approach may be influenced by the availability and quality of satellite imagery, as well as the heterogeneity of agricultural landscapes. Future work could focus on addressing these challenges through the development of more sophisticated DCGAN architectures capable of generating higher-fidelity synthetic images and incorporating additional environmental variables for improved accuracy. Furthermore, research could explore the integration of real-time weather data and other relevant agricultural indicators to enhance the predictive capabilities of the model. Additionally, there is a need for comprehensive validation and verification of the proposed approach across diverse geographical regions and crop types to ensure its generalizability and robustness. Finally, investigating the scalability and computational efficiency of the model for large-scale applications would be beneficial for practical deployment in agricultural decision-making and policy formulation.

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