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IC-CGAN: Imbalanced class-conditional generative adversarial network with weighted loss function

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ABSTRACT

This research proposes an advanced deep learning model that deals with the over-distribution of plant leaf disease classes by using an imbalanced class-conditional generative adversarial network (IC-CGAN) that is coupled with a weighted loss function. IC-CGAN model provides a solution to class imbalance through the synthesis of tomato leaf disease images and adding them to the dataset which as a consequence, improves the accuracy of disease detection. The weighted loss function essentially does a crucial job of solving the problem of imbalance in class during the training stage. Mixing of these models leads to the generation of realistic leaf disease synthetic images and balancing class distribution in the dataset, hence improving of tomato disease detection model's accuracy. This study is another step toward the development of effective disease detection systems for agricultural purposes by addressing the concern of class imbalance with IC-CGAN through the vector-weighted loss function. The proposed IC-CGAN has a high chance of enhancing the disease detection at its early stage with a much higher level of accuracy (99.95%), precision (99.98%), recall (99.98%) and F1-score (99.98%) in tomato plant leaf disease detection.

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1. INTRODUCTION

The early and accurate diagnosis of diseases in tomato plants is the key factor in keeping the health and yield of crops [1]. Conventional approaches used for disease detection are primarily based on visual inspection by trained experts, which is very tedious and elaborate, and can also be subjective [2]. In recent years, deep learning techniques have stood as a major alternative for the automated identification of tomato leaf diseases [3], [4]. Such methods can examine digital images of leaves and identify deleterious symptoms with high accuracy [5]. However, the imbalanced nature of tomato leaf disease datasets is one of the major challenges to building deep learning models for tomato leaf disease detection [6], [7]. These sets of images exemplify the predominance of images of healthy leaves over images of injured leaves [8]. This disparity may interfere with the machine's capacity to find those crucial informative features for disease diagnosis [9]. Addressing this imbalance is vital for emerging accurate and reliable deep learning models for tomato leaf disease detection [10]. Nowadays, tomato leaf disease detection is a critical task in precision agriculture, as its early diagnosis prevents crop losses and reduces economic impact [11]. Even though, conventional approaches rely on the visual inspection by trained experts which is time-consuming and independent. Recent deep learning techniques have shown promise, but they are slowed down by the imbalanced nature of leaf disease datasets [12]. The existing solutions such as data augmentation and oversampling have limitations and may not effectively address the class imbalance issue [13], [14]. Moreover, these methods present noise or bias, affecting the model's performance. Further, the loss function involves focusing on the characteristics relevant to diseased leaves which may become a prominent feature [15]. To lessen the class imbalance and duly improve the performance of tomato leaf disease recognition models, this study merges an imbalanced class-conditional generative adversarial network (IC-CGAN) with a weighted loss function [16].

Abbas *et al.* [17] introduced a deep learning technique for detecting tomato leaf disease by utilizing a conditional generative adversarial network (C-GAN) to create synthetic images of tomato leaves. Moreover, this research utilized the DenseNet121 model to train, and the model was fine-tuned on actual and synthetic images. The suggested C-GAN-based augmentation approach enhanced the generalizability and prohibited overfitting issues. However, the replication of data occurred in DenseNet121 when the feature maps were spliced with the prior layers. Deshpande and Patidar [18] introduced tomato plant leaf disease detection using GAN and deep convolutional neural network (DCNN). The DCNN was utilized to increase the feature representation and correlation, while the GAN was employed for data augmentation to cope with data imbalance problems. An extensive experimentation was performed on ten classes of tomato plant disease from the PlantVillage leaf disease database. The suggested approach retained a better classification approach by diminishing the dropout rate, but the random connection of feature maps led to overfitting issues in DCNN. Ahmad *et al.* [19] introduced an efficient approach to categorize diseases using convolutional neural network (CNN) based on the symptoms of the leaf's disease. Initially, the dataset was evaluated based on class imbalances, and the step-wise transfer learning approach was utilized in the process of reducing the convergence time of CNN. The suggested approach was evaluated using the PlantVillage dataset and pepper disease dataset, which offered effective solutions based on accuracy. However, the proposed approach faced issues related to high running time and computational costs. Roy *et al.* [20] implemented the detection of tomato leaf disease for agro-based industries by utilizing a novel principal component analysis (PCA) DeepNet. This research not only brought forward an unknown method for detecting disease in tomato leaves employing deep neural networks, but also provided an effective solution for companies. The distinctive approach combined a widely known machine learning model from the PCA family with a futuristic deep neural network called PCA DeepNet. another contribution was the GAN for emitting a varied dataset. Additionally, the state-of-the-art detection network also employed the region-based convolutional neural network known as fast region-based CNN (F-RCNN). However, the system only aimed at detecting tomato leaf diseases, and it was therefore necessary to apply the same algorithm to find diseases in other crops.

Paul *et al.* [21] developed a convolutional neural network based on real-time application for the classification of tomato leaf disease. With customized, lightweight and well-performing CNN and deep learning (DL) with VGG-16 and VGG-19 models, the classification of tomato foliar diseases was solved at least with this investigation process. The 11 classes/leaves were depicted as antibodies and represented 11 human diseases with tomatoes image. This was performed to ensure that the neural network was trained and controlled with accurate parameters that fit the model. Consequently, a benchmarking methodology was used to evaluate the performance of the newly developed technology-enhanced model relative to its previous technology-based system. Hossain *et al.* [22] introduced the detection of tomato leaf disease by image processing over deep convolutional neural networks. The first technique used the original dataset and applied a series of filters with gaussian and median filters. Hence, there were four types of pre-processing established in a way that helped neural networks select the most appropriate combination of filtering and color models. Next, DNN models were selected to be run over the filtered outputs to find the best-fitting methodology based on accuracy. For instance, this method partly used hybrid models, which integrated the models such as decision trees and support vector machines with the convolutional neural network models. This enabled both accuracy and speed to be improved in detection systems. Cho *et al.* [23] presented the performance of enhanced classification over GauGAN-based data augmentation for tomato leaf images. This research concentrated on a data enhancement approach, which was based on the generative adversarial neural network (GAN) framework for disease categories assessment and early detection in plants. However, the presented approach required to focus on fine-tuning approaches and integration through other data enhancement strategies to generate more robust and generalizable models. Nonetheless, in the development of deep learning-based classification models, class imbalance was a significant factor that compromised the accuracy. As a solution to this problem, this model exploited the public tomato leaf disease images and proved that GAN was capable of helping with this task. Moreover, the developed classification model was contrasted against models learned using traditional data augmentation techniques, as well as against mix-up and cut-mix algorithms. This enabled the development of more accurate and reliable classification models, capable of handling complex real-world scenarios.

Abouelmagd *et al.* [24] suggested an optimized capsule neural network for tomato leaf disease classification. This research described an advanced computation vision strategy including a modified capsule neural network (MCapsNet) to identify and assign a particular tomato leaf disease category from 10 datasets of conventional image datasets. To deal with challenges such as the overfitting scenario, an approach based on data augmentation and data preprocessing techniques was used during the training phase. CapsNet had the edge over CNNs due to its outstanding ability to localize any kind of correlation within the image. The recognition accuracy of diseases was improved in CapsNet while the disease classification was developed to classify by differentiating between ten different kinds of unhealthy Bush bean plants. However, the developed approach was required to utilize unmanned aerial vehicles (UAVs) to gather plant leaf images, which enabled more effective and comprehensive monitoring of diseases. Zhang *et al.* [25] introduced IBSA-Net for tomato leaf disease identification based on transfer learning with small sampled data. IBSA-Net was a combined form of inverted bottleneck network and shuffle attention mechanism which was incorporated with hard swish activation and an IBMax function. The suggested approach extracted the multi-level features and located the disease region with fine granularities. However, the misjudgment and inappropriate detection were identified due to growth defects of tomato leaves. Pandian *et al.* [26] introduced a dense convolutional neural network with five dense blocks, referred to as 5DB-DenseConvNet to detect plant leaf disease. The architecture of 5DB-DenseConvNet was comprised of five dense blocks and four transition layers. The size of the dataset was improvised with the help of different augmentation approaches and GAN. The Bayesian approach was utilized for enhancing hyperparameter values of 5DB-DenseNet. However, the DenseNet architecture faced issues related to data replication that affected the categorization efficiency of the model. As a resolution to the aforementioned issues, image generation is utilized to have a balanced dataset in the proposed technique with an enhanced accuracy of disease detection models. Generative adversarial networks are introduced as a novel technology in creating synthetic data, and still the data is limited or has an issue of imbalance, specifically for image classification tasks. From this perspective, a specific synthetic image generation of the diseased leaves is observed. Through this process, augmentation is introduced to the dataset, which is a result of the fact that healthy and diseased leaves are equally represented during the training. The integration of a weighted loss function into the GAN framework is added to provide functionality to handle the class imbalance. The loss function tends to assign higher weights to the minority class (diseased leaves) during the training process. Toward this aim, this research develops a new method that employs an imbalanced class-conditional generative adversarial network (IC-CGAN) with a weighted loss function through which artificial images of tomato leaf diseases are generated. Further, the proposed IC-CGAN is analyzed with state-of-the-art methods such as VGG19, ResNetV152, InceptionV3 and MobileNetV2. This method hence contributes to changing the way of farming globally and helps detect diseases at the early stages to enable better crop management and harvest as described below:

- This research addresses the critical problem of balanced class distribution in tomato leaf disease databases by proposing the approach, IC-CGAN for increasing the accuracy.
- Thus, achieving data balance and classifying the healthy leaves and diseased leaves is represented by the model with a balanced representation during the training process.
- The weighted loss function is integrated with the features of IC-CGAN to enhance the accuracy of tomato leaf disease diagnosis models. The designed or synthetically generated abnormal leaves based on the weighted loss function for minor classes during training lead to the addition of more knowledge to the model about the disease features.
- The proposed IC-CGAN loss function eliminates the class imbalance problems which stimulates agricultural practices to the next level.

The further structure of this research is as follows: section 2 describes the process of the proposed methodology, section 3 explains the description about class imbalance handling using IC-CGAN and weighted loss function, while section 4 demonstrates the result analysis and its discussion. At last, section 5 states the conclusion of this research.

2. PROPOSED METHOD

Deep learning offers a promising solution for automating tomato leaf disease detection but faces a hurdle of unbalanced data sets. These datasets are more likely to contain healthy leaf images than those infected by diseases, thereby, not being able to evaluate them. Thus, there is an error in detecting the diseased leaf in reality due to the higher levels of severity of disease in leaves. Rather than a class imbalance and low disease detection precision solution, this study suggests a unique approach that targets the class imbalance problem and disease detection precision. The generation of the synthetic leaf images is done using the IC-CGAN. The system itself “learns” from details available in the existing set of images of diseased leaves and then uses such resulting variations instead of relying on the huge dataset by balancing the problem in model training. Also, there is the introduction of a weighted loss function during training operations. This part of the model tries to emphasize the features' uniqueness to unhealthy leaves, thereby using a higher weight to the minority class (diseased leaves) which in turn balances the effects of having the majority class (healthy leaves). The approach of joint image generation (the diseased leaf image data) and weighted loss function learning help refine any tomato leaf disease detection model. This readjusts the farming practices to the extent of allowing more precise and earlier detection of diseases, which is a characteristic of a revolution as shown in Figure 1. The method for classifying tomato leaf disease using the approach described in the abstract is broken down into several key steps which are explained below.

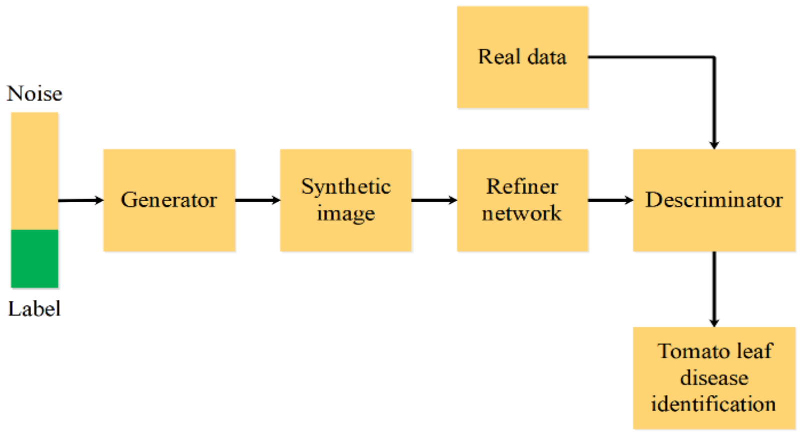

Figure 1. Architecture of the proposed method

2.1. Data acquisition

The tomato leaf disease dataset offered by PlantVillage [27] for machine learning is highly enriched and suitable to be used for training and evaluation of deep learning models in disease detection. Information about the exact details of the image collections is not known to the public either, but the dataset likely includes images of tomato plants, photographed under strictly set conditions and pictures of different tomato varieties and various disease stages. This helps the model meet up with a variety of real leaf views and diseased shapes. Proper identification of all images is conducted by professionals who, apart from indicating whether a leaf is healthy or diseased, also address the specific disease type. Such an annotation machine involves supervised learning and teaches the model to understand the connection between image features and the existence of a disease. Secondly, it is also possible to divide the dataset into training, validation, and testing subsets. The model is trained on the training set with the setting of hyperparameters, while optimization is performed on the validation and test sets, providing a blind validation of the model’s learning capabilities and generalizability to the unseen data.

2.2. Data preprocessing

In the tomato leaf disease classification task using deep learning, preprocessing the images is a crucial step to ensure consistency and improve the model V performance. This process essentially standardizes the data format and removes unwanted variations that hinder the model's ability to learn discriminative features for disease classification. The following are the pre-processing techniques used in the proposed methodology.

2.2.1. Resizing

Images can have varying sizes. Resizing them to a uniform dimension (*e.g.*, width x height) ensures that all images are fed into the model with the same input shape [28]. This simplifies processing and avoids issues during calculations within the neural network layers. Therefore, resizing using a simple notation is expressed in (1).

$$New\_Image = Resize(Original\_Image, Target\_Width, Target\_Height) \quad (1)$$

2.2.2. Cropping

In some cases, irrelevant background information might be present in the image. Cropping focuses on the region of interest (ROI) – the tomato leaf itself [29]. This reduces the amount of data the model needs to process and potentially improves its focus on disease-related features. Cropping is numerically expressed in (2).

$$Cropped\_Image = Original\_Image[y1{:}\,y2, x1{:}\,x2] \tag{2}$$

where $(x1, y1)$ and $(x2, y2)$ represent the top-left and bottom-right corner coordinates of the ROI.

2.2.3. Color normalization

Images exhibit variations in color balance due to lighting conditions during capturing [30]. Color normalization techniques aim to standardize the color distribution across all images. This is achieved using various methods such as subtracting the mean color intensity or applying normalization functions. An example equation for mean subtraction is given in (3).

$$Normalized\_Image = Original\_Image - Mean(Original\_Image\_Channels) \tag{3}$$

Where, $Mean()$ calculates the average color intensity for each channel (Red, Green, Blue) of the image.

2.2.4. Noise reduction

Images are susceptible to be corrupted by noise introduced during capture or transmission [31]. The techniques of filtering are applied to remove this noise and improve image quality. The specific filtering method and equation is depended on the type of noise encountered. Applying these preprocessing steps with appropriate equations or functions significantly improves the quality and consistency of the tomato leaf disease image dataset as shown in Figure 2, ultimately leading to better performance in disease classification models.

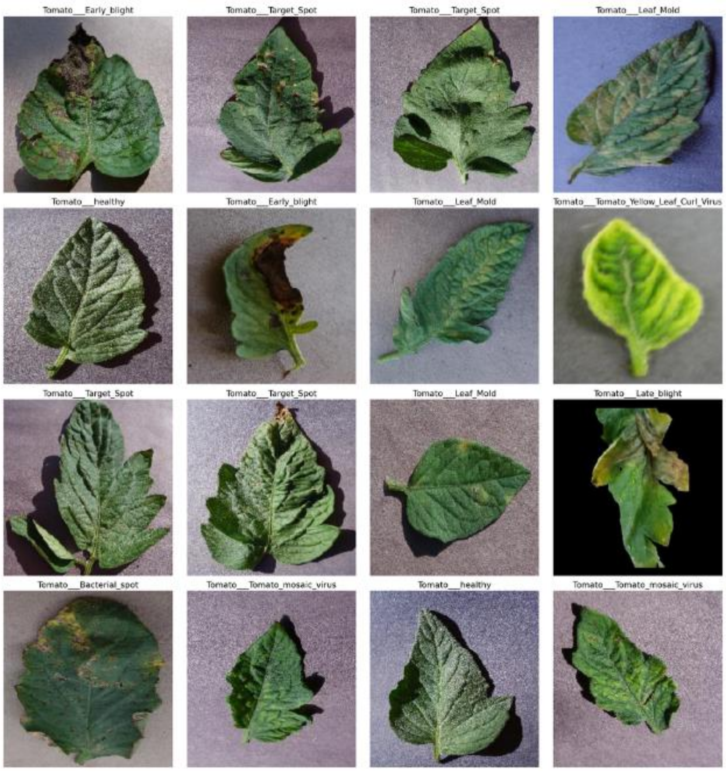

Figure 2. Sample input images

3. CLASS IMBALANCE HANDLING USING IC-CGAN

The proposed IC-CGAN is developed to generate high-quality synthetic images of the minority class which helps to balance the dataset. Due to the IC-CGANs, the healthy leaves outperform the diseased ones which guarantee the proper working of a model with less possibility of misdiagnosis. The proposed IC-CGAN serve as a powerful tool to enhance data augmentation and the rebalancing of classes. Also, it employs the notion of GANs to populate the dataset with realistic images of tomato leaf with diseases [32]; this diversity in training examples supports in a more complete learning experience for the model.

At the core, IC-CGAN architecture lies between two key components: the generator and the discriminator. The generator (G) is assigned to rendering synthetic tomato leaf disease images conditioned on the latent and class variables. Mathematically, the generator tries to learn a function that creates a mapping of z, where the random noise vector is selected from a hidden space x_{synth} and class attribute c defines the class label as in (4). Throughout the generator, there is an aim to produce such realistic images, not possible to distinguish from the true diseased leaf samples in the training dataset.

$$G: (z, c) \rightarrow x_{synth} \tag{4}$$

On the other hand, D which is a discriminator, audits the whole process of a binary classifier to examine whether input pixels in disease leaf images are real or augmented. The role of the discriminator is to construct a discriminator function if D is to be written as $D(x)$, where x is an image. Discriminator develops adversarial ability from training set by enhancing its parameters on the input image set with actual samples and distinguishes between the actual and the generator's synthetic outcome as given in (5). The fierce rivalry reaching out between the generator and discriminator makes the generator go ahead and produce more real and more real samples that in turn bypass the discriminator to become more discreet in its judgment.

$$[D: x \rightarrow [0,1]] \tag{5}$$

The IC-CGAN training strategy is intended to be iterative, and in this process, the generator and discriminator engages in a strategic cat-and-mouse game that results in the compatibility of the neural network model with the image source. In each iteration, the generator racks up a different batch of diseased leaf images, demonstrating the power of latent space and classes to conduct the synthetic process. Along with this, the discriminator which is trained to determine how genuine either of the real or the fake images is, continues to learn and refine its skill in distinguishing between the real and fake images. The generator gets to fine-tune itself such that all features of diseased tomato leaves move towards for differentiating real from the artificial samples of diseased tomatoes as numerically presented in (6).

$$D_{real}(x) = 1, \{D_{synth}(x) = 0\} \tag{6}$$

The overall performance of the IC-CGAN depends largely on the excellently conducted class condition type segregation, which in turn contributes to the realism of diseased leaf image generation. The disease-specific discrimination within the generator based on the priori class labels representing particular disease types enable the system to construct a high-quality and balanced dataset including different disease manifestations and variants. Moreover, it is not just the correction of class imbalance, but also the deepening of the model in terms of the realistic comprehension of image features of disease morphology and object orientation, as a result of which more accurate classification of unseen samples which the model is not trained on before. This is mathematically expressed in (7).

$$[D(x): Discriminator's\ classification \rightarrow \{0,1\}] \tag{7}$$

The use of graphical convolution with generative adversarial network architecture mobilizes a principled approach in dealing with the issue of class imbalanced datasets, specifically in tomato leaf disease classification. The IC-CGAN technology cognizes the creation of photorealistic images of sick leaves that extend the actual work, balance the classes, and refine the accuracy and stability of machine learning models by the CGAN framework [33]. Due to this novel method of data utilization, the use of IC-CGANs in plant disease diagnostics and agricultural sustainability represents a giant leap forward as a way to overcome the challenge of data imbalance and to take a step forward as state of art in this area.

3.1. Feature extraction

Feature extraction from preprocessed images is a gateway to the classifier as it gives the model the power to recognize patterns and the special characteristics that differentiate the healthy and unhealthy leaves. Feature extraction is in essence, about addressing and capturing notable characteristics. Color diversity, patterns of texture, and shapes are of critical importance for appropriate classification. The acquisition of input pixel data is converted into a condensed and discerning format through the transformation process. This facilitates further analysis and decision-making after the classification pipeline in its information interpretation.

Feature extraction to the image data is the application of techniques and algorithms, aiming to reveal and record the useful information which is embedded in the image dataset. These procedures are more traditional with the usage of old-fashioned feature extraction techniques, or are the result of the advent of modern deep learning methods. There are three major features of traditional computer vision; one of them is the computation of color-based features. This is achieved by using either color histograms or color moments. Color histograms provide the number of pixels across different values of color channels so that a color palette that expresses predominantly in the image is discovered. Mathematically, a color histogram H is computed for each color channel (*e.g.*, red, green, blue) using the following formula, while a color histogram H is computed for each color channel (*e.g.*, red, green, blue) using the following formula as in (8).

$$[H(i) = \sum_{p \in Pixels} \Delta(i - p)] \tag{8}$$

where, Δ denotes the Dirac delta function, i represents the intensity level, and p iterates over all pixels in the image. By calculating color histograms for each color channel, the model gains an understanding of the color distribution and variance within the image, which is an indicative of specific disease symptoms or health conditions. Besides the color-based features, texture patterns become a significant factor in the differences between healthy and diseased leaves, as most of the diseases show up as texture changes in the leaves. Texture features reflect the spatial arrangements and the statistical properties of pixel intensities; thus, they are the ones that reveal the surface characteristics and the structural composition of the leaf. Usually, the most widely used method for texture analysis is to extract the local binary patterns (LBP) which are the texture information at the local level, and hence, the intensity values of the neighboring pixels are compared to get the LBP. Mathematically, the LBP operator [34] computes a binary code for each pixel based on its relationship with its neighboring pixels, as defined by (9). Mathematically, the LBP operator computes a binary code for each pixel based on its relationship with its neighboring pixels, as defined in (9).

$$LBP_{\{P,R\}}(x_c, y_c) = \sum_{p=0}^{P-1} s\,.(g_p - g_c)2^p \tag{9}$$

where, P, R, R, C, S in the formula $C\ (P, R, C, S)$ indicating that P means the number of neighboring pixels included, R is the circle radius around the central pixel, C is the intensity value of the surrounding and central pixel and S is the sign function. Through the LBP features computation over different regions of the image, the model effectively captures the textural variations which are the properties of the different leaf conditions. Besides, shape-based features offer essential information about the geometric traits and the morphological parts of leaves, which are the main elements for the classification. Leg shape features are the ones that include measurements of contour curvature, compactness and eccentricity that are used to determine the spatial arrangement and the curvature of leaf boundaries. The most common shape descriptor used in the leaf classification is the Hu moments which are the same for every different position, rotation, and size. Mathematically, the Hu moments are computed from the image moments using (10).

$$eta(pq) = \frac{\mu(pq)}{\mu^{(p+q)/2+1}} \tag{10}$$

where, p and q are non-negative integers denoting the image moments, and the zeroth order moment is the variable. Through the processing of Hu moments from the leaf contours, the model acquires the shape-related features that are associated with certain disease-like states or with the appearance of something unusual. The process of feature extraction from preprocessed leaf images involves the application of a wide range of tools and methods to capture and encode important visual features. Through the use of color-based, texture-based and shape-based features, the model reaches a comprehensive knowledge of the features that are responsible for the differences between healthy leaves and diseased ones. The contributing features in the dataset are discriminative cues for the classification tasks that follow. Therefore, they ensure accurate and informed decisions on the health status of the leaves. Through the integration of advanced feature extraction methodologies, the classification pipeline achieves heightened sensitivity and specificity, enabling the timely detection and mitigation of plant diseases in agricultural settings.

3.2. Model training (using weighted loss function)

The development of a deep learning model, IC-CGAN for the classification of healthy and diseased leaves in images, is not an easy task that requires a combination of several crucial techniques. Therefore, this holistic approach guarantees the deployment of a CNN structure, the resolution of class mismatch cases, as well as the model parameters' optimal learning by employing a weighted loss function. This details the specifications of what encompasses the training process, while explaining the actual methods and the techniques used. In this regard, the CNNs stand out as these spot fine spatial patterns in images, owing to their ability to perform feature extraction. In these networks, information flows through layers from input to output from the connectivity of convolution and pooling layers to the fully connected layers, further enabling feature hierarchies to emerge.

The training material is made up of an isolated group of images, each of which is labeled to show whether it portrays a healthy or diseased leaf. While this is the case, class imbalances are often seen to prevail in many such datasets, which have the unbalanced representation of the instances of two different classes of the dataset over one another. Due to the gap between classes, the model is trained with biases that affect the classification of the minority group, leading to low-ranked performance. For the redistribution purpose of the negative effects of class bias, a weighted loss function is incorporated into the training pipeline. Such loss function is obtained in the form of a standard cross-entropy loss function, which is devised for the evaluation of the difference between predicted outputs and current labels [35]. With the weighted loss function, the predicted class-wise value on the loss calculation is evaluated, with the minority class (*i.e.*, diseased leaves) expected to have a higher contribution, while the major class (*i.e.*, healthy leaves) should have very little impact. The standard cross-entropy loss function (L_{CE}) is numerically expressed in (11).

$$L_{CE} = \frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} y_{ic}\ log(\widehat{y_{ic}}) \tag{11}$$

where, N denotes the total number of samples, C represents the number of classes. y_{ic} signifies whether the ith sample belongs to class $c, \widehat{y_{ic}}$ denotes the predicted probability of the i^{th} sample belonging to class c. Incorporating class weights into the loss function, the weighted cross-entropy loss (L_{WCE}) is computed as in (12).

$$L_{WCE} = \frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} w_c * y_{ic}\ log(\widehat{y_{ic}}) \tag{12}$$

here, w_c represents the weight assigned to class c during training. In scenarios characterized by class imbalance, higher weights are allocated to the minority class (diseased leaves), thereby prioritizing the model's learning of features specific to diseased leaves while attenuating the influence of the majority class. Throughout the training process, the model iteratively updates its parameters using optimization algorithms such as stochastic gradient descent (SGD) or Adam. These algorithms minimize the weighted cross-entropy loss, facilitating the convergence of the model towards an optimal configuration. By integrating the weighted loss function into the training regimen, the model is incentivized to accurately classify instances from the minority class, thereby enhancing its capacity to discern between healthy and diseased leaves. The training process of a CNN for leaf classification encompasses the strategic utilization of advanced architectures, the accommodation of class imbalance challenges, and the refinement of model parameters through tailored loss functions as shown in Figure 3. This holistic approach fosters the development of robust and accurate models capable of discerning subtle distinctions between healthy and diseased leaves, thereby contributing to the advancement of agricultural diagnostics and plant pathology.

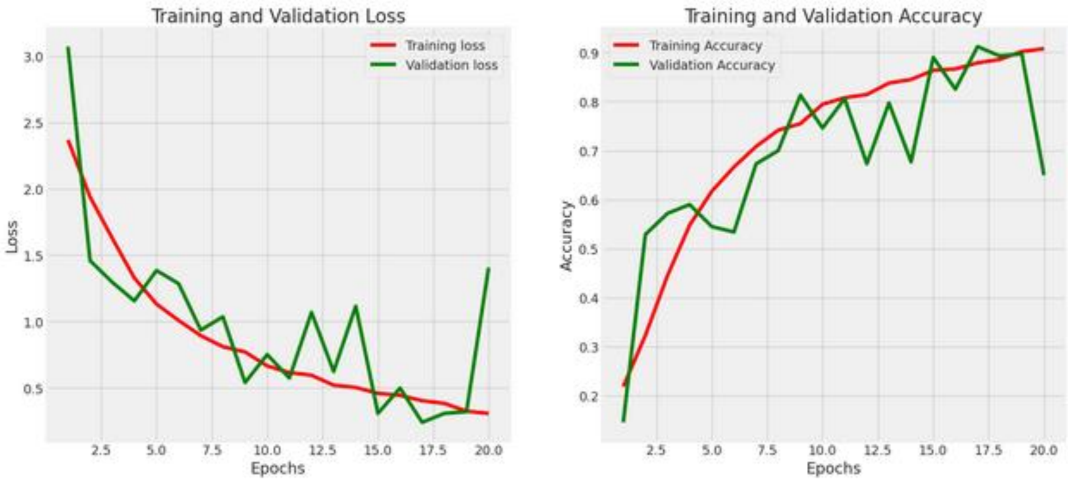

Figure 3. Loss graph of proposed GAN model

3.3. Model evaluation

In the evaluation phase, the trained model is assessed to a test dataset that is given separately as input, in which its efficiency in the classification of tomato leaves into healthy and diseased ones is determined. This procedure remains crucial for measuring the model’s generalization quality and ability to make accurate predictions on unprecedented data. The test dataset constitutes the set of the labeled images for each image, either a tomato in a healthy or diseased state is shown to reflect the real-world scenarios in which they are used in agricultural settings.

This machine model runs the images as input through the test dataset and provides the predictions for diseased and healthy leaves based on the features, while the parameters are learned through training. Consequently, the model outputs are then evaluated based on performances against the actual annotation of the test images. Another metric that plays a significant role in interpretation is the agreement between predicted and actual labels. Accuracy, precision, recall, and F1-score are calculated from the metrics to obtain a comprehensive evaluation of the model's performance. These metrics provide an essential direction of the model's capacity to determine correctly the healthy and diseased tomato leaves as well as a lesson that it potentially has a blind spot or is sensitive to certain types of biases or errors within the classification process.

The evaluation of the model with the data set from validation is required to estimate the model's capability for practical applications such as using automated agricultural monitoring systems or disease detection platforms. The correct predictions shown during training and the robust model ensure the efficiency of the model in solving issues related to plant health analysis early enough for farmers to act on them. Secondly, the information acquired during the assessment is used to guide future model improvements and the optimization of its capacity which is necessary to achieve the goals of enhancing to sustainable agricultural practice and crop management strategies.

3.4. Disease classification

After finishing the training and the validation processes, the model moves into an algorithmic state after which it analyzes the new images of tomato leaves for classification. At this time, the machine learning model's learned representations and classifications enter the vital application phase, enabling it to offer a vital health picture of the tomato plants in farming right in the field. This procedure passes through the recurrent covers of the pictures where the features are extracted, followed by the process of the predictive analysis to determine the healthiness of the leaves with the ability to identify specific diseases based on the patterns and discriminative features learned. The classification process starts with the input of a new tomato leaf image that is acquired as the initial form of information for health examination. The chosen model is optimally taught to learn the architecture features by hierarchical convolutional and fully-connected layers which serve feature extraction. Using the functions of negation operations and pooling, the model identifies the salient attributes (edges, textures, and patterns) of leaves that facilitate diseased leaf assessment.

Such features spread along the normalized network layers which appear to evolve till the final stage that provides a detailed information about the diseased leaf features. The mentioned descriptions comprise the manifestations of such attributes and complex clues linked to both good and diseased tomato leaves, and these are the ones that the model considers upon learning to decide the right prediction based upon the associations and patterns it has learned so far. The hierarchical nature of feature extraction is an essential property of the model which allows it to capture the complicated discriminative features embedded in leaf structure, texture, color, density, and states, thus facilitating a detailed and accurate classification. The modeled features are formed after the feature extraction procedure to the phase of modeling that utilizes the learned representations to forecast the health status of the tomato leaf being examined. Using training, the model extracts all those hidden features, but essential insights that are later used by advanced classification algorithms to identify disease symptoms or physiological abnormality in the images are very sophisticated or even subtle. Modeling is carried out in comparison to extracted features with the learned representation of the healthy and diseased state of leaves, followed by computing the probabilities of relevant disease categories and labeling the disease according to the most probable health condition.

In the predictive analysis, a component of the complete image evaluation concerns the assessment of the input image, where the model is responsible for checking the severity and the spread of abnormalities and pathologies. The model classifies using probabilistic reasoning and decision-making processes, hence being equipped at the core. Because of this architecture, the model assigns confidence scores to the possibilities, considering the most likely outcomes, taking into account the certainty or ambiguity inherent in the classification process. In addition to an individual binary classifier, the model predicting capabilities expand for spanning various disease classes which in turn provide the necessary granular details regarding the nature and forms of leaf diseases. By the end of the classification, the useful information for diagnosis, monitoring, and response interventions of disease in tomatoes is obtained. In this regard, the technicians, farmers, and researchers enjoy the privilege of using credible and reliable information. The identification of disease is done by locating and providing a decision-support tool that enables decision-makers to respond correctly through the application of targeted interventions and reducing the adverse impacts of crop diseases on yield and quality. Further, due to the iterative nature of the disease classification process, the model and refinement in learning the process keeps on adjusting to new disease patterns to improve its performance. Fundamentally, the classification process employs computational, domain-oriented, and empirical approaches side by side as a harmonized blend, combining their strengths to address pivotal issues in plant health and forest conservancy. Through the utilization of artificial intelligence and machine learning power, classification process starts a new age of precision agriculture, in which the combined transparency about data-driven insights and predictive analytics results in transformational innovations in crop resistance, adaptability, and performance.

This method creates attention to internal features from tomato leaf images through the use of CNNs and deep learning techniques [36]. Using this approach, the agricultural stakeholders on the right side have access to solid sensor tools for immediate disease detection and informed decision-making, hence better crop management and yield optimization at the end. The research sums up the novelty of this technique using the most advanced deep learning tools, which creates an alert in the era of precision agriculture that help combat crop diseases and also secure global food safety.

4. RESULTS AND DISCUSSION

The outcomes of the ICGAN method are explained in this section. The ICGAN method is designed and simulated in the Python 3.7 software where the system is operated with 8 GB RAM and an i5 processor. The IC-CGAN-based data augmentation along with DenseNet121-based classification is proposed for improving the classification of tomato leaf diseases. The performance metrics of accuracy, precision, recall, and F1-score are expressed in (13) to (16) for evaluating the IC-CGAN.

$$Accuracy = \frac{TP+TN}{TN+TP+FN+FP} \times 100 \tag{13}$$

$$Precision = \frac{TP}{TP+FP} \times 100 \tag{14}$$

$$Recall = \frac{TP}{TP+FN} \times 100 \tag{15}$$

$$F1 - score = \frac{2TP}{2TP+FP+FN} \times 100 \tag{16}$$

where, TP is true positive, TN is true negative, FP is false positive and FN is false negative. The results on all metrics for the proposed IC-CGAN are seen to be superior to other classifiers with scores close to the perfection. This goes to show that the dense connections are very important in the capture of the complex features and patterns that are needed for leaf classification with better performance. To sum up, the tables are a source of important information that shows the performance of the classifiers in different situations, thus proving the importance of the architectural design, feature extraction techniques, and the IC-CGAN method which increases the accuracy and the robustness of the leaf classification models. These findings are a source of advice for researchers and professionals in the creation of more efficient ways of plant disease detection and management, thus giving rise to improvement of crop health and productivity in agriculture.

The expressions of different architectures and feature extraction techniques and the significance of the proposed IC-CGAN method in the context of leaf classification tasks are portrayed in Table 1. Table 1 presents a comparative analysis of classifiers employing distinct neural network architectures, including VGG19, ResNetV152, InceptionV3, and the proposed IC-CGAN method. Each classifier is evaluated based on metrics of accuracy, precision, recall, and F1-score, which provide a visual percept into its performance in distinguishing between healthy and diseased tomato leaves, as shown in Table 2.

Table 1. Classification analysis of actual features extraction

Classifiers	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
VGG19	84.00	88.00	84.00	90.00
ResNetV152	89.50	85.00	84.00	84.5
InceptionV3	78.00	88.00	88.00	88.00
Proposed (IC-CGAN)	97.68	96.95	96.98	96.93

Table 2. Different classifier analysis for the prediction of tomato leaves

Classifiers	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
VGG19	94.99	93.98	93.95	93.96
ResNetV152	97.96	98.00	98.00	98.00
InceptionV3	88.00	98.00	88.00	92.00
Proposed (IC-CGAN)	99.95	99.98	99.98	99.98

a. VGG19: The VGG19 architecture [37] which mainly features very deep convolutional layers and a simple design, exhibiting appreciable performance in all metrics. So, it demonstrates that it is very effective in extracting the relevant features and classifying leaf images accurately.
b. ResNetV152: ResNetV152 [38], a sample of the ResNet architecture with 152 layers, shows excellent performance in all the indicators. The advantages of deeper networks in the capturing of the complex patterns and features that exist in the leaf images are the main reason of the success of this sample. The model's better precision, recall, and F1-score are evidences of its robustness in distinguishing between healthy with diseased leaves with high accuracy.
c. InceptionV3 [39]: The model with the same task and equal computer architecture to different models can be regarded as the feature extraction equally extracted.
d. Proposed (IC-CGAN): The IC-CGAN technique is the best classifier on the list and gets almost perfect scores on all evaluation metrics, as in Figure 4. Thus, the IC-CGAN method is proven to be an effective way of increasing classification accuracy and solving the problem of class imbalance by creating realistic images of the diseased leaves. The IC-CGAN method uses generative adversarial networks to create synthetic images, which increases the dataset and the learning of the model, thus solving the problem more completely.

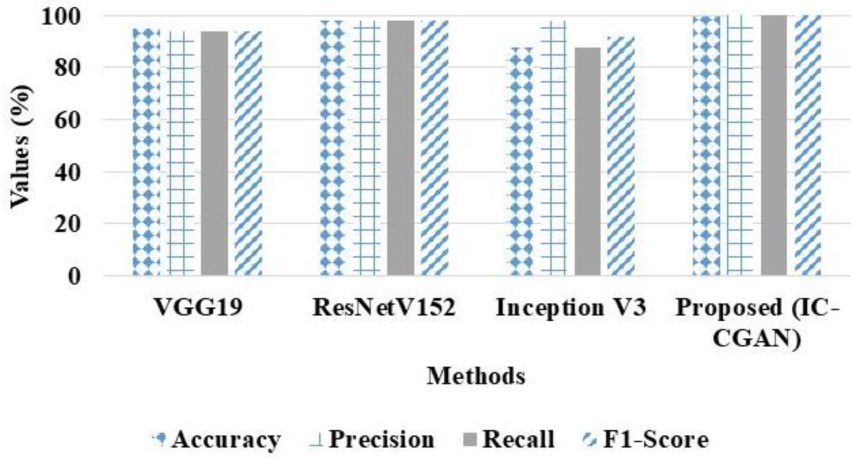

Figure 4. Comparison of different classification methods

Table 1 and Figure 5 compare the performance of classifiers without declared feature extraction. Also, the architectures of VGG19, ResNetV152, InceptionV3, and the proposed IC-CGAN method are discussed in Table 2. Classifiers believe in themselves and rely only on the raw pixel data to make classification decisions if the feature extraction is not done.

Although VGG19 error is not very high, the study shows that the model has high precision and F1-score, which means that it identifies true positives with high reliability. Nevertheless, it shows that the experimental group has a relatively lower recall, which means that there are difficulties in the correct identification of all diseased leaves. Whereas the proposed IC-CGAN technique is superior to the other classifiers without feature extraction and this is reflected by the notably superior performance in all metrics. This shows that the IC-CGAN approach is very efficient in learning discriminative features directly from the images without extracting the features and hence, it is suitable for the classification of images.

Table 3 and Figure 6 compare classifiers that use several feature extraction techniques. For example, ResNet50, VGG16, MobileNetV2, and the DenseNet201 architecture. Feature extraction is the key to identifying the relevant visual characteristics from the images, thus making the leaf classification process more accurate.

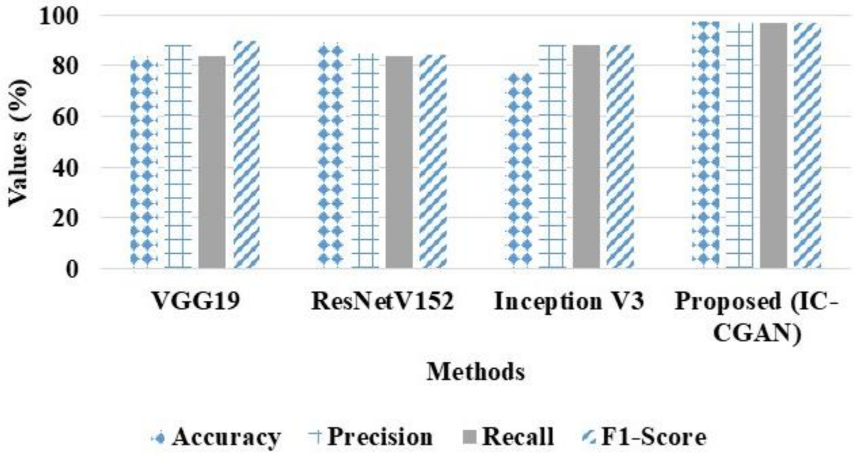

Figure 5. Comparison of different feature extraction methods

Table 3. Classification analysis of different feature extraction

Classifiers	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
ResNet50	97.46	98.52	98.65	98.58
VGG16	89.68	90.25	92.52	91.38
MobileNetV2	95.78	96.86	96.89	96.87
Proposed (DenseNet201)	99.95	99.98	99.98	99.98

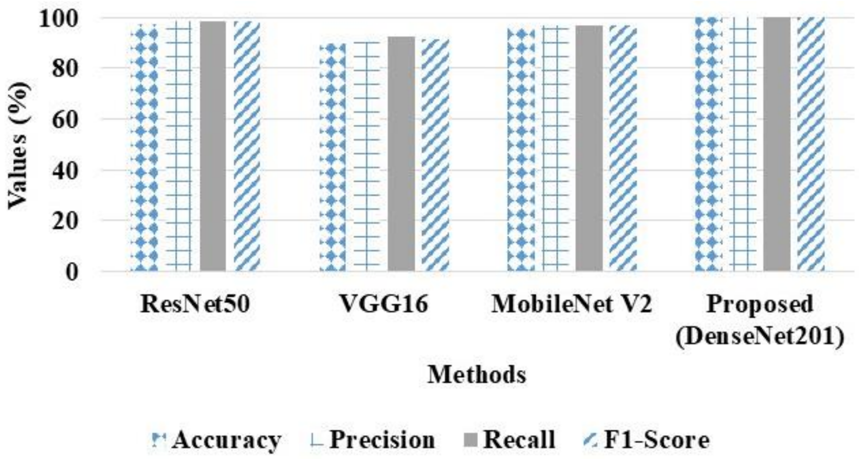

Figure 6. Comparison of different classification methods

ResNet50 shows outstanding results in all the indicators, thus bearing proof of its efficiency in the feature extraction from leaf images. The high accuracy, precision, recall, and F1-score of ResNet architectures prove the advantages of the feature extraction and classification tasks in this field. VGG16, on the other hand, shows moderate accuracy but at the same time has high precision, recall and F1-score that suggest that it is good at correctly classifying diseased leaves, while at the same time reducing the number of false positives and negatives. MobileNetV2 [40] is famous for its lightweight architecture and the efficient use of resources, proving to be effective in leaf classification. Its high accuracy, precision, recall, and F1-score are evidences of its effectiveness in feature extraction while respecting computational efficiency. To overcome the class imbalance issue, the IC-CGAN model is combined with weighted loss functions that work to emphasize learning more passed features that usually characterize diseased leaves, thereby enhancing the classification accuracy. This model is trained through iterative and validation processes to recognize unique patterns or details of tomato leaf diseases with more accurate and robust classifications that set it apart from other methods.

4.1. Discussion

This paper introduces a model termed as IC-CGAN with a weighted loss function for tomato leaf diseases classification. At the end of the analysis, the tables demonstrate smiling data around the performance of the classifiers of tomato leaf diseases. In different scenario feature extraction methods and data validation scenarios, the proposed model exhibits commendable accuracy, precision, recall, and F1-scores, as opposed to the existing methods. The proposed IC-CGAN method outperforms all other classifiers consistently, indicative of the method's high-class imbalance mitigating abilities along with its expertise in classifications without the need for a feature extraction algorithm as an explicit tool. Besides, the architectures and feature extraction mechanisms used in such networks and the advanced techniques applied are vital because the deeper networks where the modern techniques give the best results. The proposed IC-CGAN method produces better results in terms of accuracy, precision, recall and F1-score of 99.95%, 99.98%, 99.98% and 99.98% respectively for disease detection.

From the overall existing models, the existing VGG19 has a relatively lower recall, thus, still some problems occur in detecting the diseased leaves correctly, despite being quite accurate in extracting features. Similarly, InceptionV3 performs the least among the classifiers without feature extraction with outstanding accuracy, precision, recall, and F1-scores. This shows that a certain problem in disease leaf classification is classifying the features that already exist based on the raw pixel data. MobileNetV2's compact design require additional training data to achieve optimal performance. While ResNet50 demonstrates good accuracy and precision where the results are somewhat more reliable than VGG19 with a slightly lower recall and F1-score. Thus, though it detects the diseased leaves accurately, sometimes it does not detect some cases which leads to a lower recall rate.

From the overall result analysis, the existing VGG19 are seen to exhibit exceptional accuracy, precision, recall and F1-scores of 89.68%, 90.25%, 92.52% and 91.38%, respectively. On the other hand, the InceptionV3 obtains an accuracy, precision, recall and F1-scores of 78%, 88%, 88% and 88%, respectively. MobileNetV2 model offers increased accuracy, precision, recall and F1-score of 95.78%, 96.86%, 96.89% and 96.87%, respectively. While the ResNet50 model gains an accuracy, precision, recall and F1-score of 97.46%, 98.52%, 98.65% and 98.58%, respectively. From the comparative results, it is evident that the proposed IC-CGAN outperforms the existing ResNet50, VGG16, MobileNetV2, and the InceptionV2 in all the performance metrics. Even then, the proposed IC-CGAN needs an additional evaluation measure to assess the quality and diversity of generated samples, especially on larger datasets.

5. CONCLUSION

This paper develops an advanced method, IC-CGAN integrated with a weighted loss function to classify tomato leaf diseases. The proposed IC-CGAN model delivers a solution to class imbalance problem through the combination of tomato leaf disease images to enhance the classification accuracy. The weighted loss function principally overcomes the class imbalance issue during the training stage. Incorporation of these two models leads to the production of precise leaf disease and class distribution in the dataset, thus enhancing the detection model's accuracy. From the experimental analysis, it is apparent that the proposed IC-CGAN method accomplishes higher levels of accuracy, precision, recall and F1-score with respectively securing 99.95%, 99.98%, 99.98%, and 99.98% in tomato plant leaf disease detection. These findings give support to the evidence that the employment of advanced methods and algorithms is likely to be one of the most reliable approaches for the development of plant disease detection models. Also, these results contribute to global food security and sustainability by enhancing crop yields and minimize the losses. In the future, this research will be analyzed with ensemble learning techniques, transfer learning strategies, and multi-modal data sources to improve the classification accuracy and create more robust plant health monitoring systems.

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