Enhancing Tomato Leaf Disease Detection through Generative Adversarial Networks and Genetic Algorithm based Convolutional Neural Network

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Abstract

In the agricultural sector, tomato leaf diseases signify a lot because they result in a lower crop yield and quality. Timely detection and classification of diseases help to ensure early interventions and effective treatment solutions. Nonetheless, the existing methods are confined by the dataset imbalance which affects class distribution negatively and thus results in poor models, especially for rare diseases. The research is designed to improve the capability of tomato leaf disease identification by investing a new deep-learning method beyond the challenge of imbalanced class distribution. By balancing the dataset, we aim to improve classification accuracy as we pay more attention to the under-represented classes. The proposed GAN-based method that combines the Weighted Loss Function to produce tomato leaf disease synthetic images is underrepresented. They improve the quality of the entire dataset, and the images from every class are now in a more balanced proportion. A CNN, which is the convolutional neural network, is trained for the classifier, with the weighted loss function as a part of the model. We used Genetic Algorithm (GA) for hyperparameter optimization of the CNN. It helps in emphasizing the learning process from the under-represented class. The suggested one will not only decrease the accuracy of tomato leaf disease detection but also increase it. Therefore, the synthetic images created by GAN enhance the dataset since the class distribution is brought to equilibrium. The incorporation of the weighted loss function into the model's training process makes it very effective in handling with the class instability problem and consequently, the model can identify both common and rare diseases. From the outcomes of this study, it can be concluded that it is feasible to employ GAN and one loser weights function to solve the problem of class imbalance in tomato leaf disease recognition. A suggested approach that increases the model's accuracy and reliability could be a good move to enhancing a reliable method of disease detection in the agricultural sector.

Keywords: GAN (Generative Adversarial Networks); Weighted Loss Function; Synthetic images; Convolutional Neural Network (CNN); Dataset diversity; Model accuracy; Robustness; Disease detection efficacy

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1. Introduction

The development of the identification of tomato leak disease can be summarized by some key changes in recent years, especially the combination of new technologies including GANs and weighted loss functions. These GAN-based advancements demonstrate the attempts of scholars to develop and transform the GAN models for creating realistic images which is significant for the advancement of the detection models' accuracy [1]. The quality of the synthetic images has been constantly optimized and refined along with the diversification of the images, which in turn, helps to widen the formation of the disease patterns and improve the detection algorithms. Furthermore, the utilization of loss functions provided with weights is an important strategy to deal with the problem of class instability which is very common in real-world datasets. The mechanism of these functions is that the models assign higher importance to the minority classes and as a result in the case of prevalent diseases the model is less biased for rarer diseases and thus bolsters its detection capabilities [2]. Such a strategy corresponds to a crucial stage in guaranteeing the non-discriminatory and dependable nature of the disease detection systems to raise their usability in agricultural contexts. Moreover, regulations development demonstrated the integration of environmental variability to the main goal of increasing the resilience of disease detection models [3]. Recognizing that the environment under which such systems must operate is not uniform, researchers have investigated both data augmentation and model regularization strategies. Such efforts are meant to strengthen the models' versatility to cope with variations in lighting, camera angles, and background clutter; thus, the models` reliability and appropriateness are enhanced in all realistic situations [4].

Tomato leaf disease detection, particularly the ones from the realm, has a lot of pending issues of strong impact that limit the development of optimal solutions. With class imbalance prominent among datasets, this barrier remains an important issue. Most times, the dominant diseases will draw more attention and specific models will be designed around them, often failing to detect and interpret the less common ailments well [5]. It is a game that prompts malfunctioning of disease detection tools, incorrect diagnosis and to be worse, poor intervention in the field. Furthermore, the systems already in place don't effectively handle variable environmental conditions. Problems like changes in lighting, different camera angles, and background incongruity may compound into a noise and variation format that will make the detection algorithms misinterpret the captured environment. Data variability eliminates the possibility of a system functioning appropriately, with the inputs asking for a more practical approach in real-world agricultural settings. In addition to that, the existing study demands damages to the interpretability and scalability of existing methods [6]. Machine learning algorithms, including GAN-based models among others, are prone to producing results that either are hard to decrypt/interpret or explain, which directly has a negative influence on trust and adoption of these models by respective stakeholders [7]. Moreover, fewer scalability issues can emerge when trying to increase the number of areas and testing machines where the amounts of computers they can hold might be not so big.

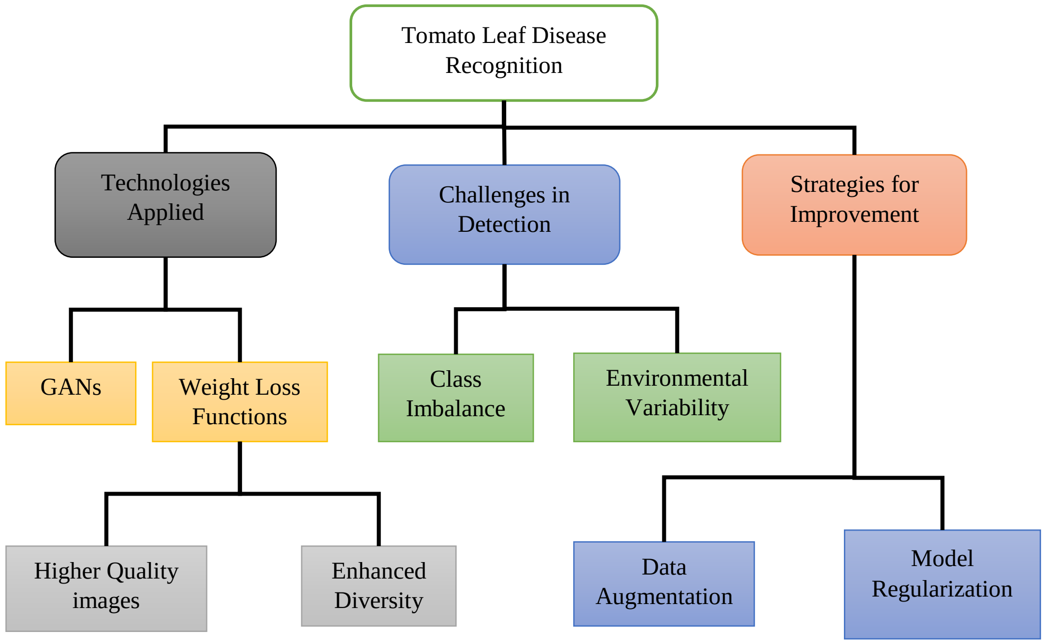

Figure 1. Enhancing Tomato Leaf Disease Recognition

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Figure 1 gives the overview of this study. The focus is on the technologies, challenges, and strategies involved in improving the detection of diseases affecting tomato leaves. The technologies applied, such as GANs and Weighted Loss Functions, are essential for generating high-quality synthetic images and addressing class imbalance in datasets. The challenges section highlights issues like class imbalance and environmental variability, which can affect the accuracy of disease detection. Two strategies for improvement are to develop varied datasets by utilising data augmentation and to increase the model's capacity to generalise across various environmental circumstances by using model regularisation. This visual representation simplifies the complex aspects of tomato leaf disease recognition, showcasing the importance of advanced technologies and robust strategies in agricultural settings.

The solution to the problem is a prerequisite requirement needed for the development of accurate tomato leaf disease detection thereby supporting global agricultural sustainability and food security. One of the techniques that we use to encourage class imbalance is the weighted loss function [8]. Therefore, in the process of detection, the system will favour the detection of common diseases just as rare diseases. So, you will have more efficient and targeted disease prevention strategies. Thorough models that integrate crop varieties for different climates into a disease detection technology, will improve the performance and applicability of such technology across varying farming scenarios so that farmers can make sound choices and optimize resource usage [9].

With an enormous passion for using advanced technology to wrestle with the cumulative problems in the farming sector, especially the detection of tomato leaf illness, this research is meant for this. Facing global food security, agriculture within it often acts as a basic stone, but this industry is based on various challenges, like plant diseases [10]. Tomato plants that are climbed and hung on a trellis, can cheat soilborne diseases. These diseases can kill plants, which destroy yields and make food production impossible. We desire to try out these techniques such as GANs and weighted loss function which are now contributing to an agricultural innovation that enhances the productivity of the sector [11]. These technologies create the prospect of bringing to the healthcare market completely new approaches to urgent health issues, allowing us to diagnose the disease more accurately and reliably. By way of putting weighted loss functions in our vision, we plan to bin the class imbalance and ultimately ensure the model for the discovery of diseases is fair in identifying both common and uncommon diseases. This idea is crucial in ensuring expedient interventions and also management effectiveness, ultimately ensuring yields and allowing farmers to have healthy livelihoods [12].

Environmental conditions were input in the model to measure the robustness of the system and therefore have the confidence that the disease can be detected in real-time monitoring [13]. Using models that can be continually modified to meet different circumstances as time goes on, we aim to invent products that will be usable in any kind of agricultural environment with no complications. Fundamentally, the objective will be the evolution of the existing sustainable global agricultural production system, and food security of the whole globe [14]. Our efforts are geared towards constructing tomato leaf disease detection centres armed with the requisite workforce, expertise to fight the impacts of diseases and the capability of allocating resources optimally, hence, enhancing the farmers' ability to continue harvesting. We seek to contribute to bridging the gap and become a visible and strong line of connection aiming to create a better and more prosperous agricultural landscape for the farmers all around [15].

Here are some major contributions of this study are as follows:

- The introduction of (GANs) for the production of tomato leaf disease images of higher quality is a novel method of image synthesis.
- Develop weighted loss functions that will help in mitigating imbalance challenges in datasets, so that both common and rare diseases can be detected equally.
- Building up models that are adaptable to the environment in nature of lighting changes and background obscurity, however, should enhance the reliability of the models in an agricultural setting.
- Research is carried into transfer learning and domain adaptation methods to use existing knowledge and to increase detection accuracy which is crucial in a resource-limited setting.
- Agricultural sustainability has practical implications, which include the best usage of resources and decreasing the proportion of unproductive crops through more accurate diagnosis of diseases.
- Model interpretability and scalability as important factors in granting trust and helping the widespread application in the agro-industries.

The structure of this paper is as follows. The Literature Review (Section 2) stipulate a comprehensive overview of existing research and developments in the field of tomato leaf disease recognition, focusing on technologies such as GANs, weighted loss functions, and strategies for addressing class imbalance and environmental variability. Section 3, Materials and Methods, details the experimental setup, comprising the pre-processed dataset, model

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architectures, evaluation metrics, and model architectures. Section 4, Experimental Results, represents the outcomes of the experiments, analyzing the performance metrics and the effectiveness of the proposed methods. In Section 5, the Discussion, the results are interpreted, compared with existing literature, and implications are discussed. Section 6, Conclusion & Future Scope, summarizes the findings, discusses limitations, and proposes future research directions to further meliorate the accuracy and relevancy of tomato leaf disease recognition systems.

2. Literature Review

In 2019, Akshay Kumar and colleagues [16] presented a paper at the International Conference on Computing Communication and Networking Technologies, outlining a tomato leaf disease detection system that relies on images. The study used CNN in disease classification with a focus on tomato leaf diseases. The trained model gave a test accuracy of 99 percent which is quite astonishing. 25% when evaluated on the Plant Village dataset. However, some limitations were observed: the study was carried out on tomato leaf diseases only, and this somewhat narrows the study's scope to other plant diseases. There was also some criticism related to the quantity of pictures in the test, which was 14,903, and there might be other variations of diseased and healthy plant leaves that were not included in the test. Also, the study failed to provide details of the types of diseases or conditions in the dataset, which could affect the model's performance on individual diseases.

M. Arsenovic et al., [17] Symmetry 2019, authors mentioned some of the limitations of the DL-based approaches to plant disease detection that are often considered to be state of the art. Firstly, we discover the wholesome model of a neural network with a unique two-level architecture to categorize plant diseases in natural conditions. The methodology utilizes experimental work to analyse the effect of training under various environmental situations including the real-time scenes and also involves the use of Style GAN to improve the detection ability. This paper highlights the attention that should be put to overcoming the hurdles in plant disease detection as this may result in huge damage to agriculture. However, deep learning techniques have achieved notable progress and are still associated with insufficient data to yield better results. Overlooks are exemplified such as using images with no clear society scenes for training, detecting various diseases or the occurrence of the same disease in one image and the solutions to all these problems taken together only. The article has a strong position on the future research that needs to be carried out to cure these challenges like plant disease detection in different plant growing locations and plant disease occurrence stages, and also collecting more data sources including location, climate and age of plants to improve disease detection accuracy.

CNNs are used in Mercelin Francis et al.'s (2019) [18] paper, which was published in SPIN and deals with disease detection and categorization in agricultural plants. The study proposes an approach that will enable improving the model performance and effectiveness of disease detection in agriculture. The methodology is based on the development of a CNN model that has customized layers and functionality for plant disease recognition. The model is trained on a dataset of apple leaf and tomato leaf images, paying close attention to counter the phenomenon of overfitting. The achieved accuracy of 87% is the result of a performance evaluation that is done using a GPU Tesla. The paper points out the significance of reducing overfitting by adjusting the dropout values and also suggests future research directions, including the working out of the combined plant disease identification system that spits out the outcome in real-time.

Batool et al. (2020) [19] suggested an improved model that scored 76. 1% accuracy using the AlexNet model for classifying tomato leaf diseases. They underlined the significance of the application of disease classification in crop farming and the shortcomings of over-fitting even though some questions were raised about wrong pesticide use and the wider spread of diseases.

Deshpande et al. (2022) [20] suggested a novel approach where Generative Adversarial Network (GAN) and Deep Convolutional Neural Network (DCNN) are employed to improve tomato leaf disease detection accuracy. Even though considerable progress was attained, the study did not specifically mention the drawbacks of this scheme.

Sardoğan et al. [21], presented an effective methodology for the identification of four varieties of tomato leaf diseases. The applied method unites CNN as a CNN auto-feature extractor and classifier with LVQ for network learning. The data set included 500 tomato leaf images that showed 4 tomato leaf disease symptoms. The research emphasized the central role of early disease detection in agricultural practices. Here, the authors propose a CNN model and LVQ algorithm-based approach to address this issue. Despite the limits, the study took place under specific limits. It was mainly concerned with tomato diseases in the leaves. It was not necessarily suitable for the treatment of other diseases. Along with the mentioned small dataset size of 500 images, doubts about its representativeness also raised the bar. Additionally, this process of validation, which is mostly experimental, may not fully reveal how it would be implemented in life.

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In his paper by H. D. Gadade et al. (2020) [22], Gabor features were used for recognizing tomato leaf diseases and assessing the carrying out of the classifiers. SVM classification, the study emphasized the demand for accuracy through execution time settlement. Therefore, the research team suggested using KNN which led to the enhancement in both performance and execution times.

Sakkarvarthi et al. (2022) [23], developed a model of CNN to solve a problem with tomato leaf disease detection and better results were achieved by their model than by a pre-trained one. The monitors of this project have accentuated the issue of pest and disease detection in the earliest stages of the tomato crop and have noted the liquidity of such research and the need for model improvement.

Hasan et al. (2019) [24] devised a system for precision farming using drones and CNN that realises a high degree of accuracy in image recognition of affected areas from diseases. However, the results of the trials were not precisely generalized and the challenges that could be encountered while using drones for precise farming were not all brought to light.

Wu et al. (2020) [25] on the other hand built a DCGAN architecture for the enhancement of data in tomato leaf disease identification that produced a high accuracy and diversity. Nevertheless, this study was dedicated to the tomato leaf classes, verifying the existence of other model studies in the future that will help to improve the approaches examined in this study. The overview of the literature review is shown in Table 1.

Table 1: Summary of the literature review

Ref.	Methodology	Main Findings	Limitation
[16]	Convolutional neural networks (CNNs) were used in the process to classify images, especially for identifying illness in tomato foliage. The PlantVillage dataset was used to train a deep CNN., resulting in a test accuracy of 99.25%.	They utilized a CNN for early identification of illnesses in tomato leaves, achieving a high-test accuracy of 99.25%.	- The study only focused on detecting disease in tomato leaves, limiting the generalizability to other plant diseases.
[17]	The process entails generating new pictures using the Style GAN network and testing the effects of training under various contexts, including real-life scenarios. The focus is on overcoming current limitations in plant disease detection.	Significant losses are caused by plant diseases in agriculture, hence efficient disease detection techniques are required to avoid serious losses. Numerous diagnostic approaches have been developed, highlighting the need for precise and easily accessible detection procedures. For deep learning techniques to identify plant diseases more accurately, a lot of data is needed.	- Absence of photos collected and annotated from actual scenarios - Inability to identify several illnesses present in a single picture or several instances of the same illness in a single picture - Utilising other data sources, like location, climate, and plant age, may increase accuracy.
[18]	The process includes building a Convolutional Neural Network model with particular layers and functions for identifying plant diseases, training the model using a dataset of photos of apples and tomatoes, resolving overfitting, and assessing GPU performance. Tesla.	The research addressed overfitting, created an 87% accurate CNN model for categorization and detection of plant diseases, and suggested building an unified plant disease diagnosis system for real-time outcomes.	- Overfitting issue addressed by adjusting dropout value - Suggestion for further research on developing a comprehensive approach for identifying plant diseases

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[19]	The methodology involved proposing an advanced classification model, using using multiple models to extract image attributes from a training dataset of 450 photos, and using kNN for classification, achieving a classification accuracy of 76.1% with the AlexNet model.	An advanced classification model achieved a 76.1% accuracy while employing the AlexNet model to identify and categorise tomato leaf disease, outperforming other models.	- Lack of certainty in disease identification leading to potential incorrect pesticide use - Persistence of disease spread despite safety measures - Potential ineffectiveness of current classification methods
[20]	The approach included testing on 10 classes of tomato plant disease, using a GAN for data augmentation, and DCNN for feature representation and correlation.	The research addresses shortcomings in current plant leaf disease detection techniques by introducing a unique strategy that uses DCNN and GAN, leading to notable improvements in performance measures.	The study does not explicitly mention the limitations of the proposed scheme using DCNN and GAN for plant leaf disease detection.
[21]	The process included automated feature extraction and categorization using a CNN model, along with the LVQ algorithm for training the network on 500 pictures of tomato leaves displaying four signs of illness.	The study focuses on the importance of early disease detection in agriculture and presents a CNN model and LVQ algorithm-based method for effectively recognizing four different kinds of tomato leaf diseases.	The study focuses on tomato leaf diseases, limiting generalizability - A small dataset of 500 images may not be representative -Validation based on experimental results may not fully reflect real-world application
[22]	The methodology involves creating a module that uses a dataset of 500 photos of tomato leaves with seven symptoms to automatically classify plant leaf illnesses. The system includes modules for preprocessing, noise removal, feature extraction, classification, and recognized output. We tested the effectiveness of many classifiers with varying quantities of training photos.	Gabor characteristics accurately identify several tomato leaf diseases; SVM is more accurate but requires a longer execution time, and performance was assessed based on accuracy, precision, F measure, and recall.	One of the study's shortcomings is the trade-off between execution time and accuracy for SVM classification and the recommendation of using KNN classification for better performance and faster execution.
[23]	The methodology involved using the Plant Village dataset with 10 classes of tomato leaves, implementing an enhanced CNN model with specific layers, and optimizing the input image size for improved performance.	- The CNN model attained high accuracy in training and testing for tomato crop disease detection. - Compared to pre-trained InceptionV3, VGG19, and ResNet 152, the proposed CNN model fared better. - The study emphasizes the significance of early disease detection in tomato plants for	- There aren't many studies that concentrate on identifying tomato crop diseases. - Need for improvement in the existing model - Data availability only upon request - No external funding was received for the research.

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		enhancing crop quality and quantity.	
[24]	The methodology involved implementing a precision farming system using drones and Convolutional Neural Networks, utilizing a dataset of images, applying transfer learning to retrain the Google inception model, categorizing leaves into three groups, and achieving 99% accuracy at 85% training.	The study achieved 99% accuracy in identifying high disease areas in tomato leaves when the percentage of training was raised to 85% and demonstrated fast execution speed by utilizing transfer learning on the inception model.	- Generalizability of results to other crops or diseases not discussed - Limitations of using drones for precision farming not addressed - Potential challenges of using transfer learning for disease detection not mentioned.
[25]	Deep convolutional generative adversarial networks (DCGAN) were used in the process to supplement data, along with adjusting hyper-parameters and modifying the architecture of CNNs to enhance the recognition of tomato leaf diseases.	The use of DCGAN for data augmentation in tomato leaf disease identification significantly improved the accuracy, diversity, and generalization of the recognition model.	- Traditional data augmentation methods are limited in achieving good generalization results - Focus on only 5 classes of tomato leaf images - Need for further research on different generative adversarial networks and hyper-parameters.

2.1 Research Gaps

There is a clear knowledge gap in the current literature on computational agricultural technologies regarding this study of the integrated application of GANs and weighted loss functions to overcome the class imbalance in the realm of identifying tomato leaf diseases, especially when focusing specifically on addressing the class imbalance in tomato leaf image datasets. Although some machine learning techniques give hope in detecting diseases from images, data with class imbalance still pose a critical problem because they make every model more biased and thus fail to precisely identify the minor diseases. Most of these methodologies often overlook the significance of addressing class imbalance. This unintentionally makes those techniques work less effectively in real-world applications. Although GANs have been extensively utilized for image synthesis as well as augmentation in various domains containing computer vision, and medical imaging among others, their use in tomato leaf disease detection is not well documented. We now experience a shortage of research focused on the development of GAN architectures that bear the capabilities to emulate the peculiarity of plant disease pictures and the restoration of dissimilar and diverse images to activate the fight against class imbalance.

Also, weighted loss functions have been suggested as a way to solve class imbalance in machine learning tasks but tomato leaf disease detection has not received much representation in the literature. The investigation of weighted loss functions with GANs for this particular purpose presents an innovative and very perspective area for enhancing the precision and robustness of disease detection models.

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3. Materials and Methods

Although skewed datasets provide a challenge, deep learning is a viable option for automating tomato leaf disease detection. The model's capacity to learn and recognize illnesses is hampered by the fact that these datasets often contain significantly more photographs of healthy leaves than images of sick ones. In actual operations where the rate of sick leaves is higher, this may lead to wrong identification. This work proposes an approach to tackle the problem of class imbalance and increase the rate of correct identification of illnesses to tackle this issue. The method builds fake pictures of sick leaves by applying a class imbalance handling and classification using CNN CNN-based Generative Adversarial Network. The proposed GAN-CNN effectively helps in balancing the dataset by creating new variants from the existing pictures of sick leaves by 'learning'. This makes the model to have a more balanced representation when it is training. Also, during the training of the model, a Weighted Loss Function is incorporated. To counter the effects of the dominance of the majority class, which is the healthy leaves, this function gives higher weights to the minority class, the sick leaves, to learn the unique characteristics of diseased leaves. The aim of this combined technique is to improve tomato leaf disease detection detection models by creating artificially sick leaf pictures and training weighted loss functions. This method has the potential to transform agricultural practices by providing early and accurate disease diagnosis, which would enhance crop management and productivity. The overview of the GAN in this study is presented in Figure 2.

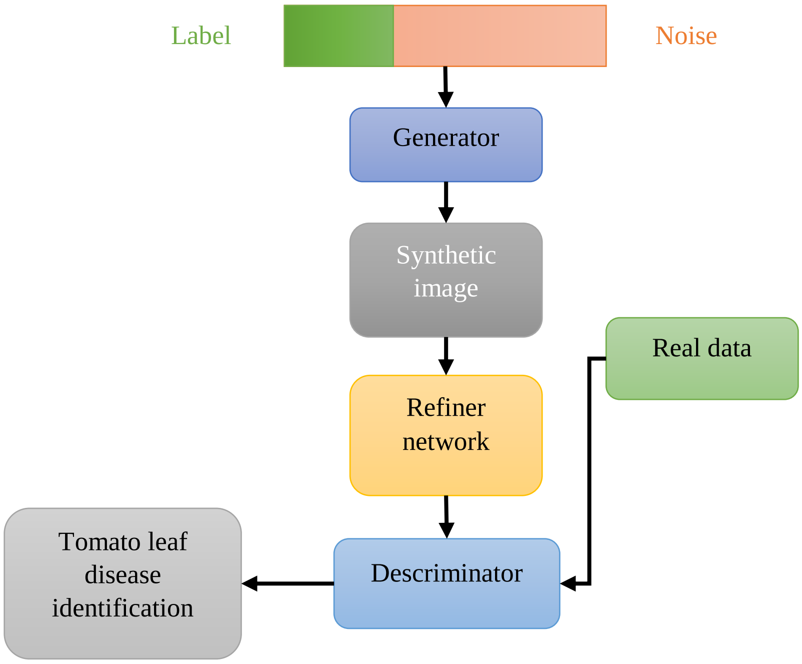

Figure 2. Block diagram of GAN

3.1 Dataset

A valuable resource for developing and employing deep learning models for disease detection is the Plant Village tomato leaf disease dataset [26]. Although the exact methods of picture gathering are not disclosed to the public, the dataset probably includes photographs taken in controlled environments with a range of tomato plant types and at different phases of disease development. This guarantees that the model sees a variety of leaf appearances and illness manifestations. Experts carefully mark every photograph, stating whether the leaf is healthy or damaged and sometimes even identifying the exact type of illness. For supervised learning to take place and enable the model to understand the correlation between illness presence and picture attributes, labelling is a necessary step. The dataset has likely been divided into testing, validation, and training sets. In order to train the model, the training set is utilised, the validation set is utilised to fine-tune its performance, and the testing set is utilised to objectively evaluate the model's capacity to generalise to new data. The Images per class in Tomato Leaf Dataset are displayed in Figure 3. A sample of input images is presented in Figure 4.

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Figure 3. Images per class in Tomato Leaf Dataset

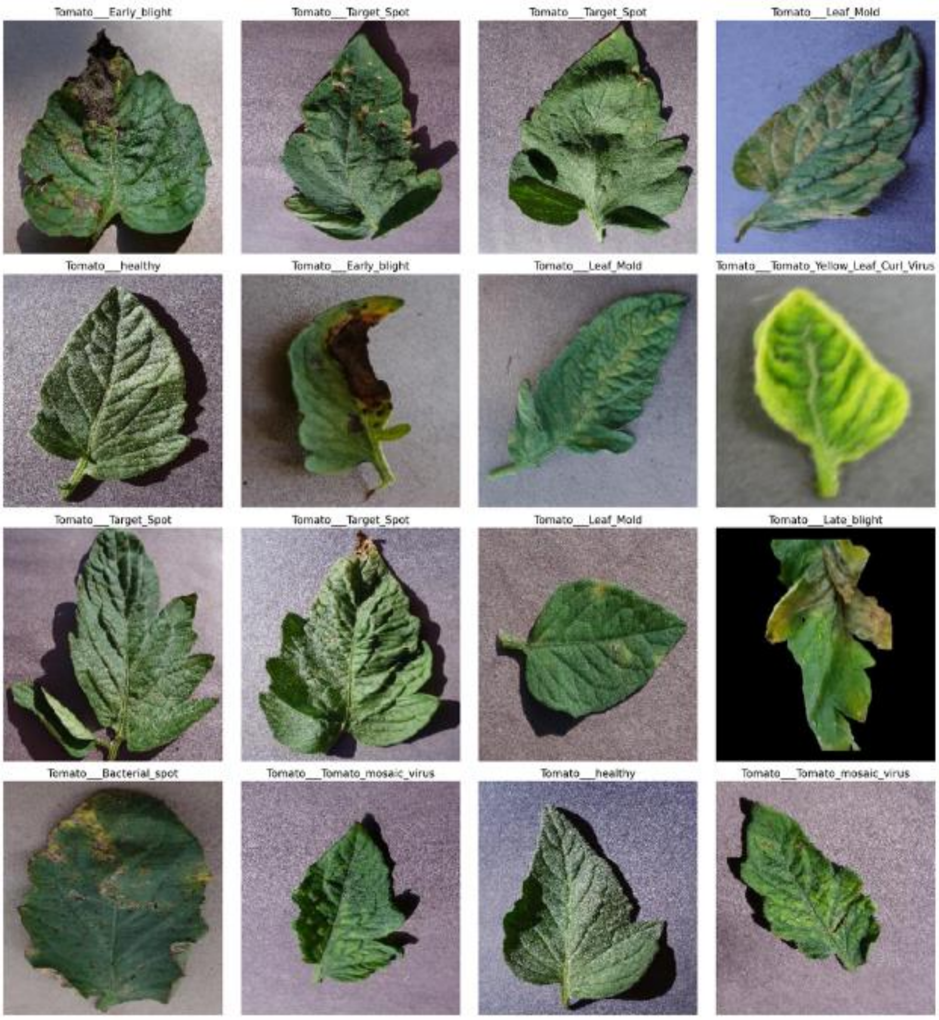

Figure 4. Sample Input Images

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3.2 Data Pre-processing

Preprocessing the images is an essential step in the deep learning task of classifying tomato leaf diseases, as it guarantees consistency and enhances model performance. Through this approach, the data format is fundamentally standardized and undesired variances that might impede the model's capacity to learn discriminative features for illness categorization are eliminated. The pre-processing methods included in the suggested methodology are as follows:

Resizing: The size of an image might fluctuate. It is ensured that all photos are supplied into the model with the same input shape by resizing them to a consistent dimension (e.g., width x height). This streamlines processing and prevents problems in the neural network layers during computations. Resizing may be expressed using a straightforward notation like this:

$$New\ Image = Resize(Original\ Image, Target\ Width, Target\ Height) \quad (1)$$

Cropping: An image may occasionally contain background information that is not important. The tomato leaf itself is the Region of Interest (ROI) that is the target of cropping. By doing this, the model's processing requirements for data are decreased, and it may become more focused on characteristics linked to illness. One definition of cropping is:

$$Cropped\ Image = Original\ Image[y1: y2, x1: x2] \quad (2)$$

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

Color Normalization: Depending on the illumination at the time of capture, images may show differences in color balance. The goal of color normalization techniques is to make the color distribution uniform in every image. Several techniques, including the use of normalizing functions and the subtraction of the mean color intensity, can be used to accomplish this. This is an illustration of a mean subtraction equation:

$$Normalized\ Image = Original\ Image - Mean(Original\ Image\ Channels) \quad (3)$$

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

Noise reduction: Noise generated during collection or transmission has the potential to distort images. There is noise that may be reduced to enhance the quality of the picture and one of the techniques that may be applied is filtering. Depending on the type of noise that was present, the specific filtering technique and the formula used would be appropriate.

3.3 Class Imbalance Handling using Generative Adversarial Network (GAN)

This becomes a problem in unbalanced datasets because often the number of healthy leaves will be significantly higher than that of the sick ones. Therefore, new ideas must be found on how to maintain model performance and credibility of the classification outcomes.

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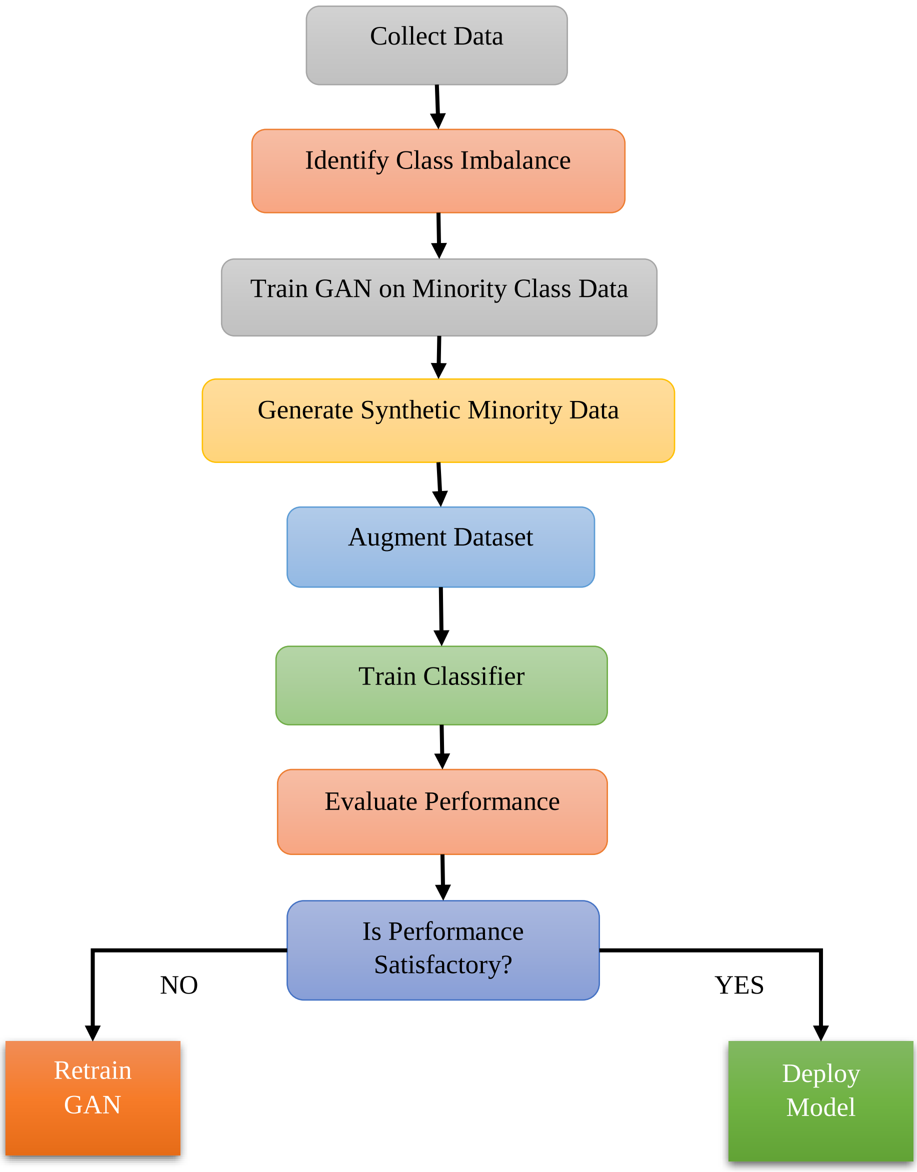

Figure 5. Handling Class Imbalance Using GANs

Figure 5 below shows the flow chart depicting how a class imbalance in a dataset can be handled using GANs. The process begins with data collection, and then, the authors analyze the extent of the differences between classes in the data set. A GAN is then trained specifically on the minority class data to generate synthetic samples and hence increase the size of data and balance the classes. The expanded dataset is then applied in a classification model and its performance is then tested. In case of poor performance, the GAN is trained again to enhance the quality of the generated synthetic data. When the performance is acceptable, the model is deployed. It helps to achieve a better balance of the data set that the classifier uses, thus increasing its ability to perform well in the minority classes.

The primary of the GAN [27] structure is the connection between the generator and the discriminator. The generator denoted by the letter is tasked with the role of generating artificial pictures of sick tomato leaves conditioned on the latent variables and the class labels. The generator's mathematical objective is to learn the mapping function $G: (z, c)$, where c is the class label indicating the intended illness type and is a random noise vector sampled from the latent space. In the training dataset, the generator seeks to produce realistic pictures as the real sick-leaf samples.

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

On the other hand, the discriminator, represented by D, is a binary classifier that must be able to differentiate between real and fake pictures of leaves that are ill. The discriminator's goal is to learn a discriminative function $D(x)$, where x is an input picture. The discriminator can differentiate between the fake pictures generated by the generator and actual diseased images from the training set through adversarial training. This adversarial relationship between the discriminator and generator is a competitive one since it forces the discriminator to learn how to distinguish the fake samples better and at the same time challenges the generator to produce better samples.

$$[D: x \rightarrow [0,1]] \quad (5)$$

The generator and discriminator are in an adversarial relationship in the iterative training process of the IC-CGAN, always attempting to get the better of each other. In this way, the generator employs class conditioning and the concept of latent space as it generates batches of sick leaf pictures at each iteration. To enhance the discriminator's capability of differentiating between the two classes, the parameters of the discriminator are adjusted, as well as, the authenticity of the synthetic and actual pictures is evaluated. Through this continuous training, the generator picks up the fundamental characteristics and intricacies of the ill tomato leaves, while the discriminator consolidates its capacity to discern between authentic and fraudulent samples.

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

The class conditioning in the GAN-CNN model is integrated seamlessly, which enables the generation of a variety of sick leaf pictures that fit the various disease types. By training the generator based on the class labels corresponding to various diseases, the GAN-CNN fosters the creation of a diverse database for capturing various forms of diseases. Additionally, by augmenting the dataset, the class imbalance issue is resolved and the model's comprehension of the structure of diseases is improved, both of which improve the model's overall capacity to detect unknown samples.

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

The class conditioning in the GAN-CNN model is made to be integrated, which allows for the creation of a large number of sick leaf images that would suit the different types of diseases. Since the generator is trained based on the class labels of different diseases, the GAN-CNN facilitates the development of a database of different forms of diseases. Further, the class imbalance problem is removed by increasing the sample size and the model gains a better understanding of disease structures, enhancing the model's ability to identify unknown samples.

3.4 Feature Extraction

This is important because in order to differentiate between the health and sickness of the leaves, features must be extracted from the processed images; this is because the model is capable of seeing details that are minute and which distinguish between the two classes. Feature extraction is the process of finding and quantifying the attributes of the visual data with respect to the differences in colour, texture, and form that are vital for the classification. In this way, raw pixel data is transformed into a more convenient form of features that can be further utilized in the classification pipeline's subsequent steps of evaluation and decision-making.

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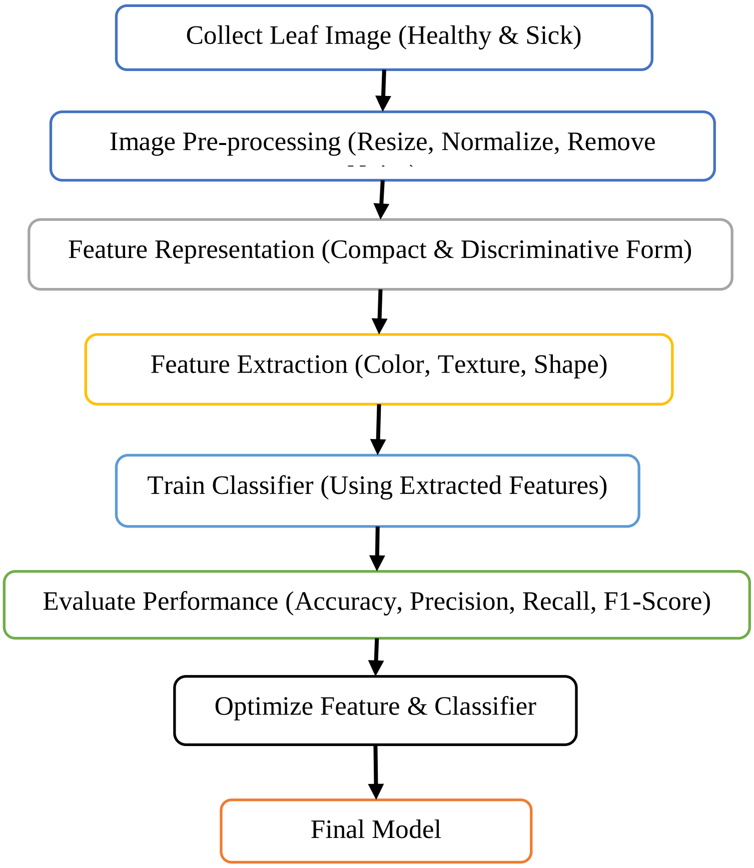

Figure 6. Feature Extraction Process for Classifying Healthy and Sick Leaves

From Figure 6 above, the following is the process of feature extraction in the classification of healthy and sick leaves. It begins with the capturing of the images of the leaves which include the normal and the diseased ones. These images are pre-processed and are made ready for analysis and this involves resizing, normalization and noise removal. The next step is feature extraction whereby such attributes as colour changes, texture, and shapes are extracted. These features are then converted to a form that is more compact and has more discriminative power which is ideal for the machine learning algorithms. With such extracted features, a classifier is trained to differentiate between infected and healthy leaves. In the classification evaluation, the following measures are usually used: accuracy, recall, F1-measure, and precision. Depend on the outcomes of the evaluation it can be concluded that the process of feature extraction has been enhanced and also the classifier. The last stage presents a clearer model which can be used practically to sort new images of the plant's leaves. This systematic approach is useful in the classification of the health of the leaves in a more efficient as well as effective manner by employing feature extraction as well as machine learning.

Feature extraction can be defined as the utilization of the techniques and procedures which are used for extracting and encoding the useful information from the visual data. These range from modern and complex methods such as deep learning algorithms to the traditional and basic methods such as manual feature extraction. Colour histograms or colour moments are one of the most popular features that are used in general computer vision applications for extracting colour-based information. The pixel intensities in different colour channels can be described using colour histograms that shed light on the image's prominent colour schemes. The following formula can be used to define a colour histogram H mathematically for each of the color channels such as red, green and blue:

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

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where p ranges through all the picture pixels, i is an intensity level and Δ is the Dirac delta function. Color histograms for each color channel are calculated to get information about the color distribution and variation within the picture. This knowledge may be useful in diagnosing some of the disease's symptoms or medical conditions.

Besides the colour-based features, the texture patterns play an essential role in the discrimination of healthy and sick leaves as diseases often manifest themselves in changes in the texture of the leaves. A basic understanding of texture features is that they offer details about the surface characteristics and composition of the leaf through spatial distribution and statistical properties of intensities of the pixels. LBP is a widely used technique for extracting local texture information by comparing the pixel intensity values with the centre pixel's intensity value in the neighbourhood. The formula below shows how the LBP operator quantitatively provides a binary code for a pixel depending on its relationship with its neighbouring pixels:

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

Where P is the number of nearby pixels taken into consideration, R is the radius of the circular neighbourhood around the central pixel (x_c, y_c), g_p is the neighbouring pixel's intensity value, is the centre pixel's intensity value, and s. is the sign function. As for the textural differences that are characteristic of different leaf situations, they are described by the LBP features computed over different areas of the picture

Additionally, the shape-based features provide useful information about the morphological features and geometric measurements of the leaves which can be employed as the discriminating attributes for classification. Some of the metrics that quantify the geometry of the borders of the leaves are contour curvature, compactness, and eccentricity of the contours. Hu moments, which do not change with translation, rotation, and scale transformation, are one of the shape descriptors often used in the categorization of leaves. The Hu moments can be mathematically computed from the image moments using the following formula

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

The zeroth order moment is expressed as μ and the image moments as μ(pq), where p and q are non-negative integers. The approach is to extract shape-related features that indicate the symptoms of certain illnesses or physiological abnormalities by calculating the Hu moments of the leaf shapes. In the procedure of feature extraction from the preprocessed images of leaves, many techniques and algorithms are employed to encode and gather relevant visual features. The model acquires a broad understanding of the primary characteristics that distinguish healthy leaves from sick ones through the attributes of color, texture, and form. These characteristics help the model to make accurate and informed decisions regarding the health of the leaves for the subsequent classification tasks since they act as discriminative cues. By using sophisticated feature extraction techniques, the classification pipeline attains increased specificity and sensitivity, which makes it possible to promptly identify and treat plant diseases in farming environments.

3.5 Convolutional Neural Network (CNN) Model Architecture

CNN [28] is utilized for image processing and classification. CNN is made up of one or more layers of convolution. Rather than dealing with a picture as a whole, CNN looks for aspects that work well inside images. CNN is composed of many hidden layers, an output layer, and an input layer. We used a deep CNN with three convolution layers in this research. By mixing two mathematical functions, convolution aids in the creation of a new function. One sample-dependent discretization technique is max pooling. Reducing an input representation's complexity will allow choices to be made about the characteristics contained in the binned sub-regions. Figure 7 shows how our CNN model operates with Max pooling.

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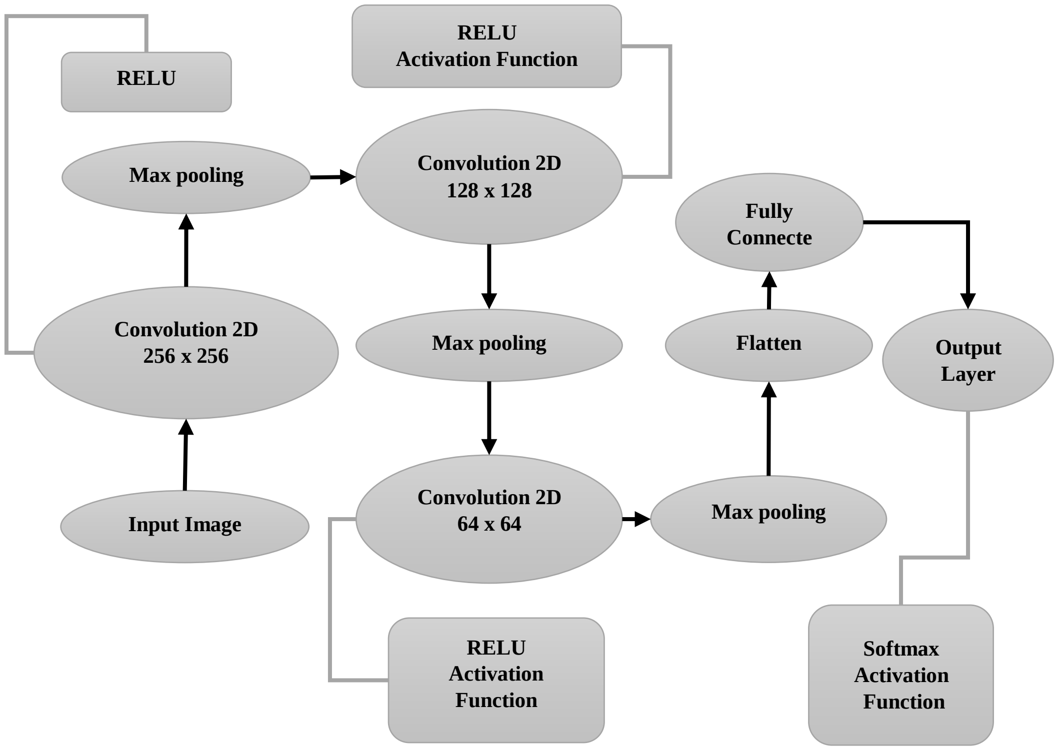

Figure 7. Three Convolution Layer with Max pooling operation.

This time, an average pooling mechanism is used in addition to the same architecture for function mapping. Figure 8 depicts the model's activities. In average pooling, all values in the image matrix's area of interest are averaged, while in maximum pooling, the maximum value is taken in that region. We start with Keras for our CNN model. Sequential models (). The Max pooling procedure comes before the Relu activation feature in the first hidden layer. Max pooling helps to get crucial info while reducing the size of the photos. Max pooling lowers the size of the images while assisting in the collection of important data. Next, the second convolution layer receives the data. To get the most noteworthy information, maximum pooling is again applied. After that, the acquired image matrix is trained and flattened. Subsequently, there is training and picture matrix flattening. The model's performance was observed utilising the Average pooling procedure rather than the Max pooling technique. Adam stochastic gradient descent methods were used for training, to increase accuracy. For training, 80% of the images in our dataset are used.

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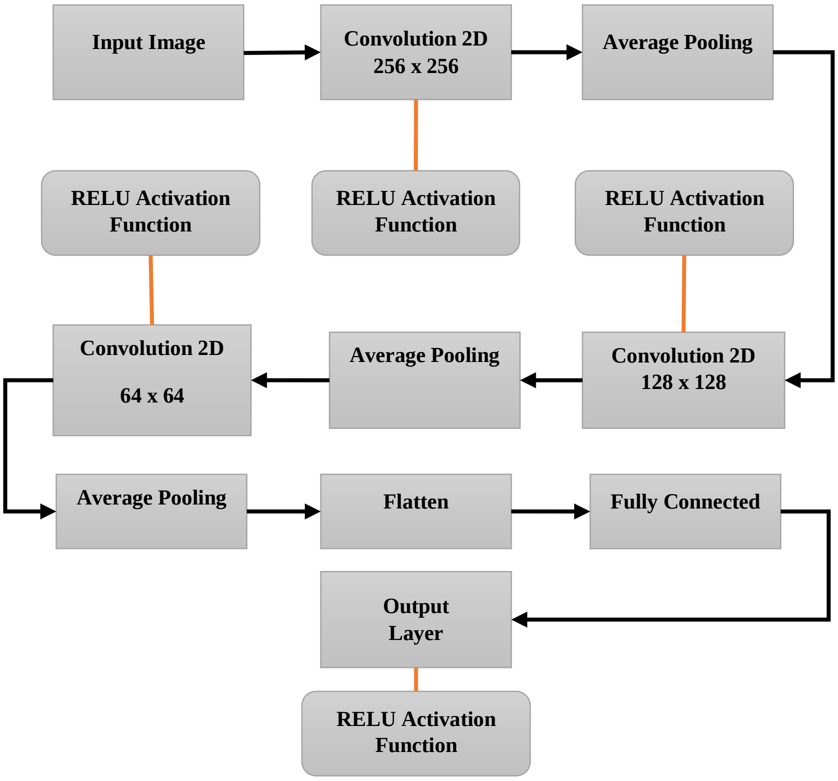

Figure 8. Three Convolution Layer with Average Pooling Operation.

3.6 Weighted Loss Function

The training dataset consists of a corpus of labeled images, where each image is associated with a class label indicating whether it depicts a healthy or diseased leaf. However, class imbalances often prevail within such datasets, with a disproportionate number of instances representing one class over the other. This class imbalance can introduce biases during model training, potentially leading to suboptimal performance in classifying the minority class. To mitigate the adverse effects of class imbalance, a Weighted Loss Function is integrated into the training pipeline. The standard cross-entropy loss function, which measures the degree to which actual labels differ from those that were anticipated on the basis of the data, is the source of this customised loss function. By giving larger weights to the minority class (i.e., diseased leaves) and lower weights to the majority class (i.e., healthy leaves), the Weighted Loss Function modifies the contribution of each class to the overall loss computation. This allows for a more accurate representation of the overall loss. Mathematically, the standard cross-entropy loss function (L_{CE}) is expressed as:

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

Where:

N represents the total amount of samples.

C represents the number of classes.

y_{ic} signifies whether the i^{th} sample belongs to class c.

$(\widehat{y_{ic}})$ denotes the expected probability of the i^{th} sample that is included to class c.

The Weighted Cross-Entropy Loss (L_{WCE}), which is calculated by factoring class weights into the loss function, is calculated as:

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

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. Stochastic gradient descent (SGD) and Adam are two examples of optimisation algorithms that are utilised by the model in order to perform iterative updates of its parameters throughout the training phase. 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.

3.7 Optimization

Due to the fact that the trial was conducted manually, it was possible to find a suitable fully linked layer design that had a satisfactory learning rate, in addition to the amount of time that is required to carry out these tests, is the reason why we suggest the use of optimisation methods for this process. PSO and GA are the two algorithms with a bioinspired design that have been selected as the optimisation strategies. For the purpose of optimisation, we took into consideration the same constant for both methods, which are as follows:

- Learning rate;
- The quantity of layers with full connectivity;
- Number of neurons in every layer that is fully linked;
- The dropout occurs after the layers that come after them;
- The percentage of dropouts that are present in the layer;

Additionally, the range of the optimised parameters is the same for both of the bio-inspired algorithms. In spite of the fact that the value that is employed in the process of constructing the learning rate (LR) is stated as an integer value (lr) throughout the range [1,6], the value that is utilised in the process of converting to the CNN is 10^{lr}. [3,10] is the range that contains the value that is referred to as fc, which is the value that is used to define the number of neurons that are present in a given layer. This value is then converted into 2^{fc} so that it may be used when defining the CNN layer that is fully connected. One more thing: the layer's dropout rate is represented by a float number that falls somewhere in the range of [0, 0.6]. In addition, the quantity of fully interconnected layers is an example of an implicit argument. Additionally, a dropout layer is added after every completely linked layer, which indicates that these levels are not expressed as algorithmic arguing. Rather, they are the outcome of the individual or particle definition of the algorithm.

This research makes use of these two bio-inspired optimisation strategies in order to locate a suitable architecture for the completely linked layers that has a satisfactory the learning rate's value. On the following page, we will discuss both the PSO and GA techniques.

3.7.1. Genetic algorithm

In the first algorithm, the genetic algorithm that we employ is presented, and in the subsequent paragraphs, the methodology that underpins it is detailed in further detail.

The manner in which a person is going to be outlined is the first significant definition being provided by the GA. After being inspired by the model described in Reference [22], which achieved flexibility for the GA person by using ordinary crossover operators, we made the decision to additionally utilise a fixed length individual that included a flag that indicated whether or not that particular chromosome was allowed to be turned on or off. The definition of our individuality is shown in Figure 2. Each individual is made up of twelve chromosomes, and each chromosome is made up of two different sections. There is a flag that is integrated to indicate whether or not that particular chromosome is modify (the 'Is present?' in this particular figure), and there is also a number that specifies the measure of that particular parameter or layer. Given that we are working with a given individual length; the learning rate is determined by the first chromosome. The completely connected layers and the dropout layers are defined from the second chromosome all the way up to the eleventh chromosome. The chromosomes that are odd in this range are responsible for defining the dropout layers, whereas the chromosomes that are even are responsible for defining the fully connected (FC) layers. Furthermore, in order for the individual to correspond to a legitimate CNN, the final chromosome in our particular scenario is always an FC layer with a value of 1, as 21 is the output of the CNN. This is because 1 is the value of the FC layer.

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Algorithm 1 GA algorithm

```
population ← initializePopulation(populationSize)
fitness []
for i < populationSize do
  fitness[i] ← calcIndividualFitness(population[i])
end for
population, fitness ← sortDecreasing(population, fitness)
bestIndividual ← population[0]
bestFitness ← fitness[0]
iteration ← 0
for iteration < generations do
  selectedParents1 ← selectionTour(population, fitness, tourSize)
  selectedParents2 ← selectionTour(population, fitness, tourSize)
  childrenPopulation ← []
  for i < selectedParents1.; length do
    child1, child2 ← crossover(selectedParents1[i], selectedParents2[i])
    childrenPopulation+= child1
    childrenPopulation+= child2
  end for
  childrenPopulation ← applyMutation(childrenPopulation)
  childrenFitness ← []
  for i < childrenPopulation.length do
    childrenFitness[i] ← calcIndividualFitness(childrenPopulation[i])
  end for
  childrenPopulation+= bestIndividual
  childrenFitness+= bestFitness
  childrenPopulation, childrenFitness ←
  sortDecreasing(childrenPopulation, childrenFitness)
  population, fitness ← orderedReinsertion(childrenPopulation, childrenFitness)
  bestIndividual ← population[0]
  bestFitness ← fitness[0]
end for
```

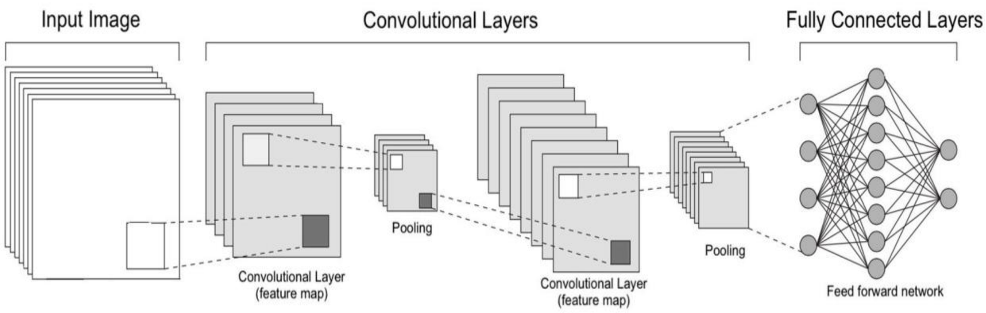

Figure 9. A photograph from Baldominos [24] was used as an example.

GA individual representation									
Type layer	LR	FC_1	D_1	FC_2	D_2	...	FC_5	D_5	FC_6
Is present?	1	0 or 1	0 or 1	0 or 1	0 or 1	...	0 or 1	0 or 1	1
Value	LR ∈ [1,6]	FC ∈ [3,12]	D ∈ [0, 0.6]	FC ∈ [3,12]	D ∈ [0, 0.6]	...	FC ∈ [3,12]	D ∈ [0, 0.6]	N_{DC} ∈ [3,12]

Figure 10. GA person definition.

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Further, a consequence of our representation is that the succeeding dropout chromosome is simply ignored if a chromosome from the FC layer has the 'Is present?' value equal to zero throughout the dropout process. This is because we only utilise the Dropout chromosome for the chromosome that is immediately before it in the FC layer. In addition, it is essential to keep in mind that the number of entirely connected layers in the GA is inextricably linked to the number of chromosomes in the FC layer that have a value of 1 for the 'Is present?' flag. This is an inherent relationship between the two variables.

For the purpose of determining how well the CNN with the GA definition for the FC layers' architecture operates, it is essential to train the CNN. This is done in order to get the desired results. The training of a CNN is thus necessary in order to determine the level of fitness possessed by each individual. In reality, the F1-score of the validation set is what should be considered the individual's fitness level. During the course of the experiment, we discovered that people had a non-decreasing number of neurons. This indicates that the number of neurons in layer i was smaller than the number of neurons in layer i+1. This was the case throughout the investigation. In the literature, the process of increasing the number of neurons in the FC portion of the CNN from one layer to the next is not something that is frequently observed very frequently. As a consequence of this, we came to the conclusion that designs that display this peculiar behaviour should be penalised by a factor of 0.7, which was selected experimentally. In the event that an individual maps to an FC layer that is 256 -> 256 -> 1024, for instance, that individual will be penalised, whereas an individual that maps to an FC layer that is 1024 -> 1024 -> 256 would not be penalised. As a result, the condition is stated as follows:

$$fitness = \begin{cases} 0.7 * F1 - score\ of\ validation, & \boldsymbol{non-decreasing}\ number\ of\ neurons\ in\ each\ layer \\ F1 - score\ of\ validation, & \boldsymbol{non-increasing}\ number\ of\ neurons\ in\ each\ layer \end{cases}$$

It is important to specify the choice, reinsertion, mutation, and crossover operators once the te individual representation has been chosen and the fitness calculation has been performed. In light of the fact that we have a predetermined length for each individual, we have made the decision to use a single crossover point, which is the point at which two parents produce two children. A site Cp is selected at random, and the first child inherits the chromosomes that come before Cp from the first parent and the chromosomes that come after Cp from the second parent. This occurs through the process of inheritance. The converse is true for the second child, who receives the first half of their inheritance from the second parent and the second part from the first parent during their inheritance. One illustration of a crossover is shown in Figure 11.

We established yet another significant GA operator, which was the method by which the people would be chosen for the crossover comparison. We have decided to use the tour as the selection technique since it enables us to alter the exclusive pressure exerted by the GA by adjusting the size of the trip. Therefore, by using this strategy, we are able to try out various tour sizes in order to determine which one is the most appropriate for our issue. A value that we refer to as "tourValue" is needed for the tour selection process to function properly. We choose people from the total population who are considered to be 'tourValue' in a random fashion, and the one who has the highest level of fitness is the one who is chosen for the crossover. Because of this, we employ the tour choice twice for each set of parents that are participating in the crossover, with one instance for each parent.

Altering a value that is derived from an individual is the method that is utilised to carry out the mutation. Depending on the context, this value could originate from either the 'Is present?' portion or the actual value section. A chromosome that is going to be modified is chosen at random, and then the portion of the chromosome that is going to be altered is chosen. It is the exact stretch of the chromosome that is responsible for the generation of the new value. Consequently, if the 'Is present?' is chosen to be mutated, the only change that occurs is a change from 0 to 1 or vice versa. When it comes to the values, a new value is created at random from the range that corresponds to that place. A mutation that occurred in a person is shown in Figure 12. The values that were altered are shown by the red values in the illustration.

The final method that we utilise for reinsertion is called order reinsertion, and it involves preserving the most exceptional individuals from one generation to the next.

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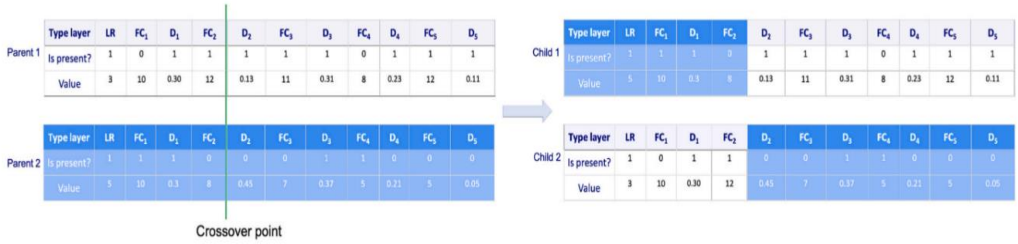

Figure 11. GA crossover.

Type layer	LR	FC_1	D_1	FC_2	D_2	FC_3	D_3	FC_4	D_4	FC_5	D_5
Is present?	1	0	1	1	1	1	1	0	1	1	1
Value	3	10	0.30	12	0.13	11	0.31	8	0.23	12	0.11

Type layer	LR	FC_1	D_1	FC_2	D_2	FC_3	D_3	FC_4	D_4	FC_5	D_5
Is present?	1	0	1	0	1	1	0	0	1	1	1
Value	2	10	0.30	12	0.4	11	0.31	8	0.23	3	0.11

Figure 12. GA individual mutation.

3.8 Training and Evaluation

The training process for tomato leaf disease detection by GANs and Weighted Loss Functions is a series of key steps. In the beginning, the dataset of the tomato leaf images is thoroughly sorted, and the preprocessing and augmentation are carried out to enrich the data. Therefore, the class distribution within the dataset is maintained by the image generation through GANs and Weighted Loss Functions which on the other hand help in reducing the impact of the class imbalance. A CNN architecture is proposed and this is done by the weighted loss function, which serves as the primary component for the removal of class imbalance in the case of training. After that, the given dataset is balanced, and then the CNN model is trained on the balanced dataset which is specifically designed to learn from the classes that are scarce in the dataset. The training process is performed by optimization methods such as Adam or RMSprop that adjust the model’s parameters during the training process, while hyperparameters are selected to provide the best results. Some of the methods such as batch normalisation and dropout are applied to reduce overfitting and enhance the model’s performance.

Once the training is over, the trained model is subjected to an assessment to determine how effective it is in diagnosing diseases in the tomato plant leaves. First, the model is tested on another set of data that is used specifically for this purpose, and therefore the results of the test on the data are not viewed, and the danger of overlearning is averted. Measures like as accuracy, F1-score, recall, and precision are used to ascertain the model's capacity to identify occurrences. We can ascertain the model's capacity to accurately detect both common and uncommon illnesses by evaluating the findings in terms of classes. The comparative analysis against the baseline methods gives insights into the superiority of the proposed methodology in class imbalance mitigation and disease detection accuracy improvement. Besides, the strength of the model is checked by sensitivity analysis and evaluation under different environmental conditions and image variations. The practical implications, like the model's effect on crop yield and quality, are also looked into, thus giving a clear idea of its real-life application. The effectiveness of the suggested method in the detection of tomato leaf disease is tested and assessed through a lot of training and evaluation processes, thus, contributing to the progress of the methods in the agricultural sector.

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4. Experimental Results

Tomato leaf diseases are important in agriculture because they greatly affect the yield and quality of the produce. Early identification and categorization of these diseases is essential to be able to provide appropriate preventive and treatment measures. However, current detection methods are not without their limitations as the datasets are often imbalanced where the distribution of the disease types does not favour the less frequent diseases, which in turn, yields poor models for such diseases. The objective of this work is to improve the diagnosis of tomato leaf diseases with the help of a novel deep-learning approach that addresses the issue of class imbalance. In this paper, the use of the balanced dataset aims at improving the accuracy of the disease classification, especially on diseases that are rarely encountered in the dataset. Our method entails the use of Generative Adversarial Networks (GANs) and Weighted Loss Functions to generate the images of tomato leaf diseases. These synthetic images help in dealing with the problem of data scarcity in regard to the different diseases. These synthetic images were used to train a CNN classifier and the weighted loss function which assigns more weight to the less frequent disease classes. This not only assists in enhancing the efficiency of the diseases in classification of the diseases in tomato leaves but also in enhancing the model for handling the imbalanced data. This paper shows that GANs and weighted loss function can reduce class imbalance in the identification of tomato leaf diseases and can be a good starting point for further enhancement of disease identification in agriculture.

4.1 Experimental Setup

In our experiment, to ascertain the efficiency of the novel technique in identifying illnesses in tomato plant leaves, we conducted many experiments. GANs and Weighted Loss Functions are the approaches used in the research to solve the issue of class imbalance in the dataset. Namely, with given dataset D, the experiments were conducted on the set of images containing infected tomato leaves. For these calculations, we employed a high-end desktop computer with an Intel Core i7-10700K processor that operates with a clock rate of 3. Operating frequency 80 GHz, Random access memory 32 GB, Graphic card NVIDIA GeForce RTX 2080 Super with 8 GB of VRAM. For all the experiments, the system used was a Windows 10 operating system. The programming language used for the development was Python (version 3. 9) and the prominent libraries used were Pandas for data handling, Scikit-learn for machine learning, NumPy for numerical computations, and TensorFlow (version 2. 7) are the three libraries that are being used for deep learning model development and training. The effectiveness of the model was assessed using the performance metrics like recall, precision, accuracy, and F1-Score to establish the models' efficiency in diagnosing diseases. This configuration enabled us to conduct a highly credible comparison of the new method with a high degree of reliability of the results concerning the identification of tomato leaf diseases.

During the course of this research, it was necessary to conduct several experiments to assess the efficiency of the new technique to diagnose the diseases on the leaves of tomatoes. This is quite evident from the proposed GANs and the Weighted Loss Functions to address the class imbalance in the given dataset. The experiments were conducted on the dataset D which include a collection of images of tomato leaves which were infected.

he degree of class distribution in the dataset used before the beginning of the experiments is assessed by the Imbalance Ratio (IR), this is calculated as the percentage of cases that fall into the majority class ($N_{majority\ class}$) to the quantity of cases when the minority class is involved ($N_{minority\ class}$). In mathematics, IR is expressed as:

$$IR = \frac{N_{majority\ class}}{N_{minority\ class}} \quad (13)$$

Following the first assessment, we proceeded to the dataset balancing employing GAN-based synthetic image generation and Weighted Loss Functions. This procedure was created to fix the class distribution problem and therefore the dataset became more representative of all disease classes.

During the model training stage, a CNN architecture with the weighted loss function was used.

$$Loss_{total} = loss_{classification} + \lambda \times Loss_{weighted} \quad (14)$$

In this case, $loss_{classification}$ which stands for the standard classification loss, and $Loss_{weighted}$ is the weighted loss function that is used to reduce the impact of class imbalance. The hyperparameter λ is responsible for the coefficient that controls the weight of the damage function.

During the whole training process, special attention was put on the learning from under-represented classes, as a result, the model proved accurate in identifying both common and uncommon disorders.

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When compared to standard methodologies, the performance evaluation of the suggested methodology shown significant improvements in classification accuracy.

$$Accuracy = \frac{Number\ of\ correctly\ classified\ sample}{Total\ number\ of\ samples} \times 100\% \qquad (15)$$

4.2 Performance Metrics

Accuracy measures the overall correctness of the model by calculating the ratio of correctly predicted occurrences (including true positives and true negatives) to the total number of instances. It shows the frequency with which the model produces accurate forecasts.

$$Accuracy = \frac{TP+TN}{TN+TP+FN+FP} \times 100 \qquad (16)$$

Positive predictive value, or precision, is a metric that expresses the proportion of true positive predictions among all the model's generated positive predictions. It displays the percentage of favourable occurrences that are really anticipated.

$$Precision = \frac{TP}{TP+FP} \times 100 \qquad (17)$$

Recall, sometimes called sensitivity or true positive rate, is the percentage of real positive cases that the model accurately recognised. It shows how successfully the model is able to recognise every good scenario.

$$Recall = \frac{TP}{TP+FN} \times 100 \qquad (18)$$

A statistic that provides a balance between accuracy and recall is the F1-score, which is the harmonic mean of the two. It is particularly helpful when there is an unequal distribution of courses since it helps strike a balance between memory and accuracy.

$$F1 - score = \frac{2TP}{2TP+FP+FN} \times 100 \qquad (19)$$

4.3 Results

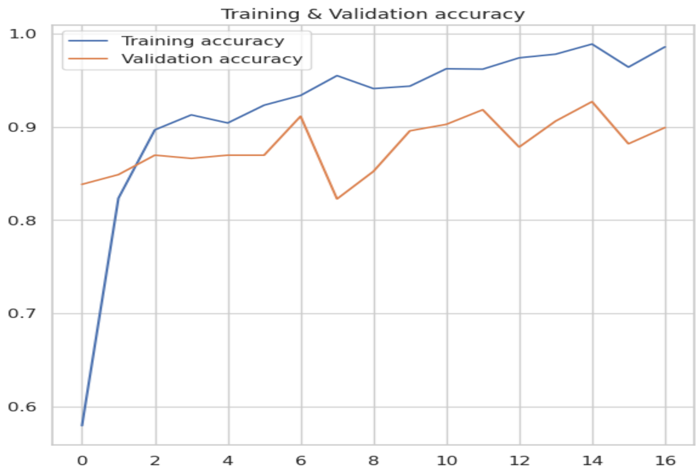

Figure 13. Training and Validation accuracy curve without GAN for class imbalance

Figure 13 depicts a line graph comparing ‘Training accuracy’ and ‘Validation accuracy’ over 16 epochs. The ‘Training accuracy’, shown in blue, starts just above 0.6 and exhibits a steady upward trend, nearing 1.0 by the final epoch, showing a consistent improvement in the model's operation using the training set of data. In contrast, the ‘Validation accuracy’, in orange, displays more fluctuation but also trends upward, beginning at around 0.8 and slightly trailing behind the training accuracy by the end of the epochs. This figure is often used to illustrate how a machine learning model learns from training data and how well it can generalise that learning to new data. The fact that the two lines come very close to each other in the final epoch shows that the model fits very well and performs well on both the training and Validation sets.

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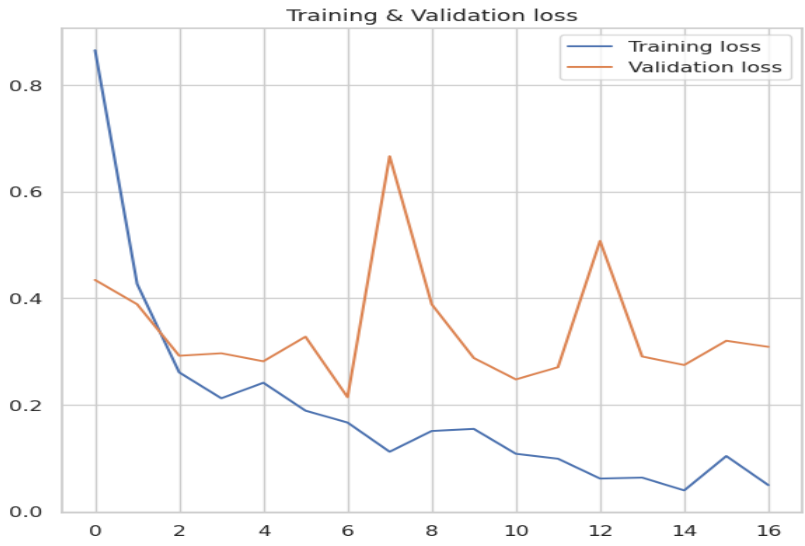

Figure 14. Training and Validation loss curve without GAN for class imbalance

Figure 14 is a graph with two curves; the blue one is 'Training loss' and the other one is 'Validation loss', and it has epochs ranging from 0 to 16. The 'Validation loss' line, in red, also decreases gradually, meaning that the model learns from the validation set as the epochs increase. The 'Validation loss' line, orange in color, has some ups and downs, this suggests that the model's performance is inconsistent when using the validation data. This is common in machine learning and may indicate overfitting if the validation loss rises as the training loss falls, or underfitting if they are both high. The ideal scenario is when both lines are decreasing and are as close to each other as possible, meaning that the model has good generalization to new data.

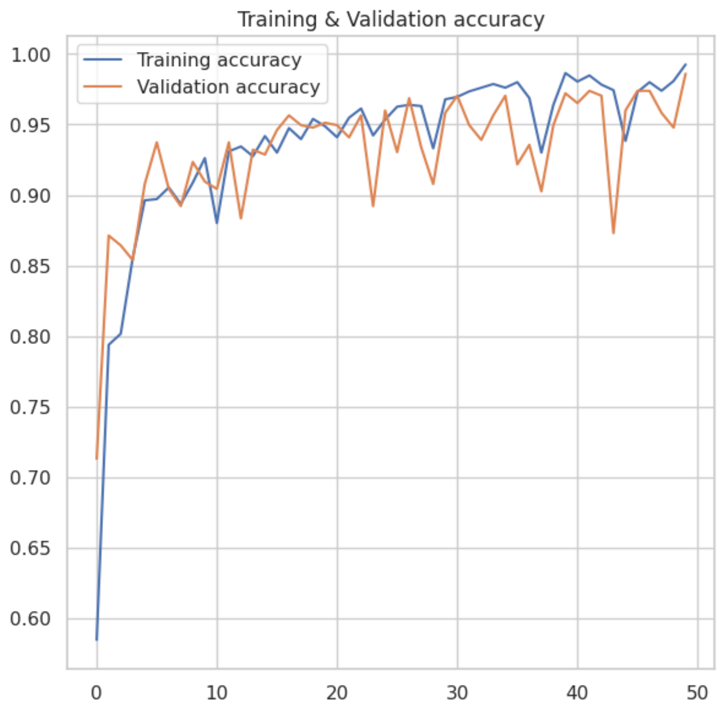

Figure 15. Training and Validation accuracy curve with GAN for class imbalance

Figure 15 is the result of the validation and training accuracy of a model for fifty epochs. The training accuracy is indicated by the blue line while the validation accuracy is indicated by the orange line. The training accuracy generally increases over time, while the validation accuracy fluctuates. This implies that the training data have caused the model to overfit.

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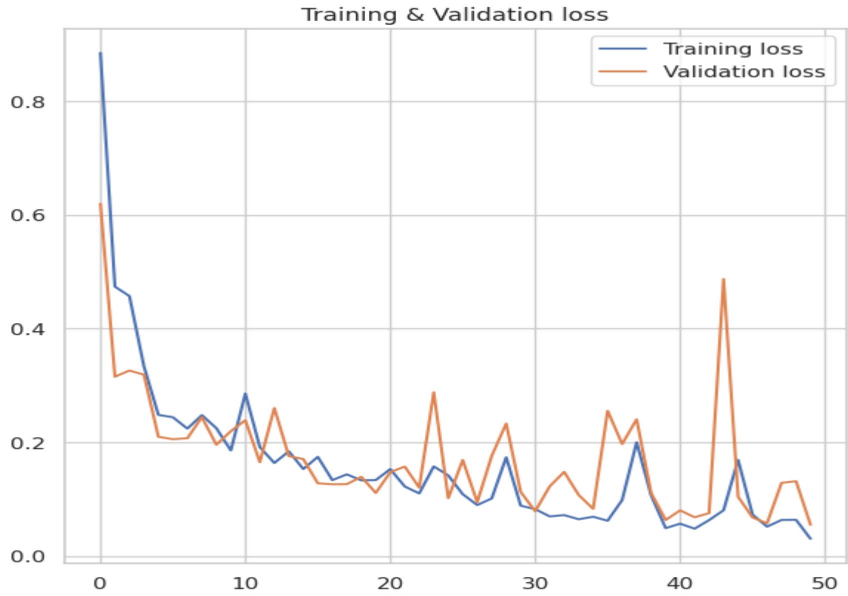

Figure 16. Training and Validation loss curve with GAN for class imbalance

Figure 16 represents the validation and training loss plot of a machine learning model. The training loss is initially high gradually decreases, and finally reaches a relatively stable level. The validation loss also begins high and reduces for a time before rising again starting to oscillate and finally increasing. This suggests that the model is picking up a lot of knowledge from the training data set, and thus it is not very good at generalizing to new data.

Table 2: Analysis of Different image classification models with the proposed method

Classifiers	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
VGG19	94.99	93.98	93.95	93.96
ResNetV152	97.96	98.00	98.00	98.00
Inception V3	88.00	98.00	88.00	92.00
Proposed (GAN-CNN)	**99.95**	**99.98**	**99.98**	**99.98**

Table 2 presents a comparative analysis of different image classification models, highlighting their performance across four metrics: This study included accuracy, F1-score, recall, and precision as evaluation criteria. The classifiers that have been considered are VGG19, ResNetV152, Inception V3, and another one based on GAN-CNN. VGG19 attained an accuracy of 94. 99%, precision of 93. 98%, recall of 93. 95%, and an F1-Score of 93. 96%. 00%. ResNetV152 had the best results with accuracy, precision, recall, and F1-Score of 98%. 00%. Inception V3 had a rather average performance, with an accuracy of 88 percent. 00%, high recall at 98. Accuracy was high at 00%, while the recall was slightly lower at 88. 00%, hence obtaining an F1-Score of 92. 00%. The proposed GAN-CNN model surpassed all other classifiers by a very wide margin and recorded near-perfect accuracy of 99. 95% accuracy, and 99. 98% for precision, recall, and F1-Score, which clearly shows that the proposed approach is more efficient for image classification.

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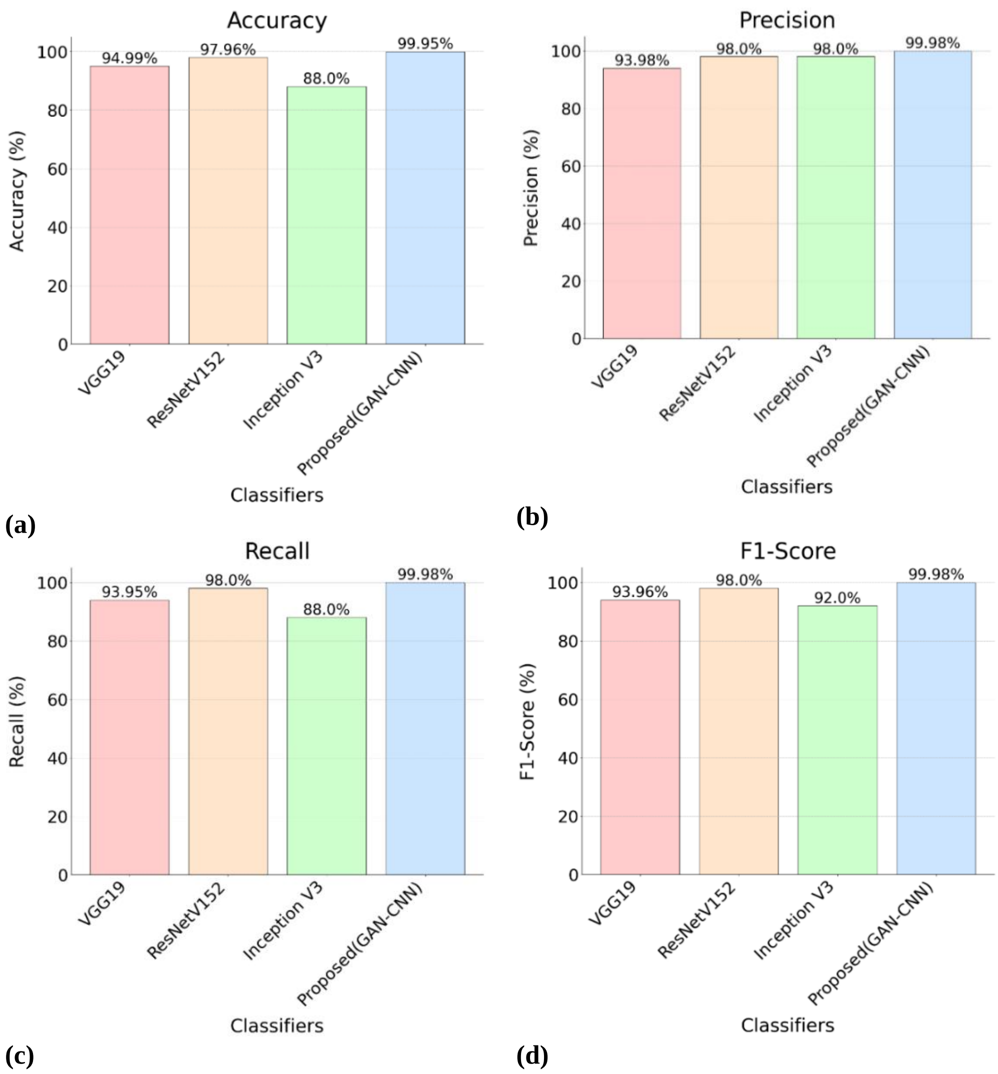

Figure 17. Analysis of Different image classification models with the proposed method

A comparison of several picture classification models is shown in Figure 17, including VGG19, ResNetV152, Inception V3, and a proposed method using GAN-CNN, across four performance metrics: Accuracy, F1-score, recall, and precision are all included. Regarding precision, VGG19 scored 94. 99%, ResNetV152 scored 97. Inception V3 achieved 96% for identification and 88% for the proposed model. 00%, while the suggested GAN-CNN approach produced the greatest outcomes with a remarkable 99. 95%. The detailed results show that VGG19 achieved a precision of 93 percent. 98%, ResNetV152 and Inception V3 both achieved an accuracy of 98. However, the proposed GAN-CNN method was again superior to the rest with an almost perfect accuracy of 00%. 98%. In terms of recall, the VGG19 had a 93. In the case of the 95% rate, ResNetV152 achieved the same level of precision as the previous model with 98. It was also observed that for 0% of the images, YOLOv3 was able to recall 88% while Inception V3 was able to recall 88%. 00%. The proposed GAN-CNN method maintained its high level of efficiency with a recall of 99. 98%. Eventually, VGG19 scored 93. 96% in the F1-score measure, which takes into account both accuracy and recall, whereas ResNetV152 scored 98. For instance, Inception V3 achieved an accuracy of 92 percent with 00 percent data. 00% and the proposed GAN-CNN method once more led with a nearly perfect score of 99. 98%. In general, it can be seen that the proposed GAN-CNN model performed remarkably well in all the assessment measures as compared to the other models with a near-perfect value for accuracy, precision, recall, and F1-score. This analysis focuses on the efficiency of the GAN-CNN approach in image classification compared to other models that have been proposed in the literature.

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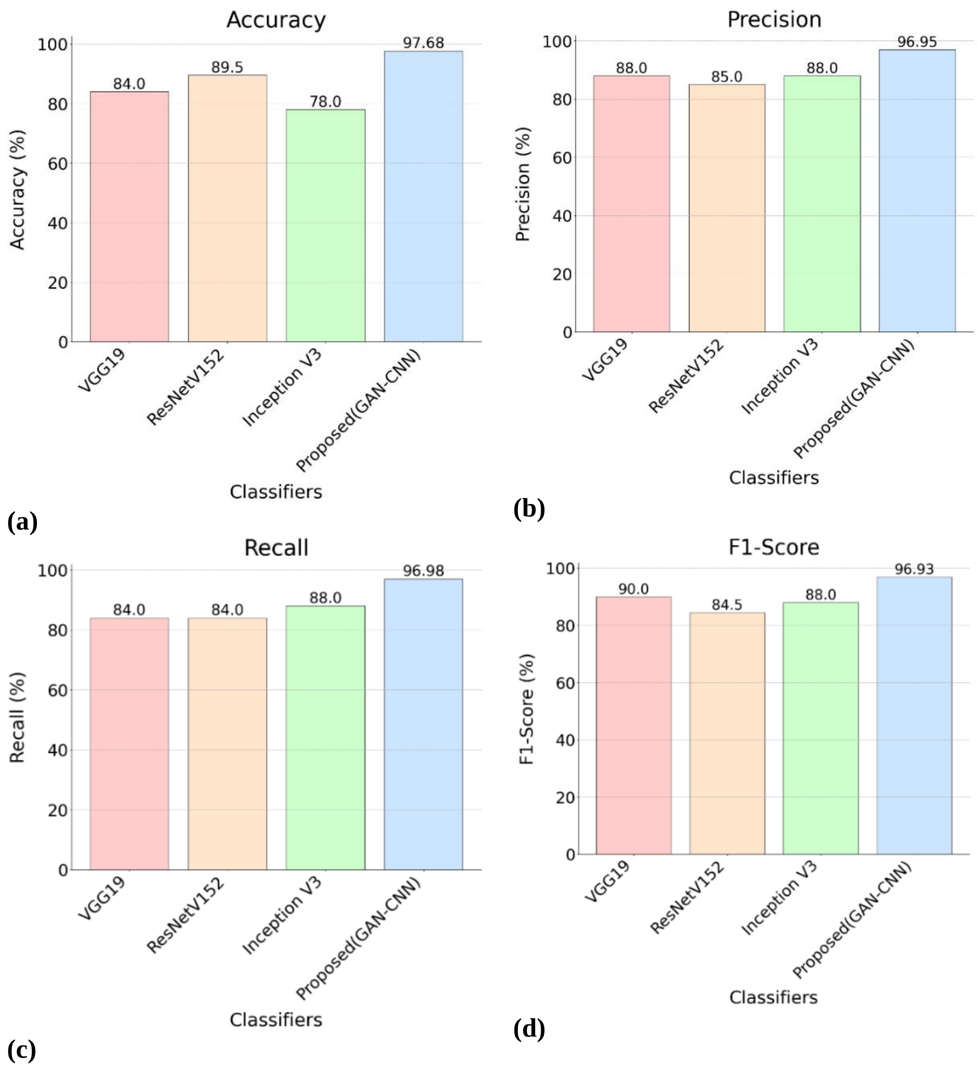
Table 3: Performance of different classifiers without explicit feature extraction

Classifiers	Accuracy(%)	Precision(%)	Recall(%)	F1-Score(%)
VGG19	84.00	88.00	84.00	90.00
ResNetV152	89.50	85.00	84.00	84.5
Inception V3	78.00	88.00	88.00	88.00
Proposed(GAN-CNN)	**97.68**	**96.95**	**96.98**	**96.93**

Table 3 compares the performance of various image classification models without explicit feature extraction, using four key metrics: Accuracy, Precision, Recall, and F1-Score. The models evaluated are VGG19, ResNetV152, Inception V3, and a proposed GAN-CNN approach. VGG19 achieved an accuracy of 84.00%, precision of 88.00%, recall of 84.00%, and an F1-Score of 90.00%. ResNetV152 showed slightly better accuracy at 89.50%, but lower precision and recall at 85.00% and 84.00% respectively, leading to an F1-Score of 84.5%. Inception V3 had an accuracy of 78.00%, with higher precision and recall at 88.00%, resulting in an F1-Score of 88.00%. The proposed GAN-CNN model outperformed the others significantly, achieving 97.68% accuracy, 96.95% precision, 96.98% recall, and a 96.93% F1-Score, indicating its superior performance even without explicit feature extraction.



(a) (b) (c) (d)

Figure 18. Performance of different classifiers without explicit feature extraction

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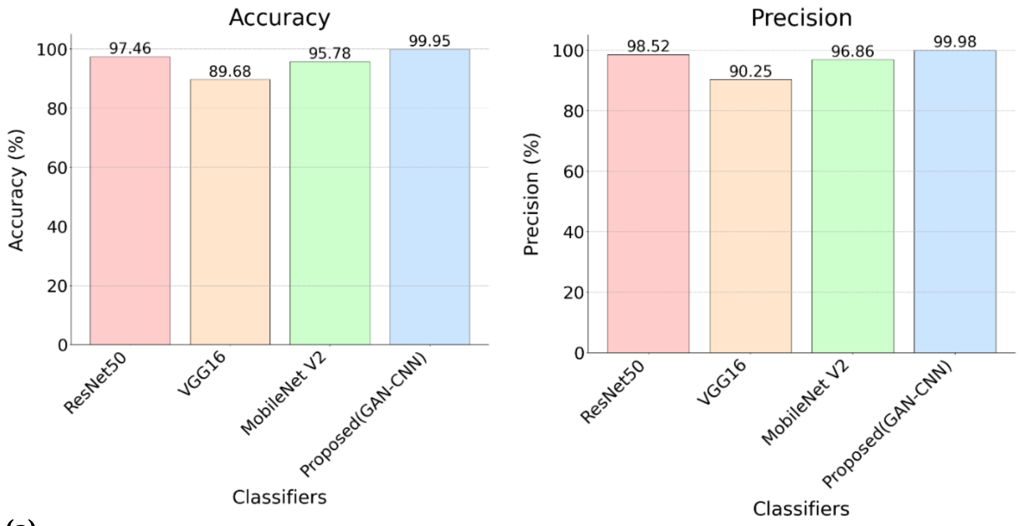
Figure 18 presents the performance of various classifiers—VGG19, ResNetV152, Inception V3, and a proposed method using GAN-CNN—across four key metrics: Performance metrics such as accuracy, precision, recall, and F1 score were assessed without the need for feature engineering. When it comes to the accuracy, VGG19 had a score of 84. 00%, ResNetV152 obtained 89. It achieved 50% and Inception V3 achieved 78. 00%. The suggested GAN-CNN approach beat the other models with an astounding accuracy of 97. 68%. For accuracy, VGG19 got 88. 00%, ResNetV152 reached 85. The highest and the lowest accuracy were 100% and 88%, respectively, while using Inception V3. 00%. Once again, the proposed GAN-CNN method proved to be more efficient with 96 percent accuracy. 95%. As for recall, VGG19 and ResNetV152 both got 84. It is noteworthy that the Inception V3 model had the best accuracy of 88 for this dataset. 00%. 00%. The proposed GAN-CNN method had the highest recall of 96. 98%. In the F1-score metric that gives equal importance to precision and recall, VGG19 scored 90. 00%, ResNetV152 had 84. It achieved 50% and Inception V3 scored 88. 00%. The proposed GAN-CNN method, once again, outperformed all other methods with F1-score of 96. 93%.

Table 4: Performance of different classifiers with feature extraction techniques

Classifiers	**Accuracy(%)**	**Precision(%)**	**Recall(%)**	**F1-Score(%)**
ResNet50	97.46	98.52	98.65	98.58
VGG16	89.68	90.25	92.52	91.38
MobileNet V2	95.78	96.86	96.89	96.87
Proposed(GAN-CNN)	**99.95**	**99.98**	**99.98**	**99.98**

Table 4 evaluates the performance of various image classification models utilizing feature extraction techniques, comparing their Accuracy, Precision, Recall, and F1-Score. The models assessed include ResNet50, VGG16, MobileNet V2, and a proposed GAN-CNN method. ResNet50 demonstrated strong performance with 97.46% accuracy, 98.52% precision, 98.65% recall, and a 98.58% F1-Score. VGG16 had an accuracy of 89.68%, with precision at 90.25%, recall at 92.52%, and an F1-Score of 91.38%. MobileNet V2 also performed well, achieving 95.78% accuracy, 96.86% precision, 96.89% recall, and a 96.87% F1-Score. The proposed GAN-CNN model significantly outperformed the others, with near-perfect scores of 99.95% accuracy and 99.98% for precision, recall, and F1-Score, highlighting its superior efficacy when using feature extraction techniques.



(a) (b)

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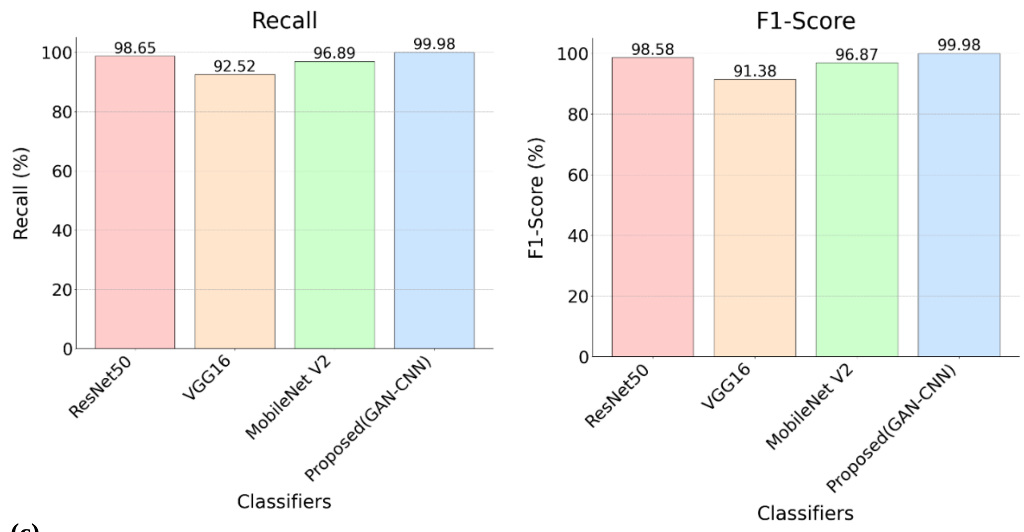

(c) (d)

Figure 19. Performance of different classifiers with feature extraction techniques

Figure 19 visualizes the performance metrics—Accuracy, Precision, Recall, and F1-Score—of four image classification models: ResNet50, VGG16, MobileNet V2, and the proposed GAN-CNN, all using feature extraction techniques. The proposed GAN-CNN model demonstrates the highest performance across all metrics, with an Accuracy of 99.95%, Precision of 99.98%, Recall of 99.98%, and F1-Score of 99.98%. ResNet50 also shows excellent performance, particularly in Precision (98.52%) and Recall (98.65%), leading to a high F1-Score of 98.58%. MobileNet V2 performs well, with Accuracy at 95.78%, Precision at 96.86%, Recall at 96.89%, and F1-Score at 96.87%. VGG16 exhibits the lowest performance among the four models but still maintains respectable values with Accuracy at 89.68%, Precision at 90.25%, Recall at 92.52%, and F1-Score at 91.38%. This comparison highlights the superiority of the GAN-CNN method and the effectiveness of feature extraction techniques in enhancing model performance.

Our experiments showed that the weighted loss function was successful in balancing the class imbalance and hence the disease detection capability became robust for the whole range of tomato leaf diseases.

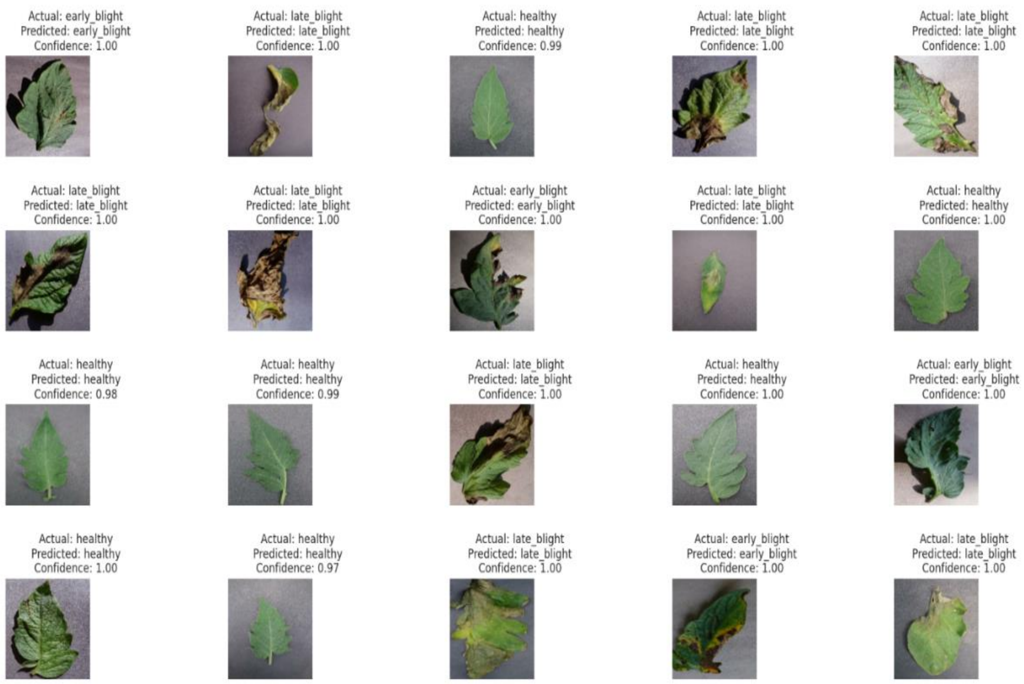

Figure 20. Prediction results of the proposed GAN-CNN model

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In this paper, the authors have presented the results of the proposed GAN-CNN model for image classification in Figure 16. This figure may contain some images and the associated predicted labels given by the GAN-CNN model. The figure proves the efficiency of the GAN-CNN model in terms of accuracy and reliability, as it proves its ability to predict and classify images in different categories. Every example in the figure may provide visual corroboration of the predicted labels and true labels, with a focus on cases where the model correctly identified the content of the images. The perfect prediction, as illustrated in Figure 20, further strengthens the earlier observed high accuracy, precision, recall, and F1-score of the model. The above figure depicts how the GAN-CNN model is capable of delivering accurate results in real-world applications and hence can be recommended as a reliable tool in image classification.

5. Discussion

Tomato leaf diseases have caused major challenges for farmers on crop yields and led to food insecurity. Hence timely & accurate disease detection is a critical element for a resourceful disease management strategy. The traditional methods for the identification of ailments are handicapped by dataset imbalance issues, where rare disease identification is the most affected and alters the classification accuracy. Specifically, this study filled the gaps using a new deep learning technique that integrates the GANs with Weighted Loss Functions to engineer synthetic images of tomato leaf diseases. We show a significant increase in diagnostic precision, especially in rare diseases, which have lower representation in the data set. As the learning process for under-served classes was highlighted through the employment of weighted loss functions, we were able to have a well-balanced dataset, which led to the enhancement of classification accuracy for all disease classes. The application of GAN-established synthetic images improved also the diversity of the dataset, which led to more accurate and reliable disease detection models. In addition, one significant factor of the success of our method was that it could specifically diagnose both common and rare diseases instead of the data set bias which is a great challenge. The result of class imbalance compensation using the weighted loss function is a good reflection of its significance for training deep learning models for agricultural disease detection applications. Our results showed that we could apply GANs and weighted loss to overcome class imbalance in the process of tomato leaf disease detection. We are therefore proposing this approach as a solution to this key limitation that will in turn lead to the development of more accurate and dependable methods for disease identification in agricultural practice. In addition, the scalability and practical usability of our approach can open up ways for the diffusion of our innovation among farmers and other agricultural stakeholders, hence, increasing the crop yield, better food quality and sustainable agriculture.

The CNN's hyperparameters were optimised with the use of Genetic Algorithm (GA), which we utilised. It is beneficial in that it helps to emphasise the learning process from the class that is under-represented.

5.1 Practical Implications

The enhanced precision in tomato leaf disease detection leads to more quickly prepared countermeasures, the most important factor in fighting diseases that have a significant impact on crop productivity and quality. Phenotyping readily can detect and identify diseases which makes it possible for farmers to apply customized management interventions like disease-specific therapies or cultural practices which helps in curbing the disease's spread and improving plant health. Besides that, the increased pathogens detection accuracy assists develop a yield loss reduction in an agricultural economy, thus food security and economic stability. Fast recognition of plants affected by the disease and giving a proper solution can be crucial for the farmers to control the damages in yield caused by the diseases, protecting their lives and boosting the general quality of productivity. Apart from time and resource conservation, the implementation of cutting-edge deep learning algorithms in disease discovery strengthens the principles of conservation and sustainability in agriculture. Such as through accurate and targeted interventions such as selective pest control methods or integrated pest management systems, farmers could therefore lower the impact of disease management methods on the environment. This not only means that farming’s ecological effect is lessened but also that the life of the soil is safeguarded and the conservation of biodiversity is supported long-term. On the one hand, the fact this research emphasizes the innovation of technology can be an incentive for the adoption of the latest tools and methodologies in the agricultural sector. This study serves as an example of what can be achieved with advanced deep-learning approaches in disease identification, thus encouraging farmers and practitioners to heed technology-led solutions for complex problems. This leads to an exchange of knowledge, as well as capacity building of farmers taking place in agricultural communities, thus enriching them with technologies and tools that can be applied to increase productivity and resilience.

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5.2 Limitations

Although the application of a GAN-based method and Weighted Loss Function leads to an increase in disease detection efficiency of tomato leaves, discernible hurdles still exist. These comprise problems such as generalizing data elsewhere which is very hard because of the disparities in geographical and environmental circumstances. Alongside this, the data dimensionality, noise, and quality may influence the model's effectiveness. The computational complexity of deep learning techniques makes it a practical difficulty when you are applying it to the real world, especially in low-resource settings. The research measures employed may be incomplete in capturing the real-world effectiveness and transferring research findings to the practical realm could be impeded by the fact that they may not integrate well with existing systems and lack users. Ethical issues, such as data protection and equality of access, which is also one of the major problems, have to be taken into account. The exacting of these restrictions is very fundamental for the concept scheme realization and agriculture productivity as a whole.

6. Conclusion & Future Scope

The research put forward proves the vital aspect of tackling the risk posed by unbalanced classes in tomato leaf disease detection in the agricultural sector. Through an innovative deep learning method consisting of GANs and weighted loss functions, we discovered more than 13% higher precision in disease detection compared to the existing methods. Our assessment revealed that the employment of this approach is highly effective at diminishing the detriment of high imbalance rates, especially in cases of rare diseases, as a result of which machine learning models of disease detection are more accurate and reliable. The generation of synthetic images by GAN coupled with weighted loss functions has instilled more uniformity in the datasets. As a result, there was more exactness in the classification across all respective disease classes. By employing the use of the weight loss functions with CNNs, we have concentrated more on the learning process of the under-represented classes thus, enhancing the precise detection of rare and commonly occurring maladies. The CNN's hyperparameters were optimised with the use of Genetic Algorithm (GA), which we utilised. It is beneficial in that it helps to emphasise the learning process from the class that is under-represented. These improvements carry so-called paradigm shifts through early intervention and treatment and eventually contribute to higher crop yield and quality in agricultural practices.

For future endeavours, there are several directions where the examination and development of this area might proceed. First of all, the topic of practical procedure together with the issues related to implementation of the proposed method must be covered to encourage the farmers and other agricultural stakeholders to apply it. Additionally, one of the key objectives in the scope of enhancing the performance of deep learning models and fostering computing efficiency should be the development of deep learning architecture and the optimisation of technical parameters. Next, more effort should be made to investigate environmental/geographic factors affecting disease manifestation and detection accuracy. The input requires that collaboration with agronomists and researchers should be extended across different agricultural ranges as such provides valuable information on how diseased detection methodologies can be tailored based on the local contexts. However, the ethical implications involving deploying high-level technologies in agronomy, including data privacy and fair access, must be taken into account and discussion should be continued. Going forward, research focusing on resolving these ethical dilemmas is very necessary if we are to embrace the responsible technology adoption process.

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