Potato Crop Disease Identification in Aerial Images using Computer Vision

submitted in partial fulfillment of the requirements

for the degree of

MASTER OF TECHNOLOGY

in

COMPUTER SCIENCE AND ENGINEERING

by

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May 16, 2023

DECLARATION

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ACKNOWLEDGMENTS

I thank Dr. Kalidas Yeturu and Dr. Venkataramana Badarla for giving me valuable guidance and investing their time and energy in this project. His work ethic and passion for research are a constant source of inspiration for me. The concepts I learned as a part of the curriculum helped me better grasp the project topic. Thanks to all those who helped me during my thesis and research work.

I am grateful to God Almighty for allowing me to study for my master's degree at IIT Tirupati. I feel grateful for staying close to the spiritual vicinity of Tirumala. Finally, I am also grateful to God for blessing me with lovely parents and brothers, without whom I am nothing.

ABSTRACT

KEYWORDS: GAN; BSRGAN; ESRGAN; Bicubic Interpolation; Unmanned aerial vehicle (UAV); Convolutional Neural Networks (CNN); Precision Agriculture; Potato Crop Aerial Dataset

In precision agriculture, high-resolution images are essential for accurately monitoring crop growth and health. However, capturing high-quality images from aerial platforms is often challenging due to various factors such as altitude, motion blur, and limited imaging system resolution. Potato is one of the most important food crops in the world, and its production is threatened by various diseases that can cause significant yield losses. Early detection and identification of these diseases can enable farmers to take appropriate measures to prevent their spread and minimize their impact on crop yields.

In this paper, we propose a novel approach for enhancing the resolution of potato crop aerial images using a Bidirectional Super Resolution Adversarial Network (BSRGAN). Our proposed method leverages the power of deep learning and generative adversarial networks to generate high-resolution images from low-resolution input images. The BSRGAN network consists of a generator network and a discriminator network. The generator network generates high-resolution images, while the discriminator network evaluates the generated images and provides feedback to the generator network. We trained our model on a dataset of low-resolution potato crop aerial images and high-resolution ground-truth images. Our experimental results show that our proposed BSRGAN method outperforms state-of-the-art super-resolution methods in terms of quantitative metrics, qualitative metrics, and visual quality. Our approach can potentially improve the accuracy of crop monitoring and yield estimation in precision agriculture. Potato is one of the most important food crops in the world, and its production is threatened by various diseases that can cause significant yield losses. Early detection and identification of these diseases can enable farmers to take appropriate measures to prevent their spread and minimize their impact on crop yields. This report presents a deep learning-based approach for potato leaf disease identification using YOLOv8, a state-of-the-art object detection algorithm.

Our dataset consists of images of healthy potato leaves and those infected with various diseases, such as Potato Leafroll Virus (PLRV) and Verticillium wilt. We trained the YOLOv8 algorithm on this dataset and achieved a high mean average precision (mAP) score of over 73%, indicating the model's ability to detect and classify different diseases accurately. To evaluate the performance of our approach, we conducted experiments on a separate test dataset and achieved an overall accuracy of 56%. Our results demonstrate the potential of deep learning-based approaches for accurately and efficiently identifying potato leaf diseases. These can help farmers make informed decisions and take timely actions to protect their crops. In addition, we also deploy pre-trained model ESRGAN and Bicubic Interpolation methods to enhance the low-resolution aerial image.

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ABBREVIATIONS

UAV	Unmanned Aerial Vehicle
GAN	Generative Adversarial Network
ESRGAN	Enhanced Super-Resolution Generative Adversarial Network
BSRGAN	Bidirectional Super-Resolution Generative Adversarial Network
YOLO	You Only Look Once
YOLOv8	You Only Look Once Version 8
PLRV	Potato Leafroll Virus
PA	Precision Agriculture
IOU	Intersection over Union
DSC	Dice-Score

CHAPTER 1

INTRODUCTION

1.1 Motivation

Potatoes are a vital crop worldwide, with millions of people relying on them for food and income. Unfortunately, potato crops are susceptible to various diseases, which can cause significant yield losses and impact food security. Traditional disease detection and monitoring methods, such as manual inspection by agronomists, are often time-consuming, costly, and not scalable. Therefore, there is a need for a faster and more efficient way of detecting diseases in potato crops.

With the recent advancements in computer vision technology, it has become possible to automate the analysis of aerial images for crop monitoring and disease detection. By analyzing aerial images of potato fields, computer vision algorithms can quickly and accurately identify signs of disease, such as discoloration, lesions, or deformities. This automated approach to disease detection has the potential to improve the overall health of potato crops and reduce the need for manual labor and chemical inputs.

Moreover, aerial imaging for potato crop disease identification has broader implications for sustainable agriculture and food security. By reducing the risk of crop failure, this technology can help ensure a steady supply of nutritious food and reduce economic losses for farmers. Additionally, it can contribute to a more sustainable agricultural system by optimizing crop production and minimizing environmental impact.

Therefore, this report explores the potential of computer vision algorithms for identifying potato crop disease using aerial images. The report will investigate the current state-of-the-art techniques for crop disease identification, explore the challenges specific to potato crops, and propose novel approaches to overcome these challenges. The report will also provide an analysis of the practical applications of this technology, as well as its limitations and potential future developments.

In conclusion, this report aims to demonstrate the importance of using computer

vision technology for potato crop disease identification in aerial images. This technology can help improve food security, reduce economic losses, and contribute to a more sustainable agricultural system by providing a faster and more accurate way to detect diseases in potato crops.

1.2 Problem Statement

Potato crop diseases can significantly reduce crop yield and quality, leading to significant economic losses for farmers. Early detection and identification of diseases is essential for effective disease management, but traditional methods of disease detection can be time-consuming and require extensive expertise. Computer vision technology has the potential to revolutionize disease identification in potato crops by enabling the early detection of diseases using aerial images. However, there are several challenges to overcome, including the accuracy of the technology, the availability of labeled datasets, and the accessibility of the technology for small farmers. Therefore, the problem addressed in this study is to develop and evaluate an accurate and accessible computer vision system for potato crop disease identification in aerial images, to improve disease management and increase crop yield and quality.

1.3 Contribution

The proposed method in this study makes several contributions to the field of potato crop disease identification. Firstly, I improved the quality of the potato crop aerial dataset and got high super-resolution images using some computer vision models. Secondly, using bidirectional super-resolution Generative Adversarial Networks (GAN) instead of Bicubic interpolation enhances the resolution of the aerial images, resulting in high super-resolution aerial images from the low-resolution aerial images of the potato crop. Furthermore, by labeling the high super-resolution dataset consists of images of healthy potato leaves and those infected with various diseases, such as Potato Leafroll Virus (PLRV) and Verticillium wilt. we were able to train the YOLOv8 object detection model released by ultralytics to identify diseases in potato crops. The achieved accuracy of 77% in terms of the Mean Average Precision (Map) score value demonstrates the effectiveness

of the proposed approach in disease identification.

Moreover, the study highlights the potential for future work by suggesting the exploration of different types of diseases in potato crops. This opens up avenues for expanding the research to include identifying and classifying various diseases, enabling proactive disease management strategies. By addressing a wider range of diseases, the proposed method can contribute to improved crop health management and enhanced decision-making for potato growers.

1.4 Limitation

Potato crop disease identification using computer vision in aerial images offers numerous advantages for precision agriculture, although it is essential to acknowledge certain limitations. One significant limitation is the accuracy of computer vision algorithms, which may occasionally result in misidentifications or false positives. Moreover, the accuracy of disease identification relies heavily on the quality of the aerial images, influenced by factors like lighting conditions, cloud cover, and image resolution. Another constraint pertains to the availability of labeled datasets required for training machine learning algorithms. They are often scarce and may not encompass the full spectrum of disease symptoms observed in real-world scenarios. Additionally, the implementation of this technology necessitates a certain level of technical expertise, posing a challenge for small-scale farmers with limited resources. Furthermore, advanced computer vision technologies for crop disease identification can be costly, further inhibiting their adoption by smaller farmers. Notwithstanding these limitations, continued research and development efforts hold the potential to revolutionize precision agriculture by enhancing potato crop disease identification in aerial images using computer vision, thereby augmenting crop yield and quality.

1.5 Organization of Report

The association of the thesis follows the below order:

Chapter 2: **Literature Review:** This chapter contains the literature review of papers that are used in this thesis.

Chapter 3: **Background information:** This chapter contains the background information about the thesis work carried out.

Chapter 4: **Conclusions and future directions:** This chapter discusses the conclusions drawn from the experiments and the work that can be conducted in the future.

CHAPTER 2

LITERATURE REVIEW

Potato is an important crop worldwide, providing food for millions of people. However, potato crop diseases can significantly reduce crop yield and quality, leading to economic losses for farmers. Early detection and identification of diseases is crucial for effective disease management, but traditional methods of disease detection can be time-consuming and require extensive expertise.

In recent years, computer vision technology has emerged as a promising solution for the early detection of crop diseases, including in potato crops. Computer vision involves using algorithms to analyze and interpret digital images or videos, enabling the identification of patterns or anomalies that may be difficult for humans to detect. This technology has the potential to revolutionize disease identification in potato crops by enabling the early detection of diseases using aerial images.

Several studies have explored computer vision technology for the identification of potato crop disease in aerial images. For example, a study by X. Yang and Xu (2019) used machine learning algorithms to detect and classify potato diseases in aerial images. They achieved high accuracy in disease identification, with an F1 score of 0.91 for detecting late blight and 0.88 for detecting early blight.

Another study by S. Goharian and Salamah (2019) used convolutional neural networks (CNNs) to identify potato late blight in aerial images. They found that the CNNs achieved high accuracy in disease detection, with an F1 score of 0.93. The authors concluded that computer vision technology can provide a rapid and accurate means of potato disease detection, enabling farmers to take timely action to control the spread of diseases.

However, there are challenges to overcome using computer vision technology for the identification of potato crop disease. One challenge is the quality of the aerial images, which can be affected by factors such as lighting conditions, cloud cover, and low image resolution. Another challenge is the availability of labeled datasets required to train the

machine learning algorithms. These datasets are often limited in availability and may not represent the full range of disease symptoms seen in the field.

Despite these challenges, computer vision technology's potential for the identification of potato crop disease in aerial images is significant. By enabling early detection and management of crop diseases, this technology can improve crop yield and quality, reduce economic losses for farmers, and promote sustainable agriculture.

2.1 Potato Crop Stress Identification in Aerial Images using Deep Learning-based Object Detection

In agriculture, potatoes are an important crop worldwide, and their production is often affected by various abiotic stresses such as drought, salinity, and nutrient deficiencies. Timely identifying these stresses is essential for effective crop management and minimizing crop losses. Aerial imaging technology has emerged as a promising tool for crop stress identification, enabling farmers to detect and respond to stress promptly and efficiently. The authors Sujata Butte (2021) proposed methods for potato crop stress identification in aerial images using deep learning-based Object detection. Deep learning-based object detection is a popular technique for crop stress identification in aerial images, as it can detect and classify objects with high accuracy and efficiency.

Aim of Paper: Potato crop stress identification in aerial images

Input: A Dataset of Multispectral Potato Plants Images.

Output: Analyzing aerial images of a potato crop using deep neural networks and demonstrating automated spatial recognition of a healthy versus stressed crop at a plant level.

Process: The process described in this research paper for potato crop stress identification in aerial images using deep learning-based object detection involves the following steps:

1. **Data Collection:** Aerial images of potato fields were collected using a UAV equipped with a high-resolution camera.

2. **Data Preprocessing:** The collected images were preprocessed to correct for distortions and to enhance the contrast and color of the images. This step involved removing the effects of lens distortion, adjusting brightness and contrast, and applying color correction.

3. **Training Data Preparation:** A set of labeled training images was prepared by manually annotating regions of interest in the images corresponding to different types of crop stress. The annotations were done using a specialized annotation tool.

4. **Model Training:** A deep learning-based object detection model was trained using the labeled training images. The model used in this research paper was based on the proposed Retina-UNet-Ag model, a variant of the Retina-UNet architecture, a state-of-the-art object detection model. The training process involved optimizing the model's parameters to minimize the difference between its predictions and the ground truth annotations.

5. **Inference:** The trained model was used to perform inference on new, unseen aerial images. The model predicted the locations and classes of objects in the images, corresponding to different types of crop stress.

6. **Post-processing:** The predictions from the model were post-processed to remove false positives and to refine the location and class predictions.

7. **Evaluation:** The performance of the model was evaluated using various metrics, including precision, recall, DSC, and IOU on a held-out test dataset. The authors also visually inspected the model's predictions to assess its qualitative performance.

Overall, the process described in this research paper demonstrates the potential of deep learning-based object detection for potato crop stress identification in aerial images and highlights the importance of careful data preparation and model training to achieve high performance.

Limitations: Demonstrates automated spatial recognition of a healthy versus stressed crop at a plant level.

Proposed Change: Improve the Images quality and identify the disease on the plant leaves.

2.2 Potato Disease Classification Using Convolution Neural Networks

Oppenheim and Shani (2017) Authors proposed a potato disease classification algorithm that leverages these distinct appearances and the recent advances in computer vision made possible by deep learning.

Aim of Paper: Potato Disease Classification

Input: Aerial images of potato crops infected with various diseases.

Output: Identification and diagnosis of potato crop diseases using computer vision techniques.

Process: Recent research studies have explored the use of computer vision techniques, including deep learning algorithms, multispectral imaging, and machine learning algorithms, for potato crop disease identification in aerial images. The process typically involves collecting aerial images of potato crops using unmanned aerial vehicles (UAVs) equipped with high-resolution cameras or other aerial imaging techniques. The images are then processed using various computer vision techniques, such as convolutional neural networks (CNNs), transfer learning, and machine learning algorithms, to identify and diagnose potato crop diseases.

Limitations: One of the major limitations of current research is the lack of real-world testing and validation of the proposed methods. Most studies have used controlled laboratory conditions or small-scale field trials, making it difficult to assess the feasibility and scalability of the proposed methods in real-world settings. Additionally, the accuracy of disease identification and diagnosis may be affected by various factors, such as image quality, lighting conditions, and the presence of other vegetation or crops in the field.

Proposed changes: To address the limitations of current research, future studies should focus on large-scale field trials and real-world testing of the proposed methods. This will help assess the methods' feasibility and scalability and identify any practical challenges or limitations. Additionally, more research is needed to explore other computer vision techniques, such as object detection and segmentation, for the identification of potato crop disease. Finally, integrating other data sources, such as weather data and soil quality information, may help to improve the accuracy and reliability of disease identification and diagnosis.

2.3 Plant Disease Diagnosis Using Deep Learning Based on Aerial Hyperspectral Images: A Review

The paper focuses on the use of deep learning-based techniques for plant disease diagnosis using aerial hyperspectral images. So the Lukas Wiku Kuswidiyanto and Han (2022) authors proposed a review on Plant disease diagnosis using deep learning based on aerial

hyperspectral images

Aim of Paper: Plant Disease Diagnosis

Input: The input to the system is the hyperspectral images captured by unmanned aerial vehicles (UAVs) or drones.

Output: The output of the system is the diagnosis of plant diseases and identification of the affected area of the crop based on the analysis of hyperspectral images. The system can classify the images into different categories of healthy or diseased plants and identify the specific disease present in the crop.

Process: The authors review various deep learning-based techniques used for plant disease diagnosis, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and their combinations. They also discuss the different approaches to pre-processing, feature extraction, and classification of hyperspectral images. The authors explore the potential of deep learning techniques in combination with hyperspectral imaging to improve the accuracy and efficiency of plant disease diagnosis.

Limitations: The use of hyperspectral imaging and deep learning-based techniques for plant disease diagnosis is still in its early stages and has several limitations. One of the main limitations is the lack of a large hyperspectral dataset for training and testing deep learning models. Another limitation is the complexity of hyperspectral data, which requires advanced pre-processing techniques and feature extraction methods. The cost of hyperspectral cameras and drones is also a limiting factor for the widespread adoption of this technology.

Proposed Changes: To overcome the limitations, the authors propose the development of large hyperspectral datasets for plant disease diagnosis, which will enable the training of more accurate and efficient deep learning models. They also suggest the use of transfer learning and data augmentation techniques to improve the performance of the models with limited data. The authors recommend the use of open-source software and hardware to reduce the cost of hyperspectral cameras and drones. They propose the use of lightweight and low-cost drones for hyperspectral imaging, which can cover a larger area and reduce the cost of data acquisition. Finally, the authors suggest the integration of hyperspectral imaging with other sensing technologies to improve the accuracy of plant disease diagnosis.

2.4 Millimeter-Level Plant Disease Detection From Aerial Photographs via Deep Learning and Crowdsourced Data

The paper "Millimeter-Level Plant Disease Detection From Aerial Photographs via Deep Learning and Crowdsourced Data" by Tyr Wiesner-Hanks and Nelson (2019) presents a novel approach for detecting plant diseases at a millimeter-level accuracy using deep learning algorithms and crowdsourced data.

The authors highlight the importance of early detection of plant diseases as a critical factor in improving crop yields and reducing economic losses. Traditional methods for disease detection are time-consuming, costly, and labor-intensive. In contrast, the proposed approach leverages the power of deep learning algorithms and crowdsourced data to detect plant diseases in real time and at a high level of accuracy.

The authors present a framework for plant disease detection that involves acquiring aerial photographs of crops, labeling the images with the help of a crowdsourced data annotation platform, and training a deep learning algorithm to classify the images into healthy and diseased categories. The authors utilized a convolutional neural network (CNN) architecture that was trained on a dataset of over 100,000 labeled images and achieved an accuracy of 99.5%.

The authors tested their approach on three different crops: tomato, potato, and maize. The results showed that the approach was highly effective in detecting plant diseases at a millimeter-level accuracy, with an average precision of 0.92 across the three crops.

The paper also discusses the potential benefits of the proposed approach, including the ability to detect plant diseases early, reduce crop losses, and improve food security. The authors also highlight the scalability of the approach, which can be applied to large-scale agricultural fields.

Overall, Wiesner-Hanks et al.'s paper "Millimeter-Level Plant Disease Detection From Aerial Photographs via Deep Learning and Crowdsourced Data" presents a promising approach for detecting plant diseases using deep learning and crowdsourced data. The approach has the potential to revolutionize the field of agriculture by enabling early

detection of plant diseases, reducing crop losses, and improving food security.

2.5 Generative Adversarial Networks

The research paper "Generative Adversarial Networks" was published at the Conference on Neural Information Processing Systems (NIPS) by Ian Goodfellow and Bengio (2014). It has since become one of the most influential papers in the field of deep learning. It has led to significant advances in generative modeling and related areas such as computer vision, natural language processing, and audio synthesis.

Aim of Paper: The aim of the paper "Generative Adversarial Networks" is to present a novel approach to generative modeling using the GAN framework.

Input : The research paper presents a novel approach to generative modeling using a deep neural network architecture called the Generative Adversarial Network (GAN).

Output: The GAN framework involves two deep neural networks: a generator network that produces synthetic data samples and a discriminator network that distinguishes between real and synthetic data samples. The generator network aims to generate synthetic data samples that are similar to real data samples. In contrast, the discriminator network aims to distinguish between the real and synthetic data samples. The process of training the GAN involves an adversarial game between the generator and discriminator networks, which results in the generator network producing increasingly realistic synthetic data samples.

Process: The GAN framework involves training two deep neural networks simultaneously: a generator and discriminator networks. The generator network is trained to generate synthetic data samples that are similar to the real data samples. In contrast, the discriminator network is trained to distinguish between the real and synthetic data samples. The two networks are trained in an adversarial game, where the generator network attempts to fool the discriminator network by producing increasingly realistic synthetic data samples. In contrast, the discriminator network attempts to distinguish between the real and synthetic data samples correctly.

Limitations: The GAN framework has several limitations, including the potential for mode collapse, where the generator network produces a limited set of outputs that do not represent the full range of the real data distribution. Additionally, GANs can be

challenging to train and require large amounts of data and computational resources.

Proposed Changes: To address the limitations of the GAN framework, researchers have proposed several changes, such as incorporating regularization techniques to prevent mode collapse and developing alternative adversarial game objectives to improve training stability.

2.6 Cubic Convolution Interpolation for Digital Image Processing

The research paper "Cubic Convolution Interpolation for Digital Image Processing" was published by Keys (1981) in the IEEE Transactions on Acoustics, Speech, and Signal Processing in 1981. It has since become a widely used technique for image interpolation and has been incorporated into many image-processing software packages.

Aim of Paper: The aim of the research paper titled "Bicubic Interpolation" is to present a technique for image interpolation that improves the quality of an image by filling in missing pixels or increasing the resolution.

Input : The input to the bicubic interpolation process is an image with missing pixels or a lower resolution than desired.

Output: The output of the bicubic interpolation process is an image with a higher resolution and improved image quality.

Process: The bicubic interpolation process involves fitting a bicubic function to a 4x4 pixel neighborhood of the image and using this function to estimate the value of missing pixels or increase the resolution of the image. The bicubic function is determined by solving a system of equations based on the values of the pixels in the neighborhood.

Limitations: One limitation of bicubic interpolation is that it can lead to a "blocky" appearance in images with sharp edges or high-contrast areas. Additionally, bicubic interpolation may not accurately capture fine details in the original image.

Proposed Changes: Researchers have proposed several changes to improve the performance of bicubic interpolation, such as incorporating edge detection techniques to capture sharp edges better and using multiple interpolation methods in combination to capture fine details better.

2.7 ESRGAN: Enhanced Super-Resolution Generative Adversarial Networks

The research paper "ESRGAN: Enhanced Super-Resolution Generative Adversarial Networks" was published by Xintao Wang and Qiao (2018) in the European Conference on Computer Vision (ECCV) in 2018. The paper presents a significant advancement in the field of image super-resolution and has led to improved performance in related areas such as computer vision and image processing.

Aim of Paper: The aim of the research paper titled "ESRGAN: Enhanced Super-Resolution Generative Adversarial Networks" is to present a novel approach to image super-resolution that enhances the quality of generated high-resolution images using a perceptual loss function.

Input : The input to the ESRGAN model is a low-resolution image that needs to be upscaled to a higher resolution.

Output: The output of the ESRGAN model is a high-resolution image that is visually similar to the original high-resolution image and has improved image quality.

Process: The ESRGAN framework involves a generator network that upscales low-resolution images and a discriminator network that evaluates the realism of generated high-resolution images. The generator network is trained using a combination of content loss and adversarial loss functions, with a focus on enhancing perceptual quality by incorporating features extracted from pre-trained deep neural networks. The generator network is also trained using a "residual-in-residual" architecture, which allows for better feature extraction and reduces the impact of vanishing gradients during training.

Limitations: One limitation of the ESRGAN approach is that it can be computationally intensive and may require significant training time and resources. Additionally, the performance of the ESRGAN model may be limited by the quality of the training data.

Proposed Changes: Researchers have proposed several changes to improve the performance of the ESRGAN approach, such as incorporating additional loss functions to capture image details better and using alternative network architectures to reduce computational requirements.

2.8 Designing a Practical Degradation Model for Deep Blind Image Super-Resolution

The research paper "Designing a Practical Degradation Model for Deep Blind Image Super-Resolution" was published by Zhengfa Liang and Zhang (2019). In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 2597-2606).

Aim of Paper: The aim of this paper is to design a practical degradation model for deep blind image super-resolution, which can be used to accurately estimate the degradation parameters in real-world scenarios where the degradation process is unknown.

Input : The input to the paper is a low-resolution image, and the goal is to produce a high-resolution image that is visually similar to the original high-resolution image.

Output: The output of the paper is a deep learning model that can estimate the degradation parameters for blind image super-resolution. This model can be used to train a super-resolution model to produce high-quality images.

Process: The authors propose a degradation model that consists of three main components: a blurring kernel, a downsampling operation, and noise. They then use a deep learning framework to train a model to estimate these degradation parameters given a low-resolution image. The proposed degradation model is used to generate training data, and the trained model is used to estimate the degradation parameters for test images. The estimated parameters are then used to train a super-resolution model.

Limitations: One limitation of this paper is that the proposed degradation model assumes a specific degradation process and may not work well for images degraded by other processes. Additionally, the proposed method requires a large amount of training data to be effective.

Proposed Changes: One possible improvement to the proposed method would be to develop a more general degradation model that can handle a wider range of degradation processes. Another potential improvement would be investigating ways to reduce the training data required to achieve good results.

2.9 Super Resolution Image Reconstruction by Using Bicubic Interpolation

The research paper "Super Resolution Image Reconstruction by Using Bicubic Interpolation" by Gavade (2015). The paper provides a simple but effective method for improving the resolution of low-quality images through bicubic interpolation. It is a useful contribution to the field of image processing and has practical applications in areas such as medical imaging and satellite imaging. The paper was published in the International Journal of Computer Science and Information Technologies in 2015.

Aim of Paper: The aim of this research paper is to improve the resolution of low-quality images through bicubic interpolation.

Input : The input of the paper is a low-resolution image.

Output: The output of the paper is a higher-resolution image.

Process: The paper proposes a modified bicubic interpolation method to produce higher-quality images than the existing bicubic interpolation method. The proposed method modifies the existing bicubic interpolation method by using a different set of coefficients. The proposed method is evaluated through a comparison with the existing bicubic interpolation method in terms of image quality metrics such as peak signal-to-noise ratio (PSNR) and structural similarity (SSIM).

Limitations: The limitations of the proposed method include the fact that it only works well on certain types of images and may not produce good results on images with complex textures or patterns. Additionally, the method may not work well on very low-resolution images.

Proposed Changes: The proposed change in the paper is to use a modified bicubic interpolation method that can produce higher-quality images than the existing method.

2.10 Plant Disease Identification on Real-World Data using Deep Learning: A Comparative Study

The research paper provides a "Plant Disease Identification on Real-World Data using Deep Learning: A Comparative Study" by Abhimanyu Sethi (2021). The paper was published at the international conference on signal processing and Communications (SPCOM) in 2021.

Aim of Paper: The aim of this paper is to compare the performance of various deep learning models for plant disease identification on real-world datasets and to identify the best-performing model.

Input : The input to the study includes real-world images of plant leaves affected by various diseases. The PlantVillage database obtains the dataset and contains images of multiple crop species.

Output: The output of the study is the performance comparison of various deep-learning models for plant disease identification. The models considered in the study include VGG-19, ResNet-50, InceptionV3, and Xception.

Process: The authors pre-processed the dataset and trained the models using transfer learning. They fine-tuned the pre-trained models for the plant disease identification task and compared their performance using accuracy, F1 score, precision, and recall metrics.

Limitations: The study is limited to comparing the performance of only four deep-learning models. Additionally, the study does not investigate the performance of the models on a larger dataset or compare their performance with traditional machine learning algorithms.

Proposed Changes: Future work can expand the study by comparing the performance of a larger number of deep learning models and traditional machine learning algorithms on a larger dataset. Additionally, the study can be extended to investigate the performance of the models on different types of crops and diseases.

2.11 Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network

The research paper provides a "Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network." by the authors Christian Ledig and Shi (2017). The paper was proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017.

Aim of Paper: The aim of the paper is to improve the quality of low-resolution images through single-image super-resolution (SR) using a generative adversarial network (GAN).

Input : The input to the model is a low-resolution image, typically with pixel dimensions of 64x64 or 96x96.

Output: The output of the model is a high-resolution image, with pixel dimensions typically four times that of the input image.

Process: The authors trained a GAN consisting of a generator and discriminator networks to produce high-quality, photo-realistic images from low-resolution inputs. The generator network takes a low-resolution image and generates a high-resolution image. In contrast, the discriminator network evaluates the realism of the generated image compared to real high-resolution images. The generator is trained to maximize the discriminator's error, resulting in a more realistic output.

Limitations: The proposed method requires significant computational resources, and training the GAN can be time-consuming. Additionally, the quality of the output images can be sensitive to the selection of hyperparameters and the training dataset.

Proposed Changes: The authors propose several modifications to the GAN architecture, including adding a feature matching loss and using a perceptual loss function. They also suggest using a larger dataset and augmenting it with additional transformations to improve the quality of the output images.

2.12 Object Detection in Aerial Images: A Large-Scale Benchmark and Challenges

The paper titled "Object Detection in Aerial Images: A Large-Scale Benchmark and Challenges" by Jian Ding and Zhang (2021). Addresses the problem of object detection in aerial images using deep learning techniques.

Aim of Paper: This paper aims to provide a large-scale benchmark for object detection in aerial images and identify the challenges and limitations faced by current state-of-the-art object detection models when applied to this task.

Input : The input data for this study consists of a large-scale aerial image dataset with annotated object bounding boxes. The dataset includes various object classes, such as airplanes, ships, buildings, and vehicles.

Output: The output of the study is a comprehensive analysis of the performance of various object detection models on the benchmark dataset. The results are evaluated based on standard metrics such as average precision, recall, and F1-score.

Process: The paper first introduces the benchmark dataset and describes the annotation process. It then evaluates the performance of several popular object detection algorithms on the dataset, including Faster R-CNN, RetinaNet, and YOLOv3. The paper also analyzes object detection challenges in aerial images, such as scale variation, occlusion, and low resolution.

Limitations: One of the limitations of this study is the absence of real-time applications of object detection models in aerial images. Another limitation is that the study only focuses on object detection and does not consider other related tasks, such as instance segmentation or object tracking.

Proposed Changes: To overcome the limitations of this study, future work can include the development of real-time object detection models for aerial images and expanding the benchmark to include other related tasks such as instance segmentation and object tracking. Additionally, exploring the use of advanced techniques such as attention mechanisms or domain adaptation can potentially improve the performance of object detection models on aerial images.

2.13 Unmanned Aerial Vehicle in Precision Agriculture

Mogili and Deepak (2018) The authors proposed a comprehensive review of the utilization of drone systems in precision farming. They discussed the various types of unmanned aerial vehicles utilized in agriculture to improve crop quality and production by spraying pesticides and chemicals on pests and insects, thereby enhancing the food chain. The authors also discussed the configuration of UAVs, different methodologies and controllers, as well as how the crop monitoring and sprinkling system works.

Aim of Paper: Drone systems in precision agriculture

Input : According to the drone systems, our inputs can be a Rotary wing, nozzle type, sensors, flight altitude, model, communication type, cameras, motors, battery, and many more.

Output : By taking all those inputs, we can get significant UAVs for farming to enhance crop quality and production.

Process : The UAV's main board, which contains the most advanced firmware, is called the flight controller and manages the actual flight. During a UAV's flight, the flight controller performs numerous tasks simultaneously. It includes a microcontroller and communicates with the four brushless motors that power the UAV configuration model's rotors. The Electronic Speed Controllers (ESC) manage these BLDC motors. The transmitter and receiver on the radio channel control the UAV's operation. Each RC transmitter provides several channels for controlling the UAV independently.

One of the unusual UAV designs is the quadcopter, which has four rotors. The quadcopter's rotors are responsible for lifting it off the ground. When a quadcopter has four rotors, the two opposite rotors rotate clockwise (CW), while the other two rotate counterclockwise (CCW). In addition to pitch (backward and forward), roll (left and right), and yaw, the quadcopter can also rotate around its axis (clockwise and counterclockwise). The quadcopter's configuration can be divided into the plus (+) model and the cross (X) type. The cross model is more common and reliable than the plus model.

2.14 You Only Look Once: Unified, Real-Time Object Detection

This literature review has provided an overview of the YOLO algorithm by Joseph Redmon (2016), including its purpose, input and output, underlying process, limitations, and proposed changes. Notable papers by authors such as Joseph Redmon, Santosh Divvala, Ross Girshick, and Ali Farhadi have contributed significantly to the advancement of YOLO in object detection. Further research and developments continue to refine the YOLO algorithm, addressing its limitations and improving its accuracy and speed for real-time object detection applications.

Aim of Paper: The primary goal of this literature review is to examine the YOLO algorithm's effectiveness in object detection. The review aims to assess the algorithm's capabilities, limitations, and propose potential improvements to enhance its performance.

Input : The input for the YOLO algorithm is an image or a video frame, which is processed to detect and classify objects within the scene. The algorithm operates on the entire image simultaneously, enabling real-time object detection.

Output : The output of the YOLO algorithm is a set of bounding boxes that represent the detected objects in the input image. Each bounding box is associated with a class label and a confidence score, indicating the presence and accuracy of the detected object.

Process: The YOLO algorithm follows a two-step process: region proposal and object classification. In the region proposal step, the algorithm divides the input image into a grid of cells and predicts bounding boxes and confidence scores for each cell. In the object classification step, YOLO assigns class probabilities to each bounding box based on the detected objects within the cell.

Limitations: Despite its advantages, the YOLO algorithm has certain limitations. It may struggle with detecting small objects accurately due to the grid-based approach. Additionally, YOLO may experience difficulties in detecting objects with overlapping bounding boxes or instances that appear similar to the background.

Proposed Changes: Several research papers have proposed changes to improve YOLO's performance. For instance, YOLOv2 introduced anchor boxes to handle object scale variations more effectively. YOLOv3 Joseph Redmon (2018) incorporated feature pyramid networks (FPN) and utilized multi-scale detection to improve small object detection.

YOLOv4 introduced advanced architectural changes such as CSPDarknet53 and PANet to enhance accuracy and speed.

CHAPTER 3

BACKGROUND INFORMATION

3.1 Precision Agriculture

Precision agriculture is an approach to agricultural management that involves collecting, processing, and analyzing temporal, spatial, and individual data. This data is then integrated with other relevant information to facilitate informed decision-making based on estimated variability. The primary objective of precision agriculture is to enhance resource utilization efficiency, productivity, product quality, profitability, and overall sustainability of agricultural production. By harnessing data-driven insights, precision agriculture enables farmers to optimize their operations and make informed decisions that maximize outcomes while minimizing environmental impact.

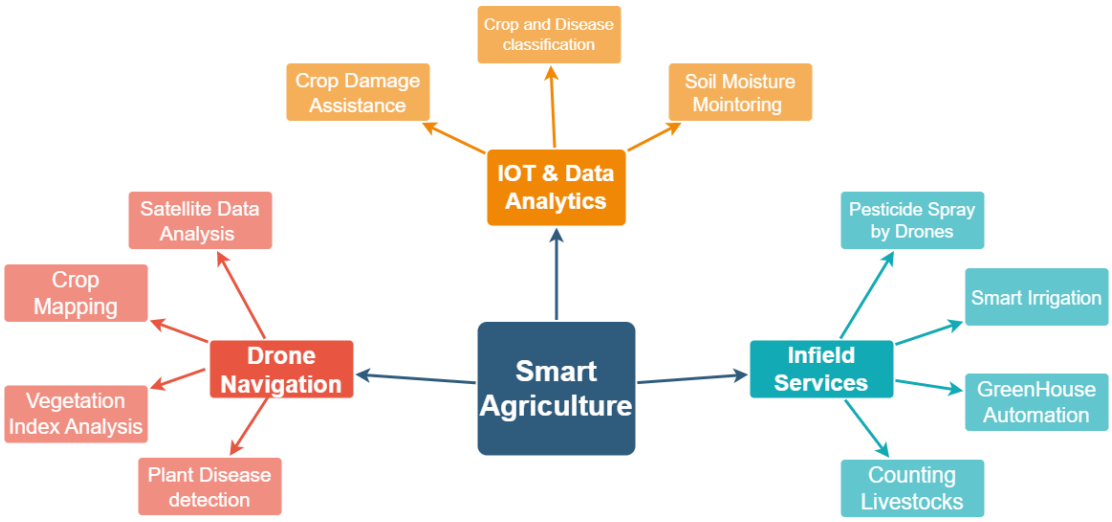


Figure 3.1: Landscape Diagram of Smart Agriculture

Potato crop disease identification is of utmost importance in ensuring the well-being and productivity of potato crops, which serve as a vital staple food globally. Conventional approaches to detecting diseases in potato crops heavily rely on manual inspection, which is time-consuming, labor-intensive, and prone to human errors. However, the advancements in computer vision and aerial imaging technologies present an opportunity to automate the disease identification process using aerial images. By harnessing the

power of computer vision algorithms and machine learning techniques, analyzing aerial images of potato crops and precisely identifying and classifying various diseases becomes feasible. This technological advancement holds the potential to significantly enhance the efficiency and accuracy of disease identification, empowering farmers to promptly implement preventive or corrective measures to safeguard their potato crops and optimize their yield potential.

3.2 Bicubic Interpolation

Bicubic interpolation is a widely employed and essential technique in the fields of image processing and computer graphics. It is primarily utilized for image resampling, allowing for image size or resolution alteration. The fundamental objective of bicubic interpolation is to accurately estimate the color values of newly generated pixels by taking into account the neighboring pixels in the original image.

During the bicubic interpolation process, a 4x4 pixel neighborhood is considered to determine the color value of each new pixel. This involves fitting a smooth and continuous function, typically a cubic polynomial, to the data within the neighborhood. The coefficients of the polynomial are computed by minimizing the error between the original image and the interpolated image.

In comparison to linear interpolation, which solely considers the four nearest pixels, bicubic interpolation produces significantly improved outcomes by capturing more intricate details and reducing image artifacts. By incorporating a larger neighborhood and employing a smooth function, the technique achieves smoother and more accurate results.

It is important to acknowledge that bicubic interpolation involves computational overhead. The process of fitting the cubic polynomial necessitates a greater number of calculations, making it more computationally intensive compared to simpler interpolation methods. Consequently, the efficiency of the implementation should be taken into consideration, particularly when working with large-scale images or real-time applications.

To summarize, bicubic interpolation is a valuable and widely employed technique

for image resizing and transformation, offering superior results in terms of quality when compared to linear interpolation. Its applications span various domains, including image processing, computer graphics, and computer vision, owing to its ability to enhance image resolution and maintain image integrity.

3.3 Generative Adversarial Network (GAN)

GAN, also known as Generative Adversarial Network, is an innovative and influential deep learning framework that has transformed the field of generative modeling. Initially proposed in 2014 by Ian Goodfellow and Bengio (2014), GANs provide a novel approach to producing synthetic data that is realistic and of high quality.

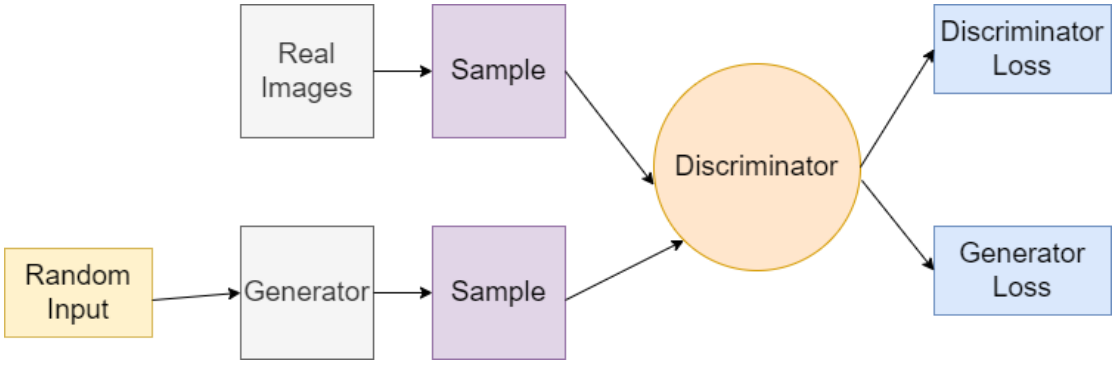


Figure 3.2: GAN Architecture

The fundamental concept underlying GANs involves training two neural networks, namely the generator and the discriminator, in a competitive setup. The generator network takes random noise as input and aims to generate samples that closely resemble the training data. On the other hand, the discriminator network acts as a binary classifier, distinguishing between generated samples and real samples from the training data.

During the training process, the generator and discriminator engage in a game-like interaction. The generator strives to create samples that can deceive the discriminator, while the discriminator learns to accurately discern between real and fake samples. This adversarial training process facilitates the continuous improvement of both networks, with the generator generating increasingly realistic samples as the training advances.

One notable advantage of GANs is their ability to generate new data that captures the underlying distribution of the training data. This characteristic makes GANs highly valuable for diverse tasks, including image synthesis, text generation, and data augmenta-

tion. GANs have demonstrated success in producing visually appealing images, realistic textures, and even highly authentic deepfake videos.

However, training GANs can be complex due to challenges such as mode collapse, where the generator fails to explore the complete data distribution, and instability issues during the training process. To overcome these challenges, researchers have proposed various techniques, such as employing different network architectures, refining loss functions, and implementing regularization methods.

In the field of computer vision, GANs have made significant contributions by enabling realistic image generation, facilitating style transfer, and supporting image-to-image translation tasks. Moreover, GANs have found applications in diverse domains, including natural language processing and healthcare.

In conclusion, GANs represent a powerful deep learning framework that facilitates the generation of synthetic data with a high degree of realism. Through the adversarial training of a generator and discriminator, GANs possess the potential to generate high-quality samples that accurately capture the distribution of the training data. Despite the challenges encountered during training, GANs have proven to be effective in various domains, unlocking new possibilities for data generation and synthesis.

3.3.1 Enhanced Super-Resolution Generative Adversarial Network (ESRGAN)

ESRGAN, an Enhanced Super-Resolution Generative Adversarial Network abbreviation, is an advanced deep learning model specifically developed to tackle image super-resolution tasks. Image super-resolution involves enhancing the resolution and quality of low-resolution images to generate high-resolution versions with finer details and improved visual fidelity.

Traditional methods for super-resolution often rely on interpolation techniques such as bicubic interpolation. However, these methods have limitations and may result in limited enhancement and loss of image details. More sophisticated and effective approaches have emerged with the advent of deep learning and generative adversarial networks (GANs).

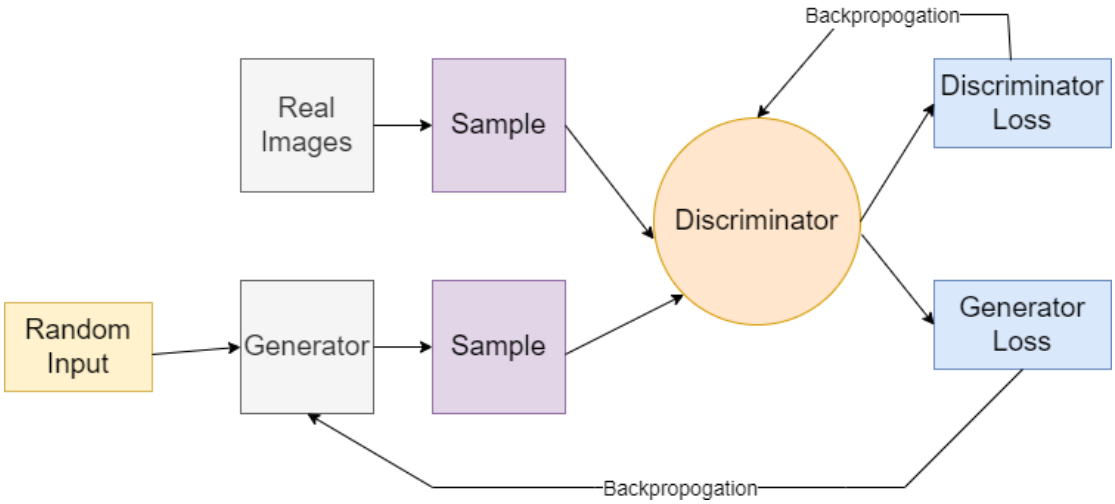


Figure 3.3: ESRGAN Architecture

ESRGAN employs a GAN architecture consisting of two key components: a generator and discriminator networks. The generator network takes a low-resolution image as input and aims to generate a high-resolution image that closely resembles the ground truth high-resolution image. Conversely, the discriminator network distinguishes between the generated and real high-resolution images.

ESRGAN is ability to leverage both adversarial loss and content loss during training distinguishes it. Adversarial loss helps the generator network produce high-resolution images that are visually appealing and realistic. The content loss ensures that the generated images preserve important structural information from the low-resolution input.

By utilizing a perceptual loss function that combines adversarial and content losses, ESRGAN can effectively reconstruct high-resolution images with enhanced details, textures, and overall quality. This approach has demonstrated superior performance compared to previous super-resolution methods, yielding visually compelling results that closely resemble ground truth images.

ESRGAN has garnered significant attention and has been applied to diverse domains, including medical imaging, satellite imagery, and digital media. Its ability to enhance image resolution and quality has practical implications, such as improving the clarity of medical scans, enhancing the visual fidelity of satellite images for better analysis, and upscaling low-resolution videos or images for improved viewing experiences.

In conclusion, ESRGAN represents a cutting-edge deep learning model that leverages

generative adversarial networks for image super-resolution. By combining adversarial and content losses, ESRGAN achieves remarkable results in reconstructing high-resolution images with enhanced details and improved visual quality. Its applications span various fields and hold significant potential for advancing image processing and visual enhancement tasks.

3.3.2 Bidirectional Super-Resolution Generative Adversarial Network (BSRGAN)

BSRGAN, short for Bidirectional Super-Resolution Generative Adversarial Network, is an advanced deep learning model created specifically for image super-resolution tasks. Image super-resolution involves enhancing the resolution and quality of low-resolution images to generate high-resolution versions that exhibit finer details and improved visual fidelity.

Traditional super-resolution methods often rely on interpolation techniques like bicubic interpolation, which can yield limited enhancement and result in the loss of image details. However, more sophisticated and effective approaches have been developed with the emergence of deep learning and generative adversarial networks (GANs).

BSRGAN employs a GAN architecture comprising two key components: a generator and discriminator networks. The generator network takes a low-resolution image as input and aims to generate a high-resolution image that closely resembles the ground truth high-resolution image. Conversely, the discriminator network is responsible for discerning between the generated high-resolution images and real high-resolution images.

What distinguishes BSRGAN is its bidirectional approach to super-resolution. In addition to the traditional forward super-resolution process, BSRGAN incorporates a backward process, which seeks to reconstruct low-resolution images from high-resolution counterparts. By training the model with both forward and backward super-resolution tasks, BSRGAN enhances the overall super-resolution performance and improves the level of detail and texture in the generated high-resolution images.

BSRGAN leverages both adversarial loss and content loss during training. Adversarial loss facilitates the generator network's production of more realistic and visually

appealing high-resolution images. In contrast, content loss ensures that the generated images retain essential structural information from the low-resolution input.

BSRGAN effectively reconstructs high-resolution images with enhanced details, textures, and overall quality by harnessing the bidirectional approach and integrating adversarial and content losses. This methodology has demonstrated promising outcomes in enhancing the visual fidelity of super-resolved images.

BSRGAN has garnered significant attention in the field of image processing and holds potential for various applications, including medical imaging, satellite imagery, and digital media. By improving image resolution and quality, BSRGAN can assist in medical diagnoses, enable more thorough analysis of satellite data, and enhance visual experiences in diverse multimedia applications.

In summary, BSRGAN represents an advanced deep learning model explicitly designed for image super-resolution. By incorporating a bidirectional approach and leveraging generative adversarial networks, BSRGAN achieves remarkable results in reconstructing high-resolution images with enhanced details and improved visual quality. Its applications span multiple domains, offering the potential for advancements in image processing and visual enhancement tasks.

3.4 You Only Look Once (YOLO)

YOLO, which stands for You Only Look Once, is an advanced object detection algorithm that has garnered considerable attention in the field of computer vision. It was originally introduced by Joseph Redmon (2016) in 2016 as an innovative approach to real-time object detection in images. Our detection network consists of 24 convolutional layers and 2 fully connected layers. To reduce the feature space of the preceding layers, we incorporate alternating 1×1 convolutional layers. Initially, we pre-train the convolutional layers on the ImageNet classification task, utilizing a resolution that is half the size (224×224 input image). Subsequently, we double the resolution specifically for the detection process.

The primary objective of YOLO is to precisely identify and locate objects within an image in a single pass. Unlike conventional object detection methods that rely on

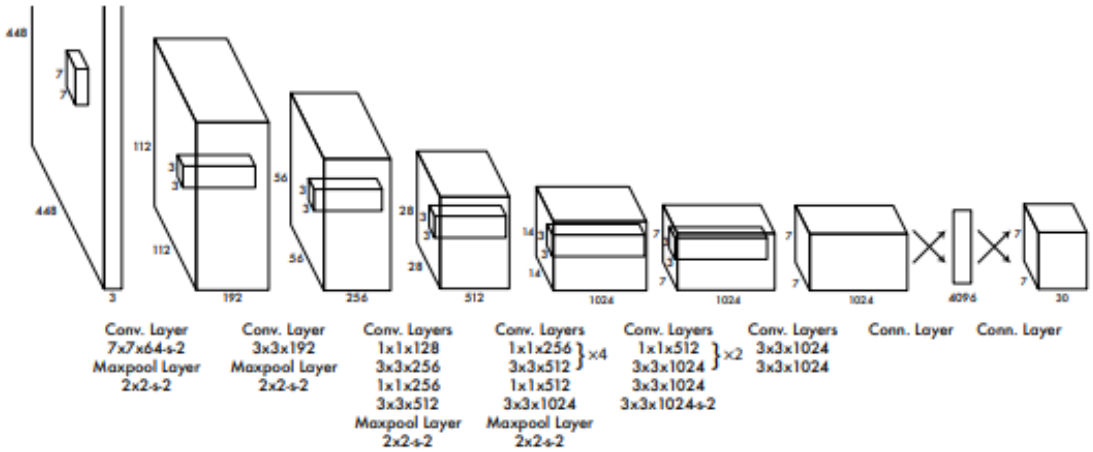


Figure 3.4: YOLO Architecture

region proposal techniques followed by classification, YOLO takes a distinct approach by treating object detection as a regression problem. It divides the input image into a grid and directly predicts bounding boxes and class probabilities from the grid cells.

YOLO operates based on a deep convolutional neural network architecture. The network processes the entire image simultaneously and predicts multiple bounding boxes, along with their respective class probabilities. These bounding boxes are further refined based on the predicted class probabilities and localization coordinates.

One of the main advantages of YOLO is its exceptional speed. By performing object detection in a single forward pass, YOLO achieves real-time performance even on devices with limited resources. This efficiency makes it highly suitable for applications that require fast and accurate object detection, such as video surveillance, autonomous vehicles, and robotics.

Over time, YOLO has undergone several iterations, with each version introducing enhancements in terms of accuracy and speed. YOLOv2, YOLOv3, and the latest iteration, YOLOv8, have made significant strides in object detection performance by incorporating techniques like anchor boxes, feature pyramid networks, and advanced network architectures.

While YOLO offers impressive speed and accuracy, it also has certain limitations. YOLO faces challenges in detecting small objects due to the coarser grid cells used for predictions. Additionally, it may generate multiple bounding boxes for the same object, resulting in redundancy.

In summary, YOLO is a pioneering object detection algorithm that has revolutionized real-time object detection in images. By treating object detection as a regression problem and directly predicting bounding boxes, YOLO achieves remarkable speed and accuracy. Its efficiency and effectiveness have made it a popular choice for various applications, driving advancements in computer vision and enabling practical implementations in real-world scenarios.

3.4.1 YOLOv8 From Ultralytics

YOLOv8, developed by Ultralytics, is an advanced object detection algorithm that stands for "You Only Look Once version 8." Object detection plays a fundamental role in computer vision and is widely utilized in various applications, including autonomous driving, surveillance systems, and robotics. The primary objective of YOLOv8 is to accurately identify and locate objects within images or video frames in real-time.

Traditional object detection approaches typically involve a two-step process, where an initial region proposal stage is followed by object classification. However, YOLOv8 revolutionizes this paradigm by adopting a one-stage detection framework. This means that instead of performing multiple separate steps, YOLOv8 simultaneously predicts bounding boxes and class probabilities for multiple objects in a single pass.

YOLOv8 is built upon a deep convolutional neural network (CNN) architecture that consists of several convolutional layers, followed by fully connected layers. These layers extract meaningful features from the input image, which are then used to predict the bounding boxes and class labels of the objects present.

What sets YOLOv8 apart is its exceptional speed and accuracy. By utilizing a unified network, YOLOv8 achieves real-time object detection capabilities while maintaining high precision. This is crucial for applications that require quick and accurate identification of objects, such as autonomous vehicles navigating complex environments or surveillance systems monitoring crowded areas.

YOLOv8 incorporates several key innovations to enhance its performance. These include feature pyramid networks, which capture multi-scale information to detect objects of varying sizes, as well as focal loss, which prioritizes challenging object instances during training to improve detection accuracy.

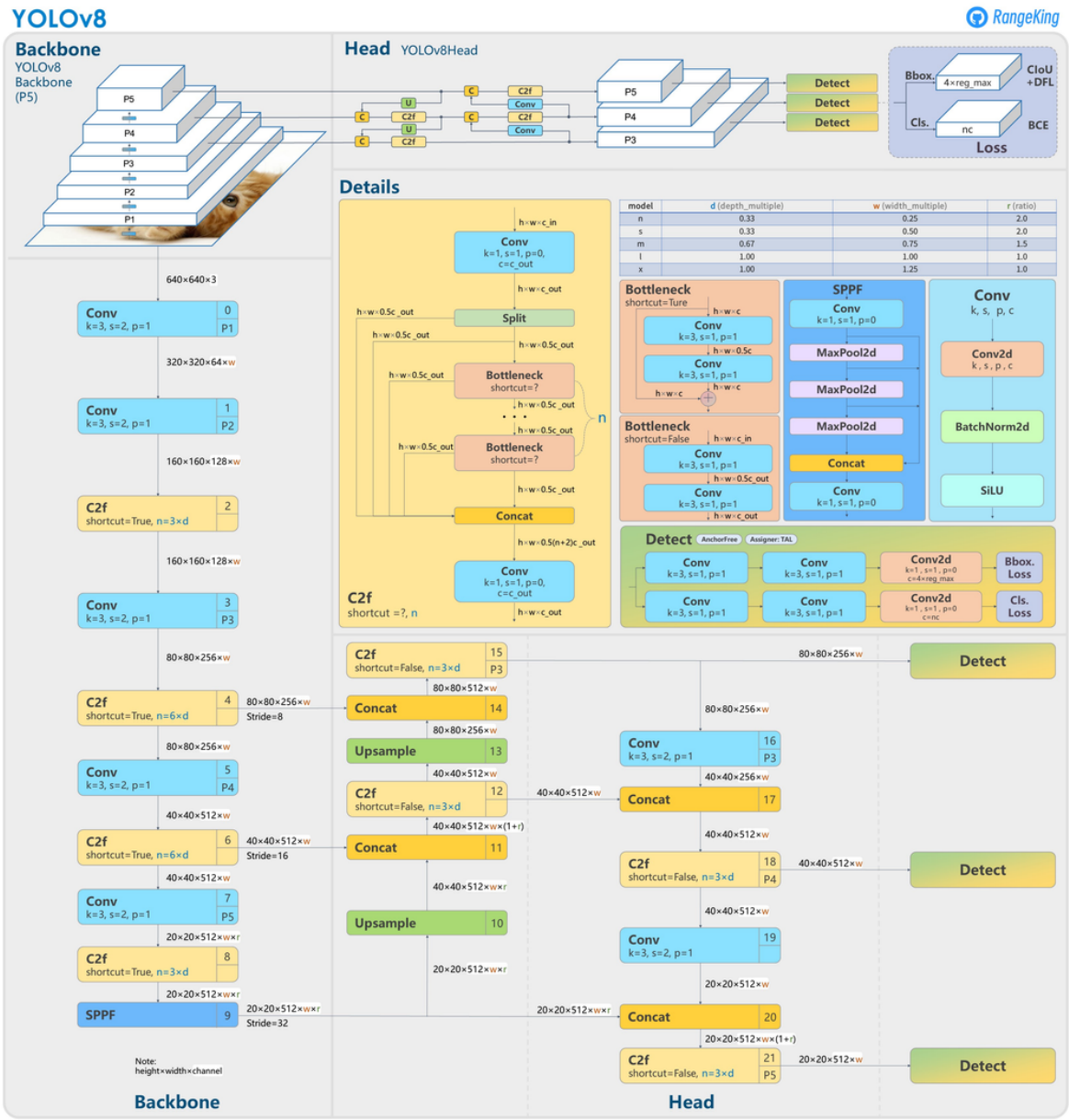


Figure 3.5: YOLOv8 Architecture, visualization made by GitHub user RangeKing

Furthermore, YOLOv8 benefits from advancements in hardware acceleration and parallel computing, enabling efficient inference on modern GPUs and specialized hardware like the NVIDIA Tensor Core. This allows for even faster and more efficient object detection in real-time scenarios.

The availability of pre-trained models and open-source implementations has contributed to the widespread adoption of YOLOv8 by the research and development community. It has become a popular choice for many computer vision tasks, and its versatility has been demonstrated across multiple domains, including autonomous driving, surveillance, and object recognition.

In conclusion, YOLOv8 is an advanced object detection algorithm that offers real-time and accurate identification of objects within images or video frames. By adopting a one-stage detection framework and incorporating innovative techniques, YOLOv8 achieves high-speed and high-precision object detection. Its versatility and performance have made it a popular choice in various computer vision applications, with significant potential for advancing research and development.

CHAPTER 4

DATASET DESCRIPTION

4.1 Potato Multispectral Images Dataset

The dataset Vakanski (2021) comprises aerial images of potato crops, which can be utilized to train machine learning models for precise evaluation of crop health in applications related to precision agriculture. These images were obtained from a field situated at the Aberdeen Research and Extension Center, which is affiliated with the University of Idaho. To capture the images, a Parrot Sequoia multispectral camera was mounted on a 3DR Solo drone. The Sequoia camera incorporates various sensors, including an RGB sensor with a resolution of 4,608×3,456 pixels (16 Megapixels), and four monochrome sensors with a resolution of 1,280×960 pixels (1.2 Megapixels) that capture specific narrow bands of light wavelengths: green (550 nm), red (660 nm), red-edge (735 nm), and near-infrared (790 nm). The drone was flown at a low altitude of approximately 3 meters (10 feet) over the potato field during image acquisition. The primary objective of this data collection was to capture indications of drought stress in Russet Burbank potato plants caused by premature plant senescence.

The dataset comprises a total of 360 RGB image patches, each measuring 750×750 pixels and saved in JPG format. These image patches were obtained by performing cropping, rotating, and resizing operations on the original aerial high-resolution images. The patches specifically correspond to regions containing healthy plants, Potato Leafroll Virus (PLRV) plants, and Verticillium wilt plants. To accurately label the crop regions within the images, we utilized the graphical annotation software makesense.io. This manual annotation process allowed us to classify the crop regions into three distinct categories: healthy, Potato Leafroll Virus (PLRV), and Verticillium wilt. It is important to note that the testing subset of images is entirely separate from the training subset. In other words, the image patches used for model testing were extracted from different aerial images, ensuring an independent evaluation of the trained models' performance.

The dataset has been specifically created to facilitate the training of machine learning algorithms for the purpose of quantifying the health status of crops in a field. The dataset includes images featuring healthy plants, as well as plants affected by Potato Leafroll Virus (PLRV) and Verticillium wilt by the AHDB (2023). Our aim in designing the dataset was to ensure a balanced representation of these different classes of crops across the images. However, it is important to acknowledge that one limitation of the dataset is the relatively small number of available images.

4.1.1 Examples of Images in the Dataset

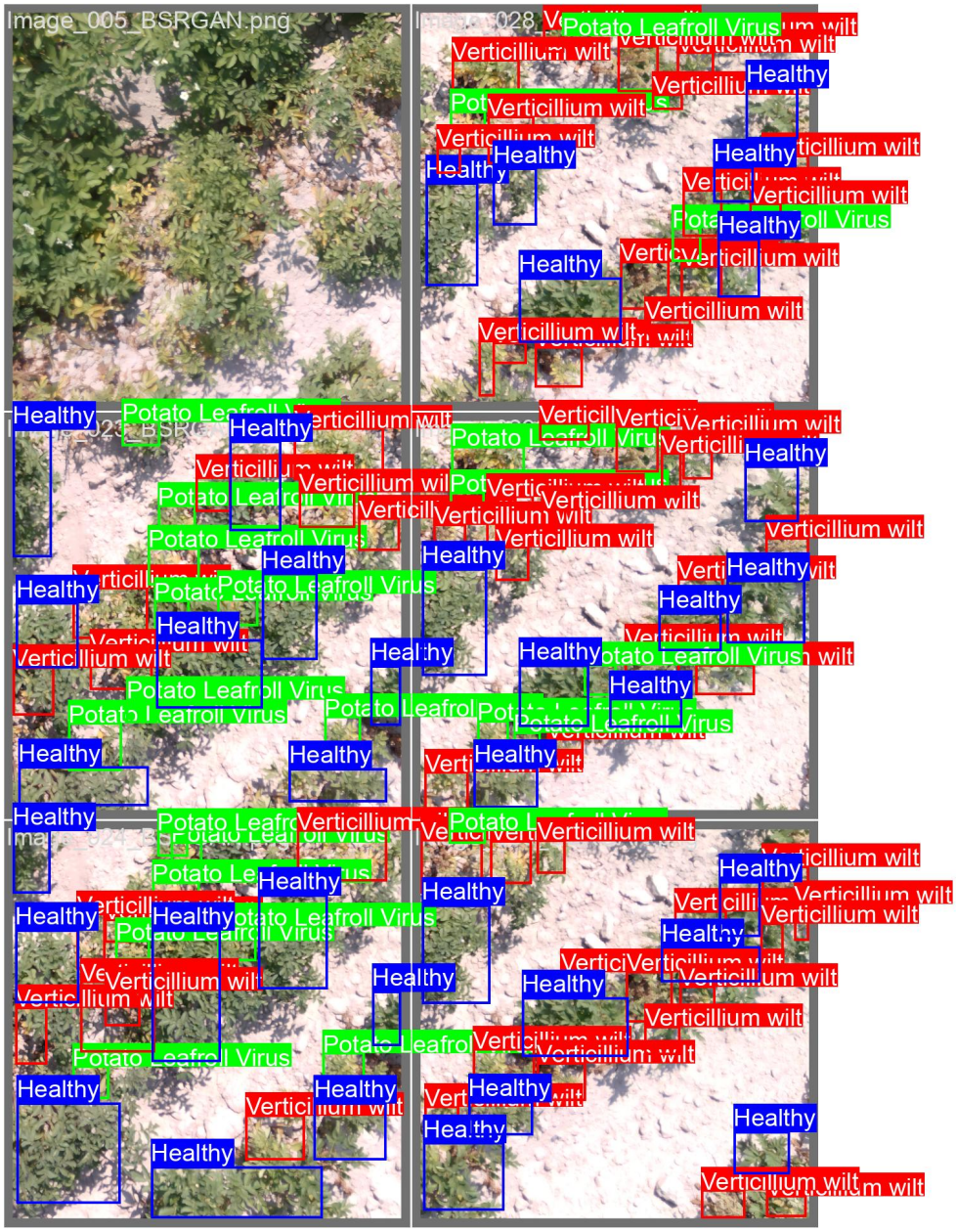


Figure 4.1: batch labels

4.2 Types of Disease on Potato Plants

Here, we were working on the three types of disease named healthy, Potato Leafroll Virus (PLRV), and Verticillium wilt. I took the two different types of disease named Potato Leafroll Virus (PLRV) and Verticillium wilt on potato plants to label them from the following article AHDB (2023).

4.2.1 Potato Healthy Leaves

Identifying healthy potato leaves involves looking for specific characteristics. Firstly, they should exhibit a consistent and lively green color, indicating optimal photosynthesis and chlorophyll production. Secondly, healthy leaves have a smooth texture without any signs of wilting, curling, or drooping. They are typically medium to large in size with rounded edges, displaying an oval shape. The leaf structure showcases a well-defined central vein (midrib) from which smaller veins branch out evenly, distributing vital nutrients across the leaf. Furthermore, healthy leaves should be free from spots, discoloration, or lesions, which may indicate nutrient deficiencies or diseases. Ensuring uniform growth, where leaves are similar in size, color, and overall appearance, is important. Lastly, the absence of pests like aphids, mites, or caterpillars indicates a healthier leaf condition. By attentively observing these characteristics, gardeners can evaluate the well-being of their potato plants and promptly address any issues that may arise.

Figure 4.2: potato healthy-leaves

4.2.2 Potato Leafroll Virus (PLRV)

PLRV, previously a prevalent virus in seed stocks, is primarily spread by aphids through persistent transmission. Once an aphid becomes infected with the virus, it remains infective throughout its lifetime.

The initial symptoms of PLRV infection, commonly observed during the first year, are typically mild and can easily go unnoticed. These symptoms may manifest as a slight rolling of leaves and a reddish or orange discoloration in the upper foliage.

Figure 4.3: Potato Leafroll Virus (PLRV)

4.2.3 Verticillium wilt

Verticillium wilt is a fungal infection that specifically targets the vascular system of potato plants, and it can affect the majority of commercially grown potato cultivars.

Typically, this disease appears as isolated patches within a field and can lead to stunted growth, premature aging of plants, and, ultimately a decrease in crop yield.

Affected plants may exhibit a loss of turgidity and wilt, particularly during hot and sunny weather conditions.

Figure 4.4: Verticillium wilt

4.3 Acknowledgments

The creation of the dataset was made possible by the generous support of a Seed Grant provided by the Office of Research and Economic Development (ORED) at the University of Idaho. I would like to express my sincere gratitude and appreciation to Dr. Kasia Duellman for her invaluable contribution in designing and preparing the experimental plots, as well as for granting us permission to collect crop images at the Aberdeen Research and Extension Center. I would also like to extend my thanks to Jordan Todd for his assistance in setting up the drone, camera, and image collection process. Additionally, I would like to acknowledge the contributions of Sujata Butte and Haotian Wang for their assistance in organizing the collected images.

CHAPTER 5

PROPOSED METHODOLOGIES

5.1 About this chapter

In this chapter, we provide a detailed explanation of our proposed approach. We begin by discussing the process of data generation, and explaining how the data used in our study was obtained. Next, we delve into the technique we employ to enhance the resolution of low-resolution images for the purpose of detecting anomalies. Finally, we present a comprehensive explanation of our proposed approach, outlining its key components and methodologies.

5.2 Potato Multispectral Images Dataset

The dataset Vakanski (2021) comprises aerial images of potato crops, which can be utilized to train machine learning models for precise evaluation of crop health in applications related to precision agriculture. These images were obtained from a field situated at the Aberdeen Research and Extension Center, which is affiliated with the University of Idaho. To capture the images, a Parrot Sequoia multispectral camera was mounted on a 3DR Solo drone.

The dataset comprises a total of 360 RGB image patches, each measuring 750×750 pixels and saved in JPG format. These image patches were obtained by performing cropping, rotating, and resizing operations on the original high-resolution aerial images. The patches specifically correspond to regions containing healthy plants, Potato Leafroll Virus (PLRV) plants, and Verticillium wilt plants. To accurately label the crop regions within the images, we utilized the graphical annotation software makesense.io. This manual annotation process allowed us to classify the crop regions into three distinct categories: healthy, Potato Leafroll Virus (PLRV), and Verticillium wilt. It is important to note that the testing subset of images is entirely separate from the training subset. In

other words, the image patches used for model testing were extracted from different aerial images, ensuring an independent evaluation of the trained models' performance.

5.3 Bicubic Interpolation

Bicubic interpolation is a widely employed and essential technique in the fields of image processing and computer graphics. It is primarily utilized for image resampling, allowing for image size or resolution alteration. The fundamental objective of bicubic interpolation is to accurately estimate the color values of newly generated pixels by taking into account the neighboring pixels in the original image.

It should be noted that although bicubic interpolation has the capability to enhance the resolution of an image, it is unable to introduce additional details that were not initially present in the original image. Consequently, the quality of the upscaled image will be contingent upon the quality of the original image.

5.3.1 Steps to Deploy Bicubic Interpolation Model on Custom Dataset

1. from PIL import Image
2. # Load the original image
3. img = Image.open("your image data path")
4. # Upscale the image by a factor of 2 using bicubic interpolation
5. upscaled$_{i}mg = img.resize((img.width*2, img.height*2), resample = Image.BICUBIC)$
6. # Save the upscaled image
7. upscaled$_{i}mg.save(\text{"}upscaled_{i}mage.jpg\text{"})$

5.3.2 Result of Bicubic Interpolation on Potato Aerial Dataset

We are deploying a bicubic interpolation model to low-resolution aerial images, but we are not getting the expected result.

Figure 5.1: Input Image

Figure 5.2: Output Image

5.4 Enhanced Super-Resolution Generative Adversarial Network (ESRGAN)

after deploying the bicubic interpolation model, we were not getting satisfactory results, so we came to another model called ESRGAN, an Enhanced Super-Resolution Generative Adversarial Network abbreviation, which is an advanced deep learning model specifically developed to tackle image super-resolution tasks. Image super-resolution involves enhancing the resolution and quality of low-resolution images to generate high-resolution versions with finer details and improved visual fidelity.

5.4.1 Steps to Deploy ESRGAN Model on Custom Dataset

1. Cloning the ESRGAN pre-trained model
2. git clone https://github.com/xinntao/ESRGAN
3. Place your own low-resolution images in LR folder
4. %cd ESRGAN
5. Download the RRDB ESRGAN X4 pth model from the given drive link and put it into the model's folder
6. https://drive.google.com/drive/u/0/folders/17VYV_SoZZesU6mbxz2dM
7. run test.py python file to train that model to on our custom dataset

8. python test.py

9. The results are in the results folder

5.4.2 Result of ESRGAN on Potato Aerial Dataset

Here, we are deploying an ESRGAN model to low-resolution aerial images, but we are not getting the expected result. here mentioned the following outputs.

Figure 5.3: Input Image

Figure 5.4: Output Image

5.5 Bidirectional Super-Resolution Generative Adversarial Network (BSRGAN)

after deploying the bicubic interpolation model and ESRGAN model, we were not getting satisfactory results, so we came to another model called BSRGAN, short for Bidirectional Super-Resolution Generative Adversarial Network, belongs to the family of Generative Adversarial Networks (GANs) and is specifically designed for image super-resolution. Image super-resolution involves generating high-resolution images from low-resolution counterparts. BSRGAN is considered "bidirectional" as it incorporates two generators and two discriminators, enabling both upscaling and downscaling of images. This feature

makes it versatile for various applications. Moreover, BSRGAN utilizes a perceptual loss function to enhance the visual appeal and realism of the generated images.

The generator network in BSRGAN takes a low-resolution image as input and produces a high-resolution image as output. On the other hand, the discriminator network evaluates both a high-resolution image and a low-resolution image to determine which one is real and which one is generated.

It is important to note that the effectiveness of different models depends on the dataset used. Each model has its own strengths and specialties. In the case of our dataset, the BSRGAN model has demonstrated remarkable results.

5.5.1 Steps to Deploy BSRGAN Model on Custom Dataset

1. Download the BSRGAN code and pre-trained models from the repository
2. https://github.com/cszn/BSRGAN
3. Or cloning the ESRGAN pre-trained model
4. git clone https://github.com/cszn/BSRGAN.git
5. Run the main download pretrained model py python file to get the dncnn3 pth model file
6. python main download pre-trained models python file
7. download BSRGAN pth file and put into the model zoo, for that run the below command
8. #download 'BSRGAN.pth'
9. python main download pretrained models py file –models "BSRGAN.pth" –model dir "model zoo"
10. Now, finally run the 'main test bsrgan.py' file to train your model
11. python 'main test bsrgan.py'

5.5.2 Result of BSRGAN on Potato Aerial Dataset

Here, we are deploying a BSRGAN model to low-resolution aerial images, so we finally got what we looked for expected result. Here mentioned the following outputs.

Figure 5.5: Input Image

Figure 5.6: Output Image

5.6 You Only Look Once Version 8 (YOLOv8)

YOLOv8, developed by Ultralytics, is an advanced object detection algorithm that stands for "You Only Look Once version 8." Object detection plays a fundamental role in computer vision and is widely utilized in various applications, including autonomous driving, surveillance systems, and robotics. The primary objective of YOLOv8 is to accurately identify and locate objects within images or video frames in real-time.

Here, after getting the high-resolution dataset then, we deploy the yolov8 model on them. and getting the expected output.

5.6.1 Steps to Deploy YOLOv8 Algorithm on Custom Dataset

1. pip install ultralytics
2. # Importing required libraries
3. import os
4. import shutil
5. import random
6. pip install tqdm –upgrade
7. from tqdm.notebook import tqdm

```
# connecting to the google drive

from google.colab import drive

drive.mount('/content/drive')

# deploy tensorboard

%load_ext tensorboard

%tensorboard –logdir runs

from ultralytics import YOLO

# Load a model
#model = YOLO("yolov8n.yaml") # build a new model from scratch
model = YOLO("yolov8n.pt") # load a pretrained model (recommended for training)
# Use the model

model.train(data="/content/drive/MyDrive/MTP/yolov8/dataset.yaml", epochs=200) # train the model

metrics = model.val() # evaluate model performance on the validation set

print(metrics)
```

5.6.2 Result of YOLOv8 on Potato Aerial Dataset

here, we deployed the yolov8 pre-trained model on the super high-resolution dataset. We made batch labels and got satisfactory results.

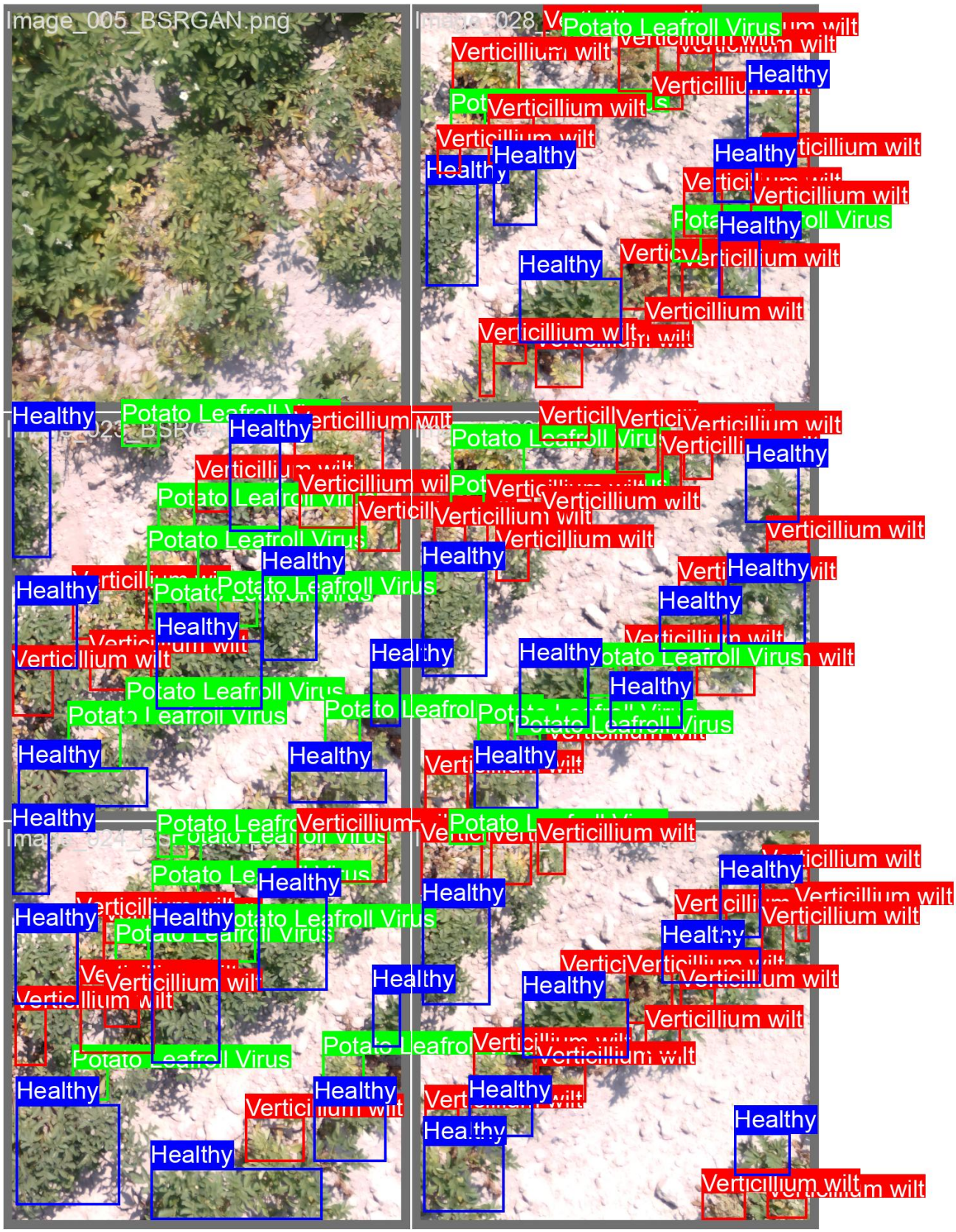


Figure 5.7: Input Batch0 Labels

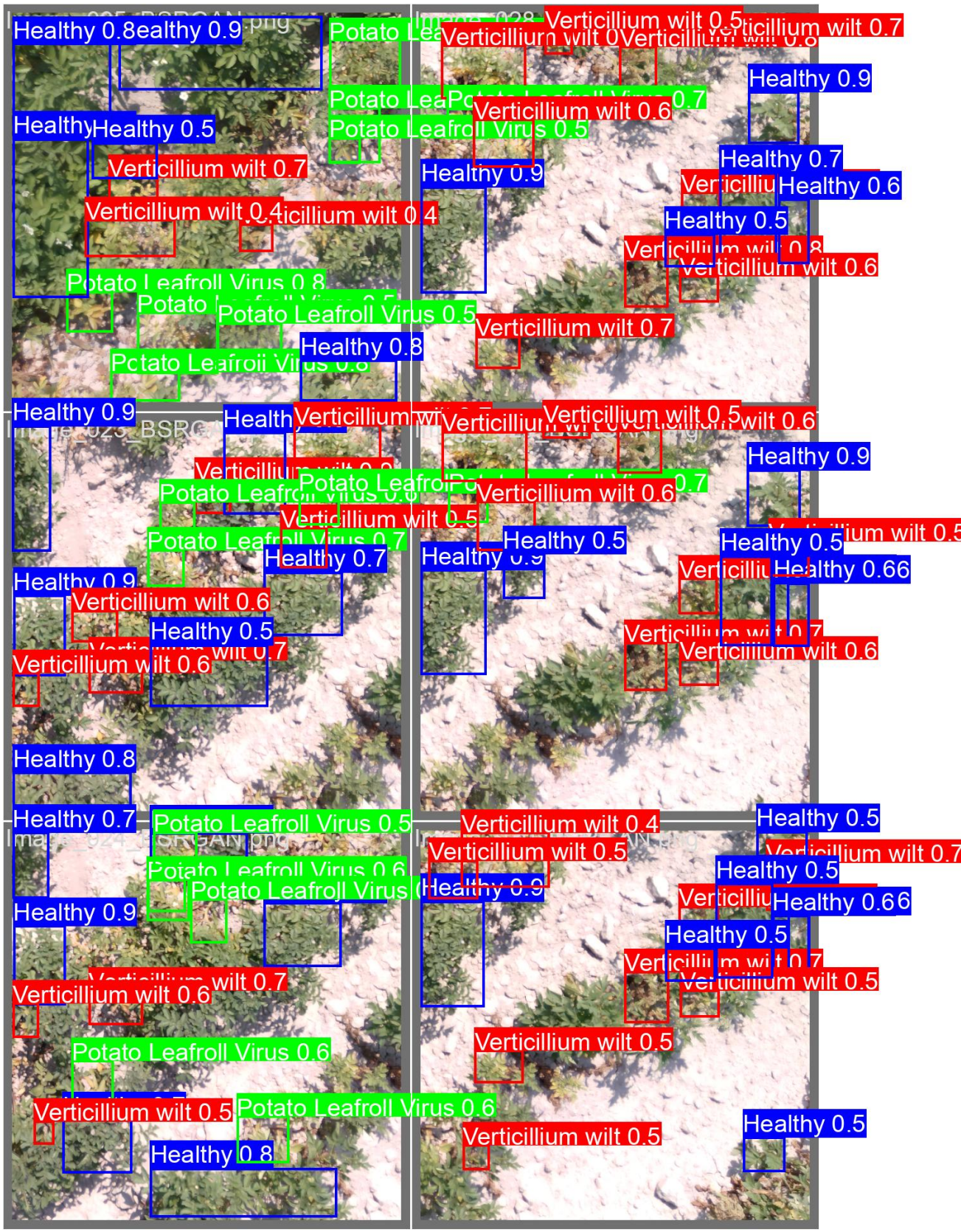


Figure 5.8: Output Batch0 Prediction

CHAPTER 6

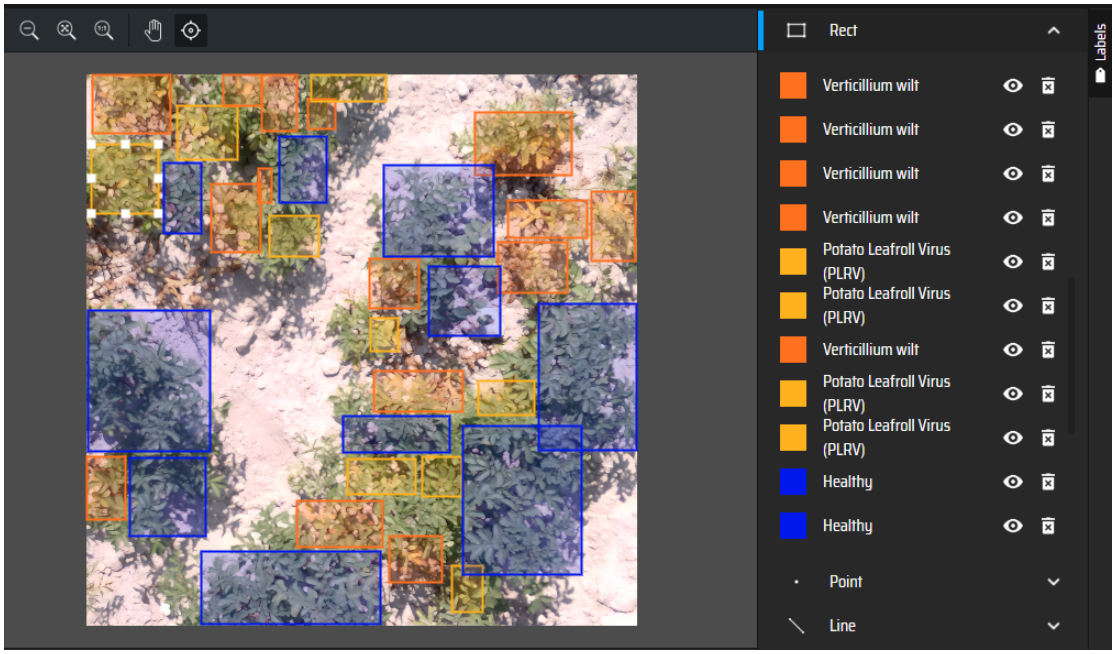
RESULTS AND EXPERIMENTS

I got the super-high-resolution dataset after applying the BSRGAN model instead of bicubic interpolation and the ESRGAN model to a low-resolution potato plant aerial dataset.

After that, I labeled the potato crop aerial super-resolution images using the make-sense.io tool on the following type of disease.

1. Potato Leafroll Virus (PLRV)
2. Verticillium wilt
3. Healthy

It took 20 to 25 minutes to label the single images by myself.



I exported all images in Yolo format so that I can apply the yolov8 algorithm to detect disease in affected potato plants.

here, I am showing the output images between all their categories after training on the Bicubic Interpolation, ESRGAN, and BSRGAN models.

We apply the YOLO algorithm on our custom high super-resolution dataset and getting the following batch detection along with the prediction on the test images.

Figure 6.1: Bicubic Input Image

Figure 6.2: Bicubic Output Image

Figure 6.3: ESRGAN Input Image

Figure 6.4: ESRGAN Output Image

Here, we were doing the first experiment on a 10% test image using the yolov8 pre-trained model to identify whether the model can detect the disease. And got the following output as mentioned.

After that, we trained our custom dataset on the 10% aerial images.

YOLOv8 Model Performance Metrics Values			
Types of Disease	Healthy	Verticillium wilt	PLRV
Precision	0.75	0.70	0.51
Recall	0.66	0.49	0.36
mAP	0.73	0.62	0.32

Now we can see the predicted output on the test images.

Figure 6.5: BSRGAN Input Image

Figure 6.6: BSRGAN Output Image

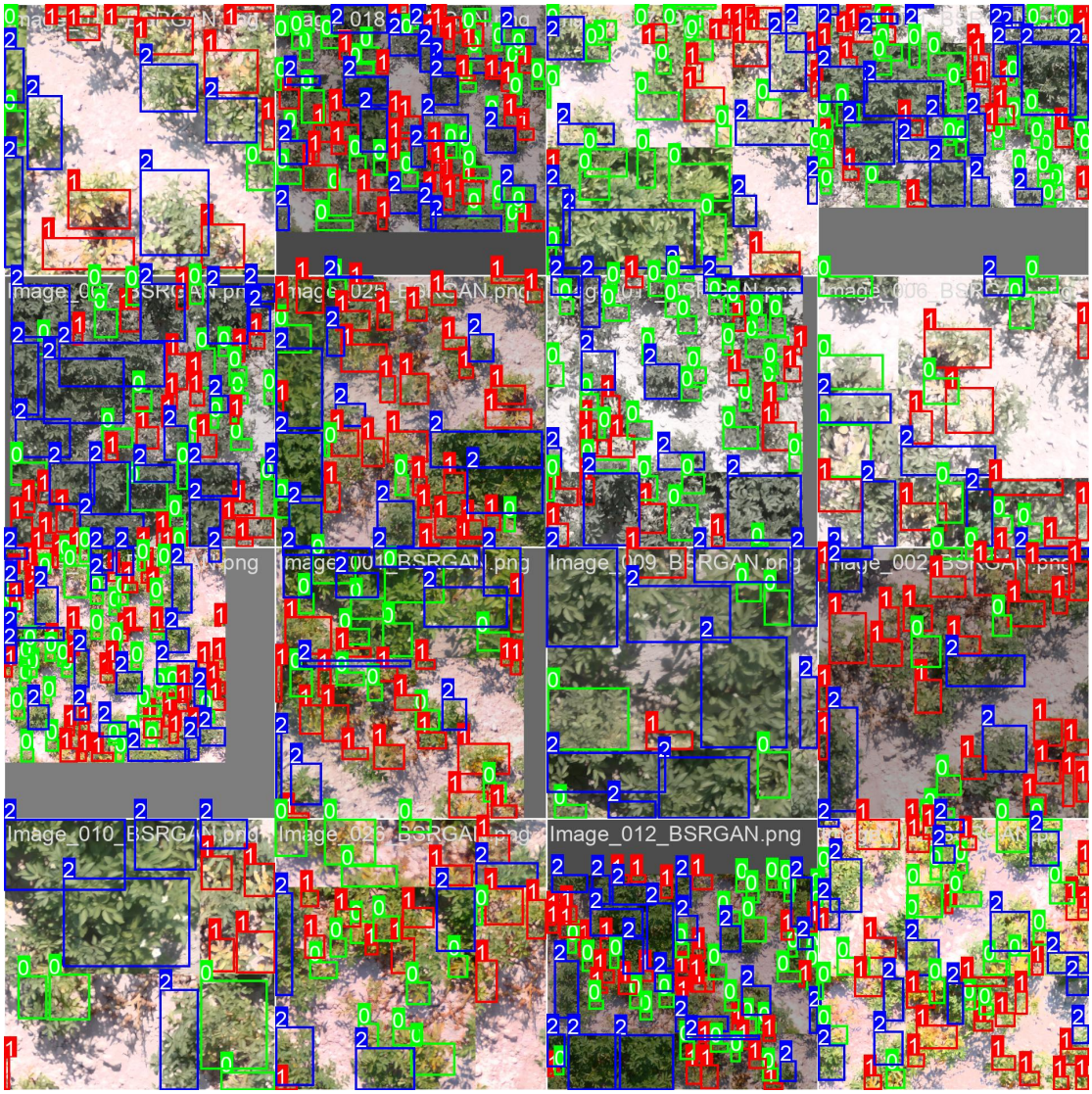


Figure 6.7: train batch0 images

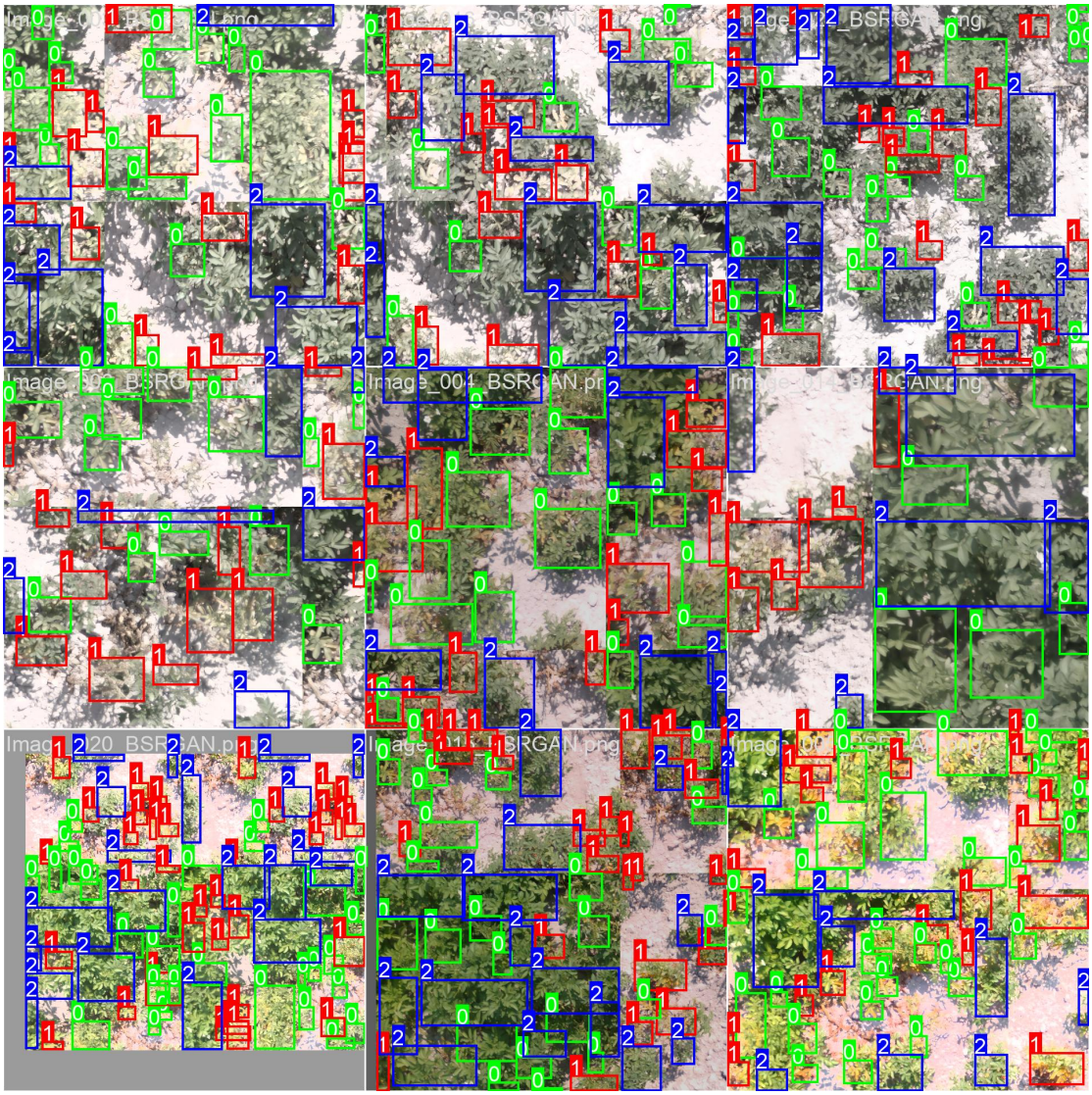


Figure 6.8: train batch1 images

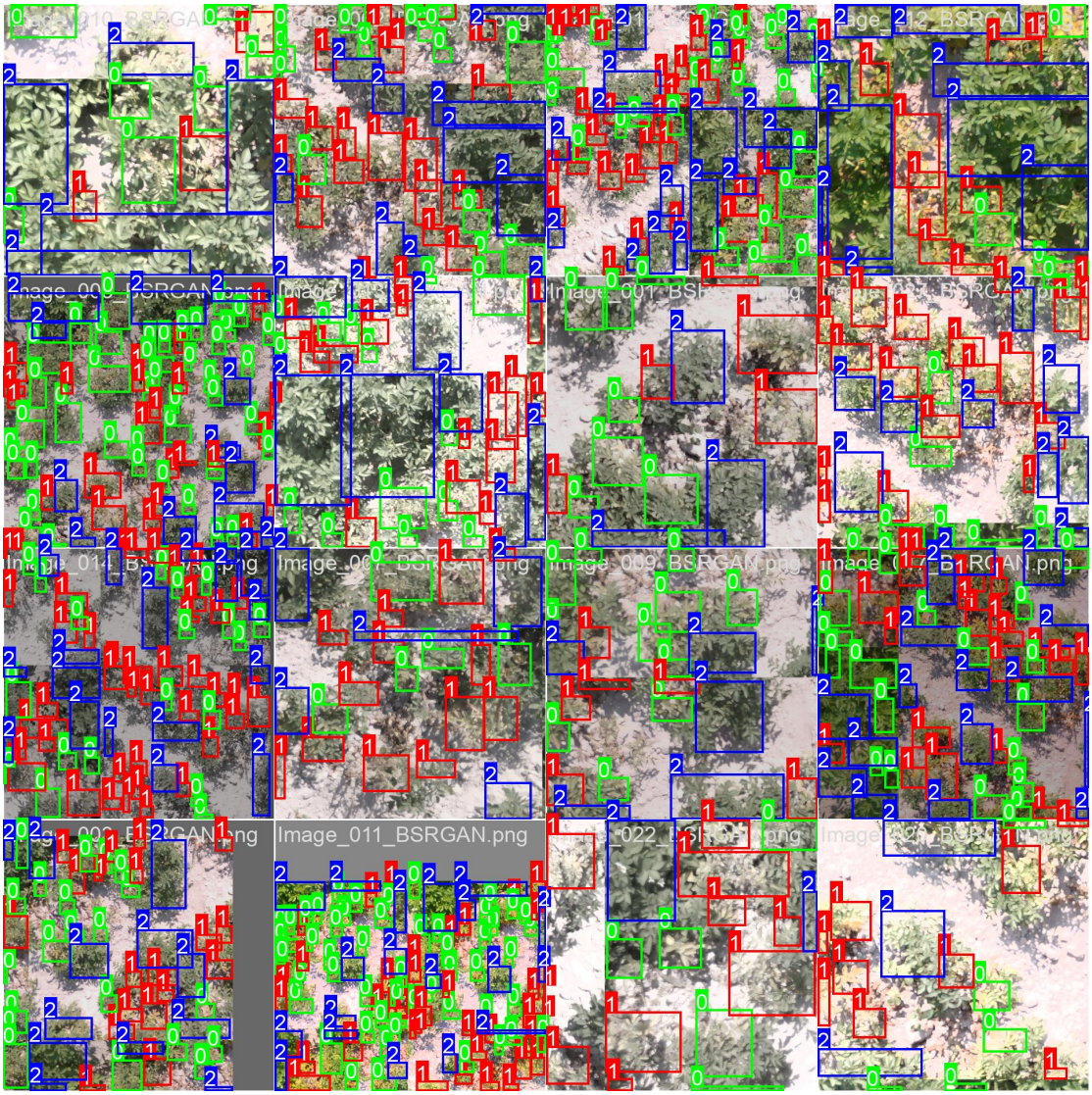


Figure 6.9: train batch2 images

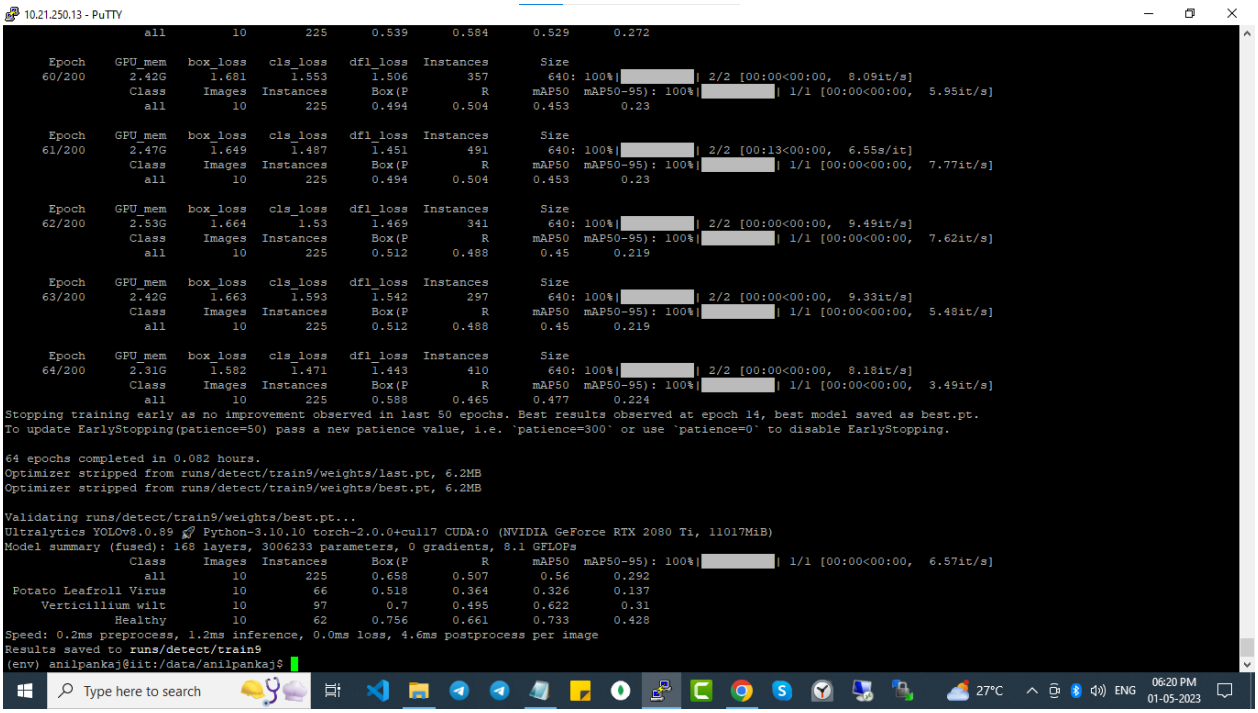


Figure 6.10: result on test image

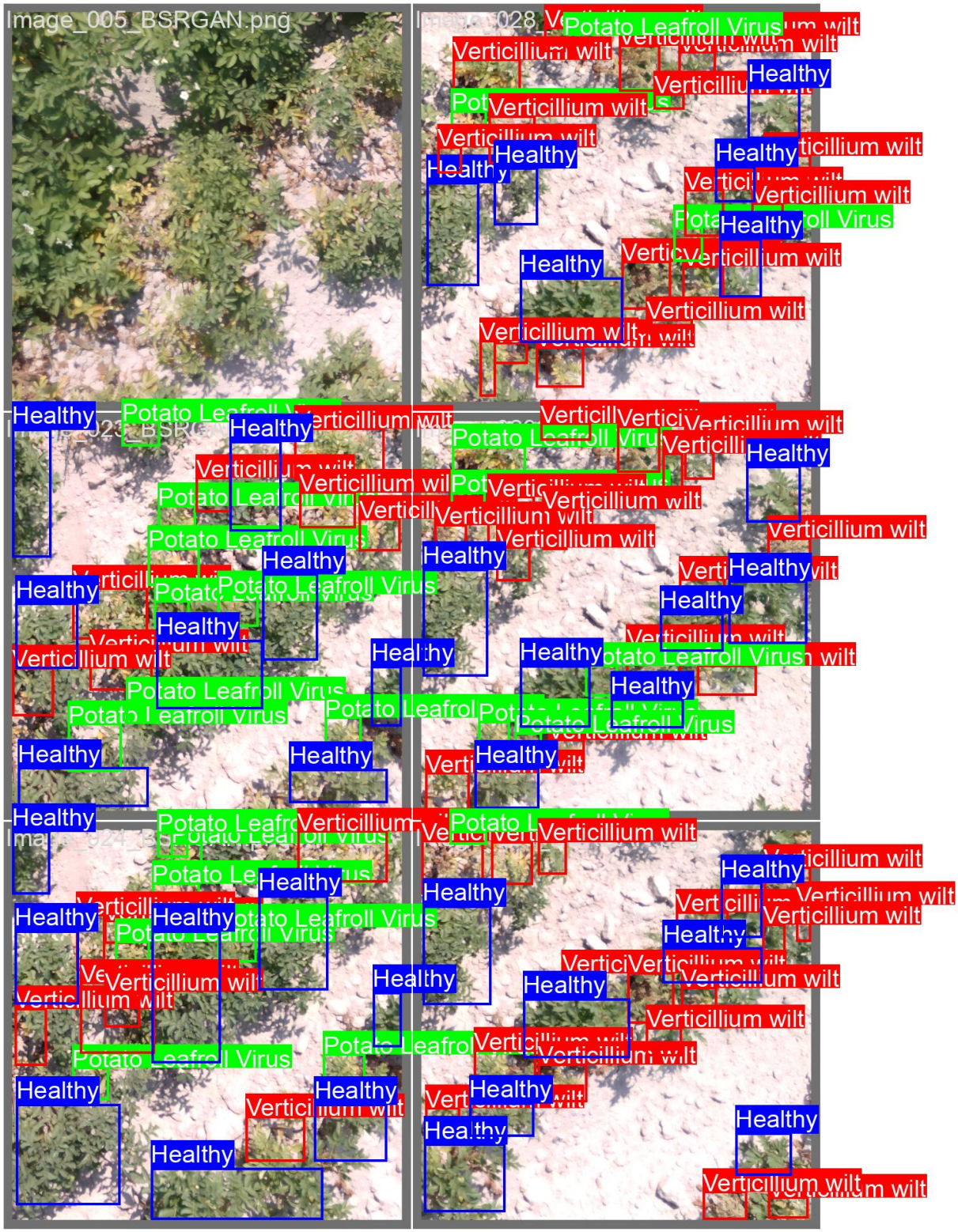


Figure 6.11: val_batch0_labels

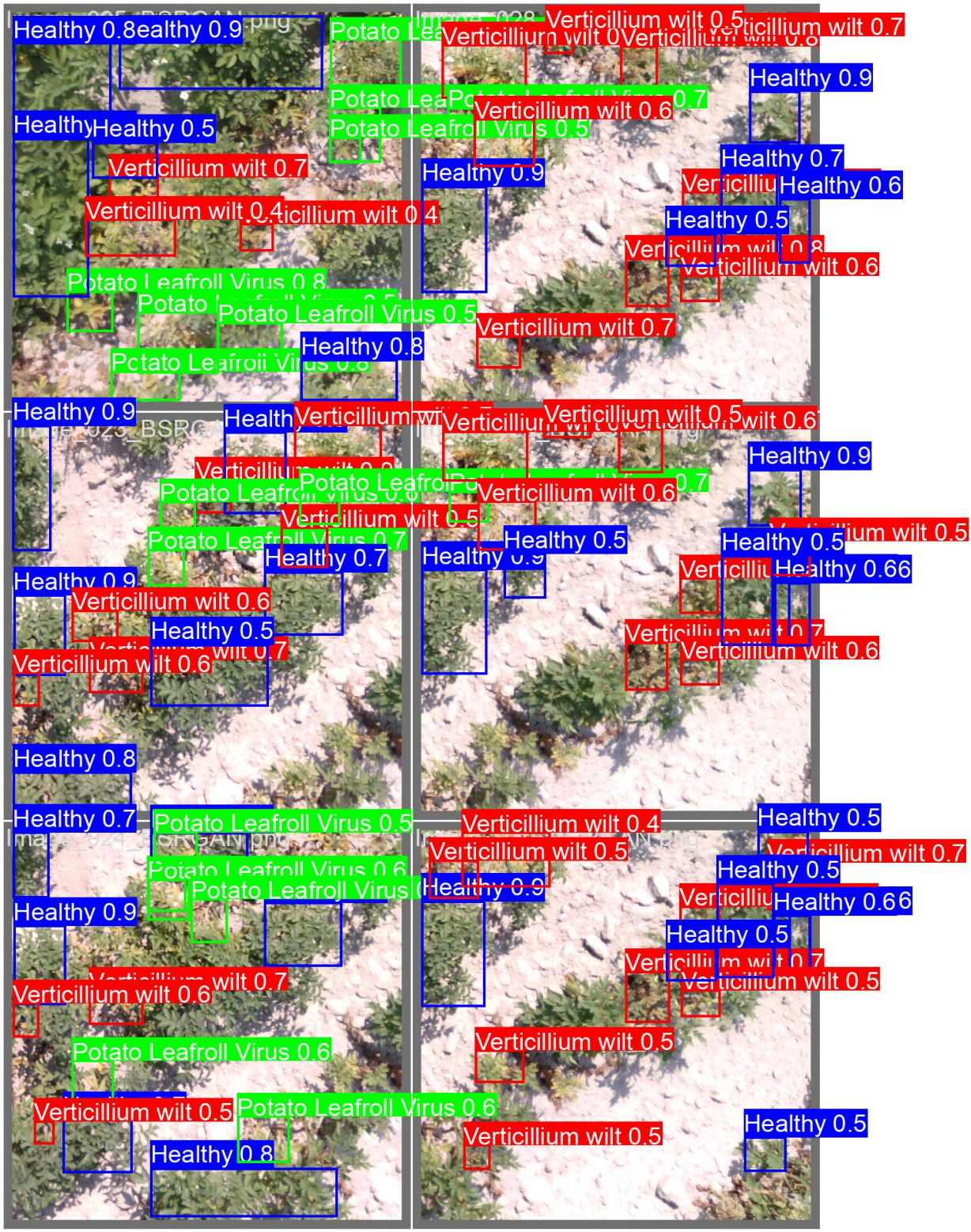


Figure 6.12: val_batch0_pred

CHAPTER 7

CONCLUSION

The research presented in this study is focused on enhancing the existing publicly accessible low-resolution aerial dataset of Russet Burbank potato crops, which holds significant importance in the field of precision agriculture for effective crop health assessment. However, the limitations of the low-resolution images pose challenges in accurately evaluating and detecting crop health conditions. To overcome this obstacle, computer vision pre-trained models are employed to generate high-resolution aerial images from the original low-resolution ones.

In this research, three distinct models are utilized for image super-resolution: ESRGAN, BSRGAN, and the bicubic interpolation technique. These models leverage the capabilities of deep neural networks to transform the low-resolution aerial images into high-resolution versions. By incorporating these models, the researchers aim to enhance the quality of the dataset, enabling more precise analysis and assessment of the potato crops' health.

To evaluate the effectiveness of the proposed approach, extensive experiments are conducted. The results obtained from the three models are compared to determine their performance in enhancing the low-resolution images. Remarkably, the BSRGAN model exhibits exceptional outcomes in terms of improving both the resolution and quality of the aerial images. The model's unique ability to upscale and downscale images proves highly advantageous for various agricultural applications.

Building upon the enhanced dataset, the researchers further implement the YOLOv8 algorithm for object detection on the custom dataset with high super-resolution images. Renowned for its efficiency and accuracy in detecting objects, the algorithm is employed to identify diverse types of diseases and abnormalities present in the potato plants captured within the aerial dataset.

The evaluation of the YOLOv8 algorithm on the custom dataset reveals promising results in disease detection and classification. Specifically, for the healthy class, the

algorithm achieves a 73% mean Average Precision (mAP) score, a 75% Precision score, and a 66% Recall score. In the case of Verticillium wilt, the algorithm attains a 62% mAP score, a 70% Precision score, and a 49% Recall score. Lastly, for the Potato Leafroll Virus (PLRV) class, the algorithm obtains a 32% mAP score, a 51% Precision score, and a 36% Recall score. These results successfully demonstrate the algorithm's capability to effectively identify and classify diseases in potato plants based on the high super-resolution aerial images.

It is worth mentioning that these evaluation results are derived from a subset of the dataset, specifically 10% of the test images. Consequently, further evaluation on a larger scale is imperative to validate the algorithm's performance and robustness in real-world scenarios.

To summarize, this research work introduces a comprehensive approach aimed at enhancing the low-resolution aerial dataset of Russet Burbank potato crops. By leveraging the potential of deep neural network models, namely ESRGAN, BSRGAN, and the bicubic interpolation technique, significant improvements are achieved in terms of image resolution and quality. Furthermore, the successful implementation of the YOLOv8 algorithm on the high super-resolution custom dataset showcases encouraging results in disease detection and classification. The findings of this study contribute significantly to the field of precision agriculture, facilitating more accurate assessment and monitoring of crop health conditions in potato plants. Nonetheless, further research and evaluation are necessary to validate the effectiveness and applicability of these methods in real-world agricultural practices.

CHAPTER 8

FUTURE DIRECTIONS

Given the research presented in this work and the outcomes achieved, several potential avenues for future exploration can be considered to enhance the study and its practical applications further. The following directions offer valuable possibilities

8.1 Expansion of the Dataset

Building upon the significant improvements made to enhance the existing low-resolution aerial dataset, future research endeavors can prioritize the expansion of the dataset. This can be accomplished by incorporating a greater variety of samples representing Russet Burbank potato crops. By augmenting the dataset's size, a more extensive and diverse range of data will be available for analysis and validation. This augmentation will ultimately contribute to the production of more robust and reliable outcomes.

8.2 Exploration of Additional Crop Diseases

Although the research focused on detecting and classifying diseases such as Verticillium wilt and Potato Leafroll Virus (PLRV), it is important to acknowledge that potato crops can be affected by numerous other diseases and abnormalities. Consequently, future investigations can delve into exploring a broader spectrum of diseases. By encompassing a wider range of diseases in the analysis, researchers can develop a more comprehensive understanding of crop health. This expanded knowledge base will be instrumental in the formulation of effective disease management strategies.

8.3 Investigation of Additional Image Super-Resolution Techniques

Although the current research utilized ESRGAN, BSRGAN, and bicubic interpolation as image super-resolution methods, there exists a scope for exploring alternative techniques and models. As the field of computer vision continually evolves, advancements in super-resolution methods present new opportunities. By delving into and evaluating different models, it is possible to further improve the quality and resolution of the aerial images.

8.4 Refinement of Existing Models

Refining the pre-trained models, such as ESRGAN and BSRGAN, through fine-tuning specifically for the Russet Burbank potato crop dataset can prove advantageous. Through the process of fine-tuning, where the models are adjusted to better align with the characteristics and features of potato plants, enhanced performance and accuracy can be achieved. This targeted approach holds the potential to yield more precise and customized results for analyzing potato crops.

8.5 Integration of Multi-Modal Data

To gain a thorough understanding of crop health, the incorporation of multi-modal data is essential. Beyond solely relying on aerial images, integrating data from diverse sources such as spectral sensors, weather data, and soil composition can offer valuable insights. By amalgamating different data modalities, researchers can attain a more comprehensive and holistic perspective of crop health. This integration enables more precise detection and assessment of diseases and abnormalities, leading to improved analysis and management strategies.

8.6 Evaluation on a Larger Scale

The evaluation of the YOLOv8 algorithm for disease detection and classification was limited to a subset of the dataset. To ensure the algorithm's performance and applicability in real-world scenarios, future research should encompass a comprehensive evaluation on a larger scale. This evaluation should encompass an extensive range of test images, facilitating a more robust validation of the algorithm's effectiveness. Conducting evaluations on a larger scale will establish the algorithm's reliability and suitability for practical applications in the field of agriculture.

By pursuing these future directions, the study can advance and broaden its scope, ultimately contributing to the field of precision agriculture and fostering the development of more sophisticated applications for the assessment and management of potato crop health.

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