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# Wheat Disease Detection Using YOLO and Drone-Captured Images

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Km. Neha<sup>1</sup>, Akash Arya<sup>2</sup> and Rajeev Singh<sup>2,\*</sup>

<sup>1</sup>*School of Computing, DIT University, Dehradun, Uttarakhand, India*

<sup>2</sup>*Department of Computer Engineering, G.B. Pant University of Agriculture and Technology, Pantnagar, Uttarakhand, India*

*E-mail: nehapanwar2016@gmail.com, Aryakash1998@gmail.com, rajeevpec@gmail.com*

*\*Corresponding Author*

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## Abstract

Mitigating crop loss and maximizing resource usage in agriculture are contingent upon the timely and precise identification of wheat illnesses. In this paper, we offer a YOLOv8-based method that uses drone-captured images to detect wheat diseases in real time. Four distinctive image classes represent our dataset: Ground, Yellow Rust, Brown Rust, and Healthy. Smart spray drones can target disease management by recognizing non-crop regions in the field, a task made possible in large part by the Ground class. This class allows our model to distinguish between areas that need to be treated and those that don't, improving chemical spraying accuracy and cutting down on waste. Using data gathered from wheat fields, the model was trained and tested, and it performed excellently in differentiating between crops that were diseased and those that weren't. The model achieved a highest precision of 0.803 and

recall of 0.850 across various classes and the overall performance included a mean average precision of 0.605, demonstrating robust performance in field conditions, which qualifies it for use in agricultural monitoring systems that operate in real-time. This effort is a step toward automated, data-driven precision agriculture, which will assist farmers in allocating resources and managing diseases in a timely and effectively manner.

**Keywords:** YOLOv8, drone imaging, machine learning, precision farming, disease detection.

## 1 Introduction

Wheat disease detection is a critical challenge in agriculture, as diseases such as Brown Rust and Yellow Rust can significantly reduce crop yield and quality [1]. These fungal infections spread rapidly, particularly under favourable conditions, leading to widespread damage if not controlled in time. Early detection is essential because it allows for timely intervention, reducing the severity of the outbreak and preventing its spread across large areas of farmland. By identifying diseased plants early, farmers can apply targeted treatments, such as fungicides, more efficiently, thereby saving resources and minimizing the environmental impact of overuse. Moreover, early detection helps ensure food security by preserving wheat production, which is a staple crop globally. Automated detection systems, particularly those using drones and advanced image processing techniques, can greatly enhance the ability to monitor large fields in real-time, offering a scalable solution for timely disease management [2].

YOLOv8 (You Only Look Once version 8) is the latest iteration of the YOLO family of object detection models, known for their speed and accuracy in real-time detection tasks [3, 4]. YOLO models are based on a single-stage detection approach, where an image is processed in a single pass to identify multiple objects and their locations simultaneously. Unlike traditional object detection methods, which involve multiple steps, YOLO simplifies the process by predicting both bounding boxes and class probabilities directly from the full image in one go. YOLOv8 uses more advanced architecture compared to its predecessors, improving detection precision, especially in complex or cluttered images. This is crucial for detecting small objects, such as diseased spots on wheat leaves. YOLOv8 offers more streamlined tools for training and fine-tuning the model, making it easier to modify and deploy for specific tasks like wheat disease detection with customized classes [5–7].

Drone imagery has emerged as a powerful tool in modern agriculture, revolutionizing crop monitoring and pest management. By using unmanned aerial vehicles (UAVs), or drones, farmers can capture high-resolution images and data over vast fields, providing valuable insights into crop health, soil conditions, and pest infestations. Equipped with advanced sensors like RGB cameras, multispectral or thermal sensors, drones allow farmers to monitor crops more efficiently and at a scale impossible with traditional methods. Drone imagery offers precise, high-resolution data, enabling the detection of subtle changes in plant health, such as early signs of disease or pest activity. This allows for timely intervention before issues escalate. Drones can provide real-time data, helping farmers make informed decisions quickly. This is particularly important for time-sensitive tasks like disease management or irrigation scheduling [8–10].

The early and accurate detection of crop diseases is essential for maintaining healthy crops, protecting yields, and ensuring food security. Diseases such as fungal infections, rusts, and blights can spread rapidly, often going unnoticed until they have caused significant damage. By identifying diseases early, farmers can intervene before widespread infection occurs, minimizing crop loss and protecting future harvests. This also reduces treatment costs, as early detection allows for targeted pesticide or fungicide applications, which lowers chemical usage and prevents unnecessary environmental harm. Furthermore, controlling diseases early helps preserve crop quality, ensuring that infections do not degrade the appearance or nutritional content of the produce, which is crucial for market value [11].

Preventing the spread of diseases is another major benefit of early detection. By containing infections to a localized area, farmers can stop them from spreading to other parts of the field or even to neighbouring farms. This containment is vital for large-scale farming operations. Early detection also enhances resource management by enabling precision farming techniques, where treatments are focused on specific areas rather than being applied uniformly across the entire field [12–14].

We developed a real-time wheat disease detection system using YOLOv8, an advanced object detection model, combined with drone-captured imagery to address the challenge of timely and precise identification of wheat illnesses [15]. The work was conducted in several key steps: First, we collected a dataset consisting of four distinct image classes – Ground, Yellow Rust, Brown Rust, and Healthy – captured by drones in wheat fields at GBPUAT Pantnagar. A total of 335 labelled images were used for training, with an additional 64 labelled images reserved for validation. The next step involved

training the YOLOv8 model on this dataset to detect and classify the images based on the specific crop diseases or healthy conditions. YOLOv8 was selected for its speed, accuracy, and ability to handle cluttered or complex images, making it particularly suitable for detecting small disease spots on wheat leaves. The model uses a single-stage detection approach, allowing it to simultaneously predict bounding boxes and class probabilities, which enabled fast and effective disease identification in real-time [16, 17]. The model's ability to differentiate between diseased and healthy areas can reduce chemical usage and improve resource management. The integration of Ground images played a crucial role in the model's ability to recognize areas that do not need pesticide treatment, further optimizing the spraying process. The overall performance of the model, with a highest precision of 0.803 and recall of 0.850, demonstrated its effectiveness in real-world field conditions. This level of performance provides a robust foundation for real-time agricultural monitoring and disease management, offering a scalable solution for precision farming. This approach represents a significant step towards automated, data-driven solutions for crop health monitoring, enabling farmers to efficiently allocate resources and mitigate crop loss due to diseases, thereby ensuring the sustainability and productivity of wheat farming [18–20].

## 2 Literature Review

Na Ma et al. (2023) proposed a lightweight real-time wheat seed detection model, YOLOv8-HD, built upon the YOLOv8 architecture. The model introduces several innovations to enhance both efficiency and accuracy. First, shared convolutional layers are incorporated into the YOLOv8 detection head, significantly reducing the number of parameters and achieving a more lightweight design, which improves the model's runtime speed.

Rosemary Ngozi Ariwa et al. (2024) presented a novel approach to plant disease detection utilizing the YOLO deep learning model, implemented using Python and its associated libraries. The researchers employed the YOLOv8 algorithm to develop a maize leaf detection system, which significantly outperformed other machine learning algorithms such as CNN (84%), KNN (81%), Random Forest (85%), and SVM (82%). The YOLOv8-based system achieved an impressive accuracy of 99.8%, highlighting its superiority in detecting maize leaf diseases compared to traditional classification methods.



Baohua Yang et al. (2022) Proposed an improved YOLOv4 (you only look once v4) with CBAM (convolutional block attention module) including spatial and channel attention model was proposed that could enhance the feature extraction capabilities of the network by adding receptive field modules. In addition, for improving the generalization ability of the model, not only local wheat data (WD), but also two public data sets (WEDD and GWHDD) were used to construct the training set, the validation set, and the test set.

Henry O. Velesaca et al. (2021) presents a comprehensive survey on recent computer vision-based food grain classification techniques. It includes state-of-the-art approaches intended for different grain varieties. The approaches proposed in the literature are analyzed according to the processing stages considered in the classification pipeline, making it easier to identify common techniques and comparisons.

Tu-Liang Lin et al. (2022) employ Faster Region-Convolutional Neural Networks (R-CNNs) and Mask R-CNNs to develop a sophisticated knowledge-based system for the automatic identification of plant pests and diseases. Their work stands out by combining object detection and instance segmentation techniques to handle complex agricultural images, which often contain overlapping leaves, occlusions, and variable lighting conditions. Results demonstrated that Mask R-CNN achieved superior performance in detecting and segmenting diseased areas compared to Faster R-CNN, especially in scenarios where the affected regions were irregularly shaped or partially hidden.

Sapna Nigam et al. (2023) proposed an EfficientNet architecture-based model for the automatic identification of major wheat rust diseases. To develop and evaluate the model, they prepared a comprehensive dataset specifically targeting wheat rusts. In addition to EfficientNet, they explored various classical Convolutional Neural Network (CNN) architectures, including VGG19, ResNet152, DenseNet169, InceptionNetV3, and MobileNetV2, for comparing the performance in wheat rust disease detection.

B. Nageswararao Naik et al. (2022) proposed a method for detecting and classifying chilli leaf diseases using a squeeze-and-excitation-based Convolutional Neural Network (CNN) model. To enhance the accuracy and robustness of the model, they utilized 12 different pretrained deep learning networks, including AlexNet, DarkNet53, DenseNet201, EfficientNetB0, InceptionV3, MobileNetV2, NasNetLarge, ResNet101, ShuffleNet, SqueezeNet, VGG19, and XceptionNet. By leveraging these architectures, their approach aims to effectively identify and classify various chilli leaf diseases, contributing to improved agricultural disease management.

## Objectives

1. To develop a YOLO-based real-time detection model for wheat diseases using drone-captured images, aiming to accurately classify wheat health into four categories: Ground, Yellow Rust, Brown Rust, and Healthy.
2. To enhance smart spraying capabilities by utilizing the Ground class to identify non-crop areas, thereby improving the targeting accuracy of pesticide and fungicide applications while reducing chemical waste.
3. To investigate the impact of drone imagery on precision agriculture, exploring how UAV technology can provide high-resolution data for early detection of crop diseases, optimizing resource allocation, and ensuring timely intervention.

## 3 Materials and Methods

### 3.1 Dataset

A dataset was developed for drone-based monitoring to detect wheat crop diseases in real time, consisting of various images captured directly from the fields of GBPUAT Pantnagar. These images represent four key categories: Brown Rust, Yellow Rust, Healthy crops, and Ground. The dataset was carefully compiled to ensure comprehensive coverage across these categories. A total of 335 labelled images from the four classes – Ground, Healthy, Brown Rust, and Yellow Rust – were used to train the proposed YOLOv8 model, with an additional 64 labelled images used for validation. Ground images play a vital role in automating drone-driven pesticide spraying by helping the model identify areas where pesticide application is not needed. This extensive dataset enables the model to accurately distinguish between diseased crops and ground areas, promoting targeted and effective disease management in agriculture.

### 3.2 Data Preprocessing and Annotation

For data preprocessing and annotation, several steps were undertaken to enhance the quality and diversity of the dataset, ensuring better model performance. To address the potential imbalance and improve the model's ability to generalize, various data augmentation techniques such as rotation, flipping, and zooming were applied. These augmentations helped simulate different real-world conditions, such as varying perspectives and scales, which are

commonly encountered during drone-based image capture in the field. By augmenting the data, we were able to significantly increase the variability within the dataset, which enhances the model's robustness when identifying disease patterns and ground areas under different circumstances.

For the image annotation process, we have utilized the LabelImg tool, a widely-used annotation software that allows manual labelling of objects within images. Each image was carefully annotated to define bounding boxes around areas of interest corresponding to four key classes: Brown Rust, Yellow Rust, Healthy crops, and Ground. This manual annotation process ensured precise and accurate labelling, which is critical for the proposed YOLOv8 model to effectively learn the features of each class. The detailed annotations, combined with the augmented dataset, created a solid foundation for training the model in detecting wheat diseases and ground areas in real time.

### 3.3 YOLOv8 Model Architecture

#### 1. Input Layer:

**Drone Captured Images (4 Classes: Brown Rust, Yellow Rust, Healthy, Ground):** The input to the model consists of drone-captured images taken from wheat fields. These images cover four main categories:

Brown Rust and Yellow Rust (both are diseases affecting wheat crops),  
Healthy (images of wheat crops without any visible diseases),

Ground (images of non-crop areas such as soil or empty patches). These classes provide the necessary variety for training the model to distinguish diseased areas from healthy crops and ground regions [21–23].

**Augmentation (Rotation, Flipping, Zooming):** To improve the robustness of the model and allow it to generalize better, various data augmentation techniques are applied. These include:

**Rotation:** Rotating the images at different angles to simulate drone movements.

**Flipping:** Horizontally and vertically flipping the images to account for different drone perspectives.

**Zooming:** Zooming in and out on images to reflect changes in altitude and distance from the crops. These augmentations increase the dataset's variability, helping the model recognize features under different conditions.

## 2. **Backbone:**

**Feature Extraction Layers:** The backbone of the YOLOv8 model is responsible for extracting meaningful features from the input images. This process includes:

Detecting edges, textures, color patterns, and shapes from the input images.

Learning key characteristics that differentiate between diseased and healthy crops, and ground areas. Common backbones like CSPDarkNet or other convolutional networks used in YOLO help build hierarchical feature maps from the input data.

The backbone operates on multiple scales, allowing it to capture both fine details (such as disease spots on leaves) and larger, more general patterns (such as crop health or soil background). The proposed model has 225 layers, 3,011,628 parameters, and 3,011,612 gradients [24, 25].

## 3. **Neck:**

**FPN/PAFPN (Feature Pyramid Network / Path Aggregation Feature Pyramid Network):** The Neck serves as a bridge between the Backbone and the Head. It refines the extracted features by:

Enhancing multi-scale feature extraction, which is crucial for detecting objects of varying sizes. For instance, rust diseases can appear as small patches, while ground areas are large and continuous.

Combining low-level and high-level feature maps from the Backbone to ensure that the model is effective at detecting both fine and broad features in the images.

Using FPN (Feature Pyramid Networks) or PAFPN (Path Aggregation Feature Pyramid Networks), which aggregate information from different layers of the backbone to ensure that important details are preserved at every scale [26].

## 4. **Head:**

**Bounding Box Prediction:** The Head predicts the location of objects (in this case, diseased areas, healthy crops, and ground) by outputting bounding boxes. This is done by:

Predicting coordinates (x, y, width, height) that define the boundary around each object in the image.

Each bounding box corresponds to one of the four classes (Brown Rust, Yellow Rust, Healthy, or Ground). The model generates multiple boxes for different objects in the image and refines them during training.

**Class Prediction:** Along with predicting the bounding boxes, the model also needs to classify what each detected object is. The class prediction head is responsible for:

Assigning a class to each bounding box, determining whether it contains Brown Rust, Yellow Rust, Healthy crops, or Ground.

This classification is done using probabilities or confidence scores, which reflect how sure the model is about its prediction. The class with the highest score is chosen as the label for the object [27–29].

5. **Output:**

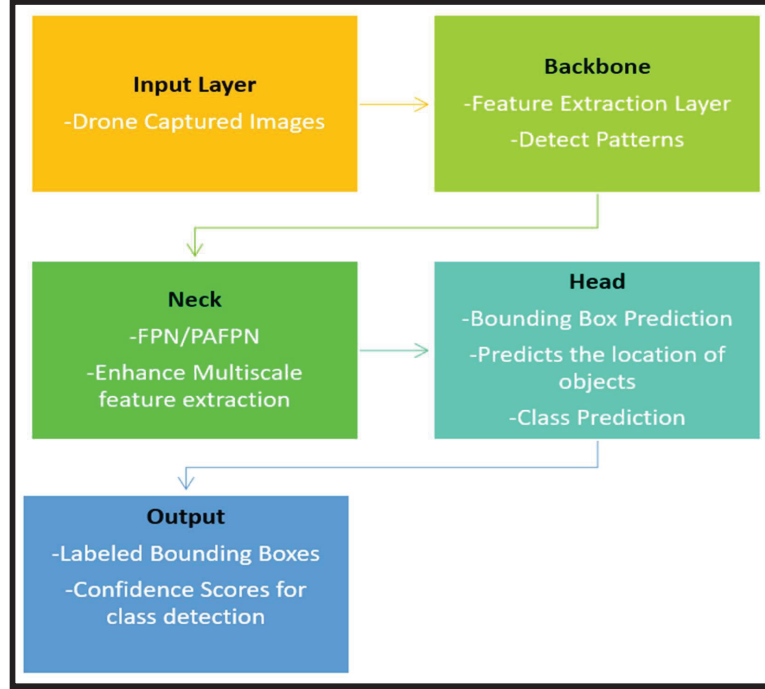
**Labelled Bounding Boxes (Brown Rust, Yellow Rust, Healthy, Ground):** The final output consists of bounding boxes around the detected objects, each labelled with one of the four categories (Brown Rust, Yellow Rust, Healthy, or Ground). These bounding boxes are essential for identifying diseased regions that need treatment or areas (like ground) where no action is necessary.

**Confidence Scores for Disease Classification and Ground Identification:** Along with the bounding boxes, the model provides confidence scores for each classification. These scores range from 0 to 1 and represent the model's certainty about the predicted class.

These confidence scores are crucial for making decisions about pesticide spraying since high-confidence predictions are more reliable for targeting diseased areas, while low-confidence predictions might require further inspection. Figure 1 below illustrates the key steps of the YOLOv8 architecture [30–32].

### 3.4 YOLOv8 Architecture and its Advantages

YOLOv8 belongs to the YOLO family of real-time object detection models. It builds on the advances made by its predecessors (such as YOLOv7 and earlier versions) while incorporating key improvements in accuracy, speed, and flexibility. The architecture of YOLOv8 is designed to efficiently perform object detection, classification, and localization tasks. YOLOv8 typically uses a version of the CSPDarknet backbone, which was introduced in YOLOv4. CSPDarknet is a variation of the Darknet architecture that uses Cross-Stage Partial connections. YOLOv8 uses a modified version of the Feature Pyramid Network (FPN) and Path Aggregation FPN (PAFPN) [33]. The most highlighted advantages of YOLOv8 model are listed below.



**Figure 1** The key steps of the YOLOv8 architecture.

**Anchor-Free Detection:** Simplifies model design and training, leading to improved performance on smaller datasets.

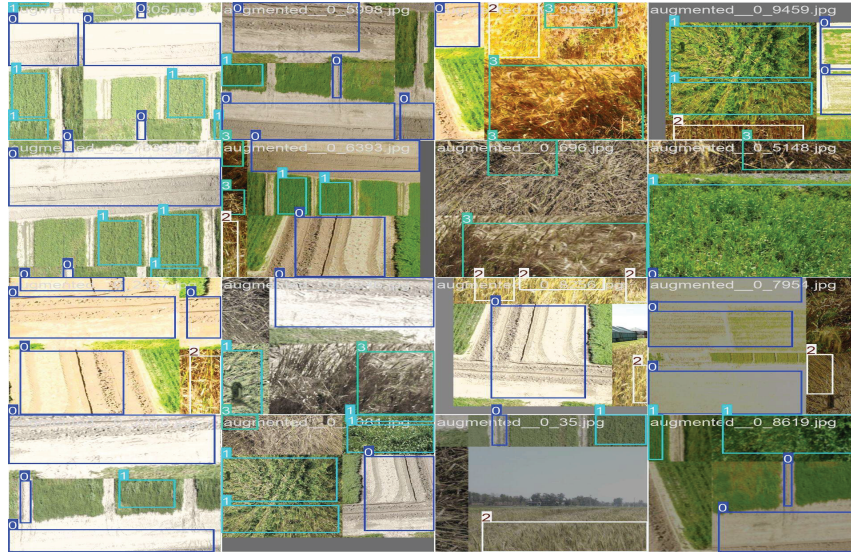
**Enhanced Multi-Scale Feature Extraction:** Improves object detection across different object sizes, making it more effective for applications like disease detection in agriculture.

**Speed and Accuracy Balance:** YOLOv8 achieves real-time detection speeds while maintaining high detection accuracy.

**Efficient Use of Resources:** Designed to run on devices with limited computational power, such as drones, making it ideal for real-time monitoring and spraying applications in agriculture [34–36].

### 3.5 Training Process

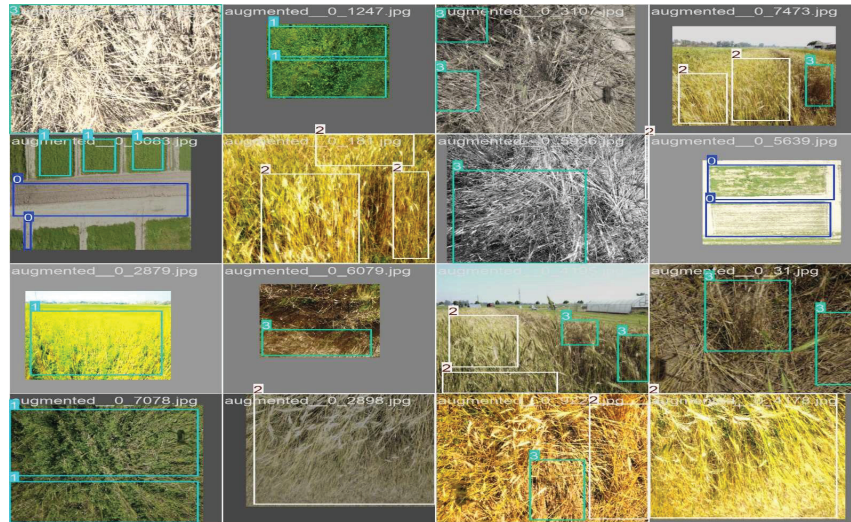
The training of the proposed YOLOv8 model for wheat disease detection was conducted using Google Colab with a Tesla T4 GPU (15,102 MiB



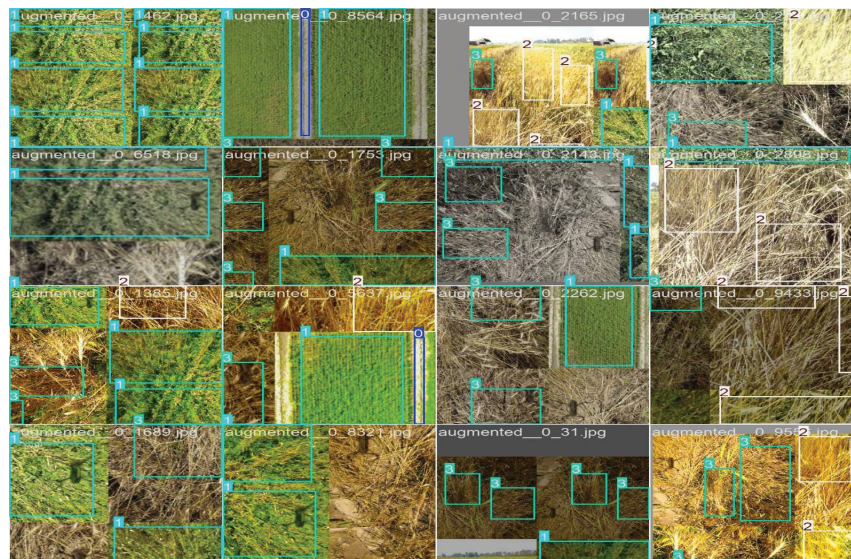
**Figure 2** Visualization of training bounding boxes detected by YOLOv8 model for wheat disease detection.

VRAM), which provided ample computational resources for handling the model's requirements. The training environment utilized YOLOv8.2.99, running on Python 3.10.12 and PyTorch 2.4.1 with CUDA support (cu121), ensuring compatibility with the hardware. This setup enabled efficient GPU acceleration, reducing training time and optimizing performance. The model architecture consists of 168 layers with 3,006,428 parameters, and no gradients were retained in the final fused model. The training involved setting the initial learning rate to 0.01, with a batch size of 16 to balance computational efficiency and learning. The model was trained for 100 epochs, using the Adam optimizer with a momentum of 0.9 and a weight decay of 0.0005 to prevent overfitting and improve generalization. The class 0 represents the "Ground", class 1 represents the "Healthy", class 2 represents the "Yellow Rust", and the class 3 represents the "Brown Rust". The Figures 2, 3, and 4 display the training samples of the YOLOv8 model. They provide a visual representation of the training process of the YOLOv8 model, showcasing its ability to detect multiple classes (ground, healthy, and diseased crops) across a variety of augmented images. The bounding boxes with class labels demonstrate how well the model has learned to localize and classify regions within drone-captured wheat field images.





**Figure 3** Visualization of training bounding boxes detected by YOLOv8 model for wheat disease detection.



**Figure 4** Visualization of training bounding boxes detected by YOLOv8 model for wheat disease detection.



### 3.6 Evaluation Metrics

Evaluation metrics are essential to assess the performance of an object detection model like YOLOv8. These metrics help to understand how well the model is detecting and classifying objects in images. For object detection tasks, especially for models like YOLOv8, the evaluation is generally based on precision, recall, average precision (AP), and mean average precision (mAP), along with additional performance indicators such as F1-score and inference time [37, 38].

**Precision:** Precision measures the accuracy of the positive predictions made by the model. In object detection, it is defined as the ratio of true positive detections (correctly detected objects) to all detections (true positives + false positives).

**Recall:** Recall measures the model's ability to find all the relevant objects in the images. In object detection, it is the ratio of true positives (correct detections) to the total number of ground truth objects (true positives + false negatives).

**Average Precision (AP):** Average Precision is a comprehensive metric that considers both precision and recall across different confidence thresholds. AP is calculated as the area under the precision-recall curve. The higher the AP, the better the model is at detecting objects at various confidence levels.

**Mean Average Precision (mAP):** mAP is the mean of the average precision values for all classes in a dataset. It is widely regarded as the primary performance metric for object detection models like YOLOv8. mAP is calculated by averaging the AP over different classes and Intersection over Union (IoU) thresholds [39, 40].

$$mAP = 1/C \int_{i=1}^C AP_i$$

- **Common mAP Thresholds:**

- **mAP at 0.5:** This evaluates AP with IoU set at 0.5, which means a detection is considered correct if the IoU between the predicted and ground truth box is at least 0.5.
- **mAP at [0.5:0.95]:** This evaluates AP across multiple IoU thresholds ranging from 0.5 to 0.95 in steps of 0.05, providing a more stringent and detailed evaluation of the model's performance.

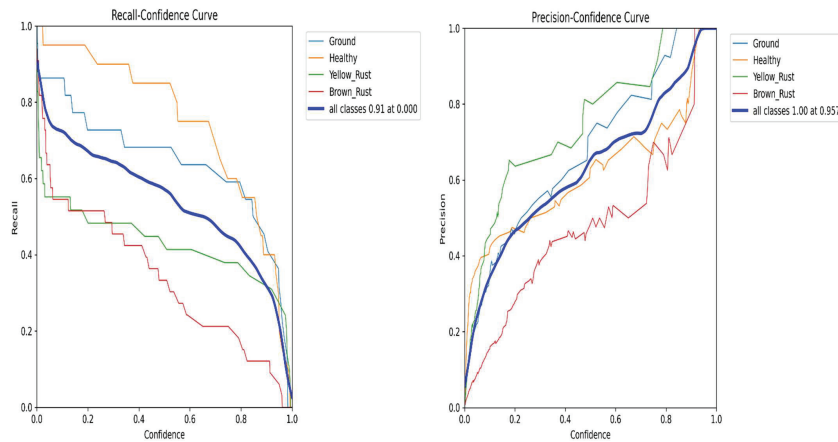
**F1-Score:** The F1-score is the harmonic mean of precision and recall, providing a single metric that balances both. It is especially useful when precision and recall are important, and neither can be neglected.

**Inference Time:** Inference time refers to the amount of time taken by the model to process an input image and produce a prediction. For real-time object detection applications, such as drone-based crop monitoring, inference time is crucial for assessing the model's efficiency.

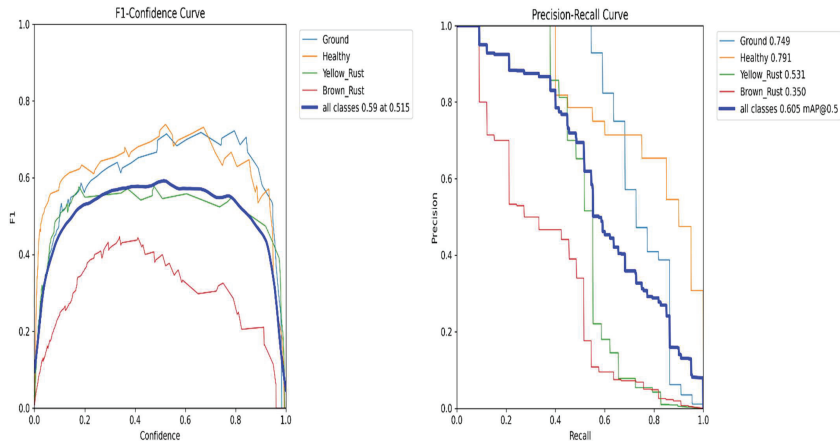
**Confusion Matrix:** The confusion matrix is a visualization tool used to understand the performance of a classification model. It summarizes the counts of true positives, true negatives, false positives, and false negatives across all classes [41–43].

## 4 Results And Discussion

Figure 5 presents the recall-confidence and precision-confidence curves, while Figure 6 shows the F1-confidence and precision-recall confidence curves. The graph represents four classes: Ground (blue), Healthy (orange), Yellow Rust (green), and Brown Rust (red). Recall-Confidence Curve for the different classes in the YOLOv8 model's evaluation, shows the relationship between recall and confidence for each class in the dataset. The thick blue line represents the combined performance of the model across all classes, with a recall of 0.91 at a confidence threshold of 0.0. This indicates strong overall detection ability when confidence thresholds are low. The YOLOv8 model



**Figure 5** Recall-confidence and precision-confidence curves for YOLOv8 model.

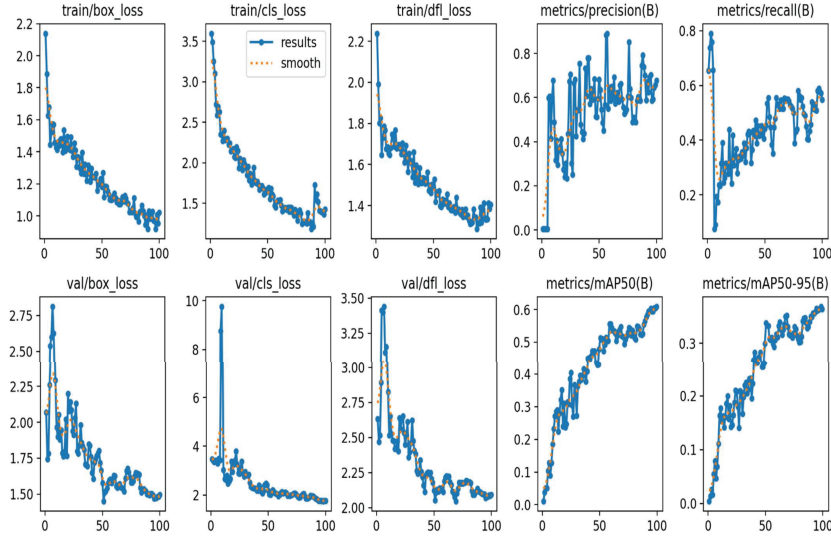


**Figure 6** F1-confidence and precision-recall curves for YOLOv8 model.

demonstrates strong detection capabilities, with high recall for healthy crops (above 0.8) even at higher confidence levels.

The precision-confidence graph demonstrates the precision for the four classes: Ground (blue), Healthy (orange), Yellow Rust (green), and Brown Rust (red), along with the overall performance (thick blue line). The thick blue line, representing the combined performance for all classes, shows that the model achieves perfect precision (1.00) at a confidence threshold of 0.957. The combined precision (thick blue line) reaches 1.00 at a confidence threshold of 0.957, demonstrating that at high confidence levels, the model makes highly accurate predictions across all classes. The YOLOv8 model achieves perfect precision (1.00) for all classes when operating at a high confidence threshold, emphasizing its capability to make highly accurate predictions with fewer false positives.

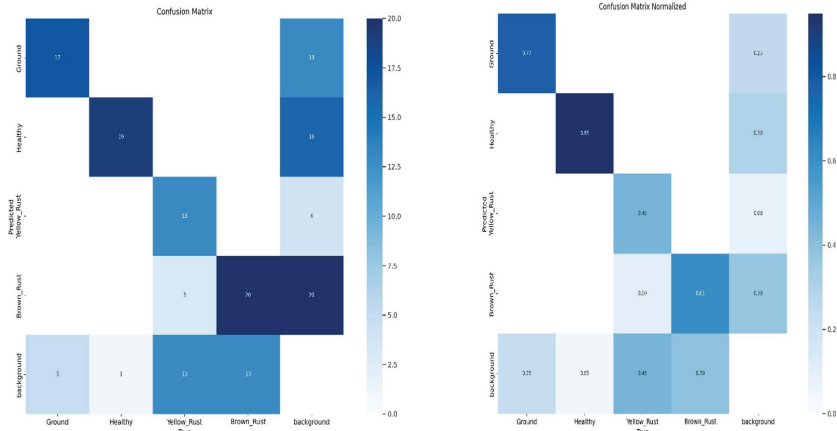
In Figure 7, the training and validation performance of the model for wheat disease detection across 100 epochs is shown. The training box loss decreased consistently from approximately 2.2 to 1.0 over 100 epochs. This indicates improved localization of bounding boxes as training progressed. The training classification loss reduced significantly from around 3.5 to approximately 1.0. This suggests the model effectively learned to classify the different wheat disease categories. The Distribution Focal Loss (DFL) loss steadily decreased from 2.2 to 1.3, reflecting improvements in bounding box regression. The validation box, classification, and DFL losses followed similar trends to the training losses. They started higher and gradually decreased to approximately 1.5, 2.0, and 2.0 respectively. Precision started at a moderate



**Figure 7** Training and validation performance metrics of the YOLOv8 model for wheat disease detection across 100 epochs.

level with some fluctuations but improved steadily. By the end of training, it stabilized at around 0.7. Recall also showed improvement, starting at 0.0 and increasing to approximately 0.55. This indicates the model's ability to correctly identify positive samples improved over time. The mAP@50 metric increased steadily from near 0.0 to approximately 0.7. This highlights the model's accuracy in detecting wheat diseases at high IoU thresholds. The mAP@50-95 metric also improved from near 0.0 to around 0.3. This reflects the model's robustness across varying IoU thresholds.

During the training phase, the model performs well for Healthy and Brown Rust, with high accuracy shown by diagonal values in both normalized and standard matrices (e.g., 0.95 for Healthy and 0.61 for Brown Rust). However, Yellow Rust is challenging to classify, with significant misclassifications into Brown Rust and Background. Ground and Background classes also show some confusion, likely due to visual similarities. Overall, the model demonstrates strong performance, but further optimization is needed to enhance the detection of Yellow Rust and minimize misclassifications. Figure 8 demonstrate model's overall strong performance, with notable strengths in detecting Healthy and Brown Rust. Table 1 provides a comprehensive summary of all the performance metric values, presented in a tabular format. Figures 9 to 12 display the training and validation images generated

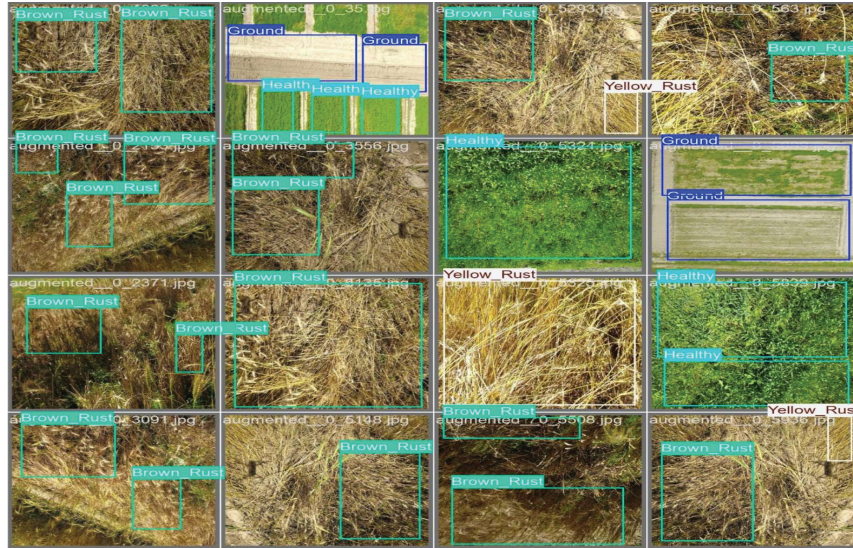


**Figure 8** Confusion matrices representing model performance.

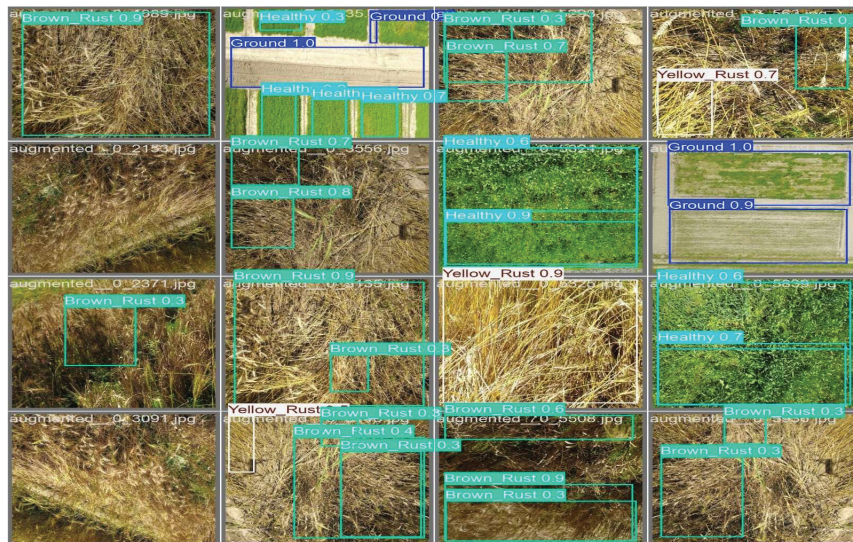
**Table 1** Training and validation performance metrics of the YOLOv8

Metric	Initial Value	Final Value	Trend
Training Box Loss	2.2	1.0	Consistently decreased, indicating improved bounding box localization.
Training Classification Loss	3.5	1.0	Significant reduction, reflecting better disease classification accuracy.
Training DFL Loss	2.2	1.3	Gradual decline, showing enhanced regression for bounding box coordinates.
Validation Box Loss	2.75	1.5	Decreased steadily, suggesting better generalization in localization.
Validation Classification Loss	10.0	2.0	Sharp decline, confirming effective disease classification on validation data.
Validation DFL Loss	3.5	2.0	Gradual reduction, reflecting improved generalization in bounding box regression.
Precision (B)	0.0	0.7	Increased steadily, indicating better identification of true positives.
Recall (B)	0.0	0.55	Improved consistently, reflecting the model's ability to capture more true positives.
mAP@50 (B)	0.0	0.7	Demonstrated steady improvement, highlighting accuracy at high IoU thresholds.
mAP@50-95 (B)	0.0	0.3	Improved gradually, reflecting robustness across varying IoU thresholds.



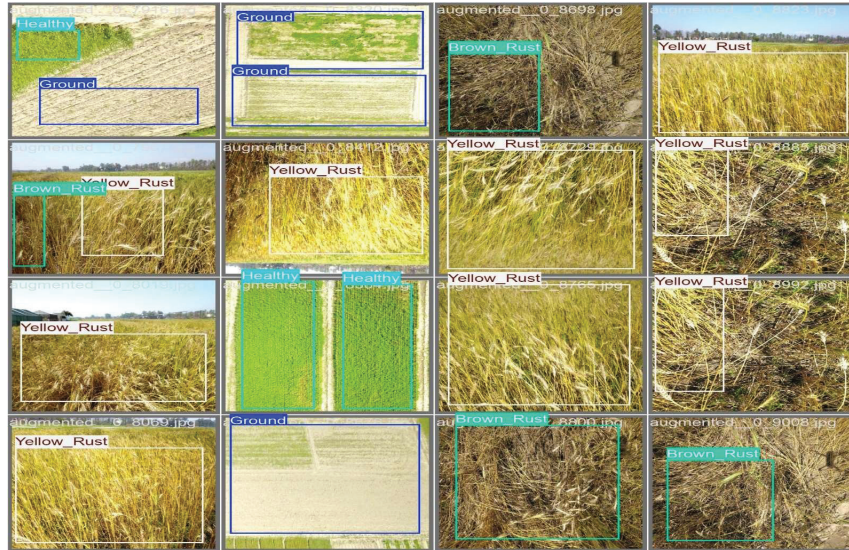


**Figure 9** Bounding box areas for various classes throughout the model training process.



**Figure 10** Detected classes during both the training and validation.





**Figure 11** Bounding box areas for various classes throughout the model training process.



**Figure 12** Detected classes during both the training and validation.

**Table 2** Performance metrics across all classes

Class	Images	Instances	Precision (P)	Recall (R)	mAP@50	mAP@50-95
All	78	104	0.661	0.572	0.605	0.367
Ground	11	22	0.724	0.682	0.749	0.372
Healthy	13	20	0.631	0.850	0.791	0.581
Yellow Rust	28	29	0.803	0.423	0.531	0.336
Brown Rust	26	33	0.484	0.333	0.350	0.181

after model training, highlighting the detected disease classes during both the training and validation phases.

During the validation, the model achieved a commendable precision of 0.661 and a recall of 0.572 across all classes. The mean Average Precision (mAP@50) is 0.605, reflecting the model's strong ability to localize and classify objects accurately. The mAP@50-95, a more stringent metric assessing localization performance across varying IoU thresholds, reached 0.367, providing a solid foundation for real-time applications like smart spraying. Table 2 below presents the overall performance across all classes.

**Ground Class:** The model performs exceptionally well in detecting ground areas with a precision of 0.724 and a high recall of 0.682, showcasing its ability to identify non-plant areas effectively. The mAP@50 score for this class is 0.749, indicating that the model provides accurate bounding box predictions with high confidence, making it suitable for excluding unnecessary areas from spraying. The mAP@50-95 score of 0.372 further validates its robustness in varying IoU thresholds.

**Healthy Class:** The model's detection of healthy plants is particularly strong, with an excellent recall of 0.850, demonstrating that it is highly effective at identifying healthy wheat plants. A precision of 0.631 and mAP@50 of 0.791 indicate that the model is reliably identifying healthy crops, contributing positively to overall field monitoring. The mAP@50-95 score of 0.581 shows that even at stricter IoU thresholds, the model maintains its accuracy, ensuring minimal misclassifications.

**Yellow Rust Class:** Yellow rust detection shows precision of 0.803, indicating the model's ability to make highly confident predictions for this disease. Though the recall is lower at 0.423, the model's precision in detection ensures that when it identifies yellow rust, it does so with a high degree of certainty. The mAP@50 of 0.531 indicates that the model still maintains reasonable detection performance, while the mAP@50-95 score of 0.336 suggests areas for further refinement in detecting this class at higher IoU thresholds.



**Brown Rust Class:** Although the brown rust class achieved a relatively lower precision of 0.484 and recall of 0.333, the mAP@50 score of 0.350 indicates that the model is still able to detect and localize brown rust cases. This is particularly significant given that brown rust detection is challenging due to its visual similarity to healthy crops in certain conditions. Despite this, the model shows room for improvement, and with further fine-tuning, its performance could improve in this area.

## 5 Discussion

The YOLOv8 model presented in this study for wheat disease detection demonstrates promising potential for real-time agricultural applications, particularly in precision farming and disease management. The model's performance across four distinct classes – Ground, Healthy, Yellow Rust, and Brown Rust – shows a high level of accuracy in identifying and classifying areas within the wheat fields, which is critical for tasks such as targeted spraying and crop monitoring. The overall model performance metrics, including a precision of 0.661, recall of 0.572, and a mAP@50 of 0.605, indicate that the YOLOv8 architecture is well-suited for detecting the defined classes with a high level of accuracy. These metrics provide confidence in the model's ability to effectively localize and classify different classes in real-world scenarios. The mAP@50-95 of 0.367 is also a solid baseline for agricultural applications, particularly given the complexity of drone-captured images, which include variations in lighting, crop density, and disease severity. The model's ability to detect the ground class is particularly strong, with precision at 0.724 and recall at 0.682. The model exhibited excellent performance in detecting healthy wheat plants, with a recall of 0.850 and mAP@50 of 0.791, demonstrating its capability to accurately identify unaffected crops. For the Yellow Rust class, the model achieved a precision of 0.803, showcasing its ability to make highly confident predictions when yellow rust is present. Although the recall is lower at 0.423, the model's high precision ensures that false positives are minimized. The detection of brown rust proved to be more challenging, with a precision of 0.484 and a recall of 0.333. Despite these lower values, the model was still able to achieve a mAP@50 of 0.350, indicating that brown rust was localized and detected to a reasonable extent.

These results underscore the applicability of the YOLOv8 model for real-time wheat disease detection in agricultural settings. The model's high precision for healthy crops and non-crop areas (ground) ensures that the system is reliable in distinguishing between diseased and non-diseased areas,

which is crucial for optimizing resource allocation in precision agriculture. The model's robustness in detecting yellow rust with high precision is particularly beneficial in managing this common wheat disease.

However, there is room for improvement, particularly in the detection of brown rust, where additional training or data augmentation techniques could help improve recall and overall detection accuracy. Similarly, optimizing the model to handle varying degrees of disease severity and visual complexities may further improve its performance, especially under different environmental conditions such as lighting and crop density variations.

In future work, we aim to refine the model through techniques such as transfer learning, where pre-trained weights can be fine-tuned on larger, more diverse datasets. Additionally, incorporating more advanced augmentation techniques and experimenting with different loss functions may help in balancing precision and recall, particularly for more challenging classes like brown rust. Furthermore, deploying the model in field conditions using drone-based real-time inference will provide valuable insights into its practical performance and areas for improvement.

The objective of integrating the model with smart spray drones aims to revolutionize crop disease management by automating detection and response processes in large-scale agricultural operations. YOLO, a real-time object detection algorithm, can be employed to identify early signs of crop diseases, pests, or other anomalies by processing high-resolution images captured by the drones. These drones, equipped with advanced sensors and cameras, can scan vast agricultural fields in a fraction of the time it would take for manual inspections. YOLO-based system can instantly identify and classify various disease symptoms, such as leaf discoloration or wilting, which are often subtle and difficult to detect with the naked eye.

The advantages of such a framework are numerous. First, it enables precise, data-driven decision-making by providing farmers with timely and accurate insights into the health of their crops. This eliminates the need for widespread pesticide use and reduces the risks of over-spraying, as the drones can deliver treatment directly to affected areas, optimizing resource use. Furthermore, the system's automation ensures consistent monitoring of large fields, reducing human error and labor costs. For example, in cotton farming, a smart spray drone integrated with YOLO could identify a localized infestation of worms and deploy targeted pesticide application, saving both time and cost compared to blanket spraying. This approach not only enhances crop yield but also promotes more sustainable farming practices by minimizing environmental impact.

## 6 Conclusion

The YOLOv8 model offers a highly effective solution for real-time wheat disease detection. Its strong performance in detecting ground areas and healthy crops makes it well-suited for use in precision agriculture, while its high precision in detecting yellow rust ensures accurate identification of diseased areas. The model provides a solid foundation for scalable, real-time agricultural applications that can enhance crop monitoring and disease management in wheat farming. The YOLOv8-based model can be integrated with farm management systems to assist farmers in making data-driven decisions. By providing real-time feedback on disease outbreaks and crop health, the system could guide spraying schedules, irrigation planning, and harvesting, leading to improved crop management efficiency. Future enhancements could involve integrating the YOLOv8 model with drone and satellite imagery for wider area surveillance and multi-spectral analysis. Additionally, incorporating temporal data and environmental parameters (such as humidity, temperature, and soil health) through IoT sensors could significantly improve disease prediction accuracy. Deploying the system via mobile or edge devices can make it more accessible to farmers in remote areas, promoting widespread adoption of smart farming technologies.

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## Biographies



**Km. Neha** holds a Master of Technology (M.Tech) degree from G.B. Pant University of Agriculture and Technology (GBPUAT), Pantnagar and she graduated from women institute of Technology dehradun in 2017 in computer science engineering with a strong academic background and a keen interest in the intersection of technology and agriculture, her research area is drone technology in smart agriculture. She is currently serving as an assistant professor at DIT University, where she is actively involved in teaching and research related to emerging technologies in agriculture.



**Akash Arya** is a dedicated Master of Technology student and researcher in the Department of Computer Engineering at G.B. Pant University of

Agriculture and Technology, Pantnagar, Uttarakhand, India. His research interests lie at the intersection of Agricultural Sciences and Artificial Intelligence, with a focus on leveraging AI technologies to address real-world challenges in agriculture. Driven by a commitment to innovation and academic excellence, Mr. Arya contributes significantly to the advancement of AI applications in precision farming, crop prediction, and sustainable agricultural practices. His work exemplifies a strong interdisciplinary approach, and he continues to serve as an inspiration to aspiring researchers in the fields of computer engineering and agricultural technology.



**Rajeev Singh** is currently working as Professor in the Department of Computer Engineering, G. B. Pant University of Ag. & Technology, Uttarakhand (India). He has more than 20 years of teaching experience. He received his Ph.D. Degree from N.I.T. Hamirpur (H. P.) and M. Tech. Degree from Indian Institute of Technology, Roorkee, both in Computer Science and Engineering. His research interest includes information systems, computer networks, network security, IoT, and Drones. He has guided more than 18 M.Tech. students. He has published several book chapters and research papers in journals and conferences of repute.